

Both selection and plasticity drive niche differentiation in experimental grasslands

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The way species avoid each other in a community by using resources differently across space and time is one of the main drivers of species coexistence in nature^{1,2}. This mechanism, known as niche differentiation, has been widely examined theoretically but still lacks thorough experimental validation in plants. To shape niche differences over time, species within communities can reduce the overlap between their niches or find unexploited environmental space³. Selection and phenotypic plasticity have been advanced as two candidate processes driving niche differentiation^{4,5}, but their respective role remains to be quantified⁶. Here we tracked changes in plant height, as a candidate trait for light capture⁷, in 5-year multispecies sown grasslands. We found increasing among-species height differences over time. Phenotypic plasticity promotes this change, which explains the rapid setting of differentiation in our system. Through the inspection of changes in genetic structure, we also highlighted the contribution of selection. Altogether, we experimentally demonstrated the occurrence of species niche differentiation within artificial grassland communities over a short time scale through the joined action of both plasticity and selection.

Niche differentiation (ND) occupies a central place in community and ecosystem ecology, explaining the maintenance of biodiversity^{1,2,8} and its positive effects on ecosystem functioning, through complementary of resource use^{9,10}. However, the mechanisms underlying ND dynamics remain unclear, particularly those explaining how each species shapes its niche through community assembling. A species niche can be described by traits that indicate how resources are strategically acquired from the environment¹¹⁻¹³. Niche differentiation is then expected when the dispersion of trait values for each species do not overlap to avoid direct competition between similar plant strategies¹⁴⁻¹⁶. This occurs either, in the case of a fixed community trait range, by constraining the average dispersion of trait values expressed by each species¹⁷, or by modifying the trait values outside the dispersion of community trait values to discover a previously unexploited environmental space¹⁸. As different species within a given community can follow both routes, the study of ND dynamics requires consideration of both

the trajectory and the deformation of the niche, i.e. the temporal change in the position and the
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33 breadth of the species niche. To our knowledge, this has not previously been done
34 experimentally. Niche differentiation dynamics may result first from the competitive exclusion
35 of phenotypes located in the overlapping part of the niche. This is expected when plasticity is
36 not sufficient to avoid species overlap¹⁹. Niche differentiation may also result from the selection
37 of phenotypes that plasticity placed in unexploited environmental space¹⁹. Although genetic
38 mechanisms play key roles in the process of ND, studies that focus on it are rare^{20,21}. The time
39 scale at which the process occurs remains particularly unclear, ranging from a single growing
40 season and stretching out to evolutionary time. Time scale likely reflects a gradient between the
41 ecological and the genetic shaping of the niche.

42 Our objective was to display ND dynamics by monitoring species trait variation over five years
43 in multispecies sown grasslands. Using seven species commonly used in sown grasslands, five
44 mixtures were assembled and sown in field trials as described in Meilhac, et al. ²². The five
45 mixtures (M-1 to M-5) varied only in within-species genetic diversity (i.e. the numbers of
46 cultivars represented per species). There were three genetic structure levels: simple structure
47 (M-1 to M-3), intermediate structure (M-4) and complex structure (M-5). Species were chosen
48 to be of contrasting strategies in relation to light capture in order to promote a ND among
49 vertical space between them: (i) a classical vertical-elongation strategy to maximise access to
50 the above-canopy light (*Lotus corniculatus*, *Dactylis glomerata*, *Festuca arundinacea*,
51 *Trifolium pratense* and *Medicago sativa*) and (ii) a horizontal-spreading strategy to maximise
52 access to the light penetrating vegetation gaps (skylights)^{23,24} (*Lolium perenne* and *Trifolium*
53 *repens*).

54 To create a measurable selection opportunity, the within-species phenotypic variability of
55 competitive traits was similar between mixtures (similar range trait variability) but the within-
56 species genetic structure was dissimilar (see Table S1, Fig. S1 and S2 in supplementary
57 information), this genetic diversity is not necessarily synonymous with phenotypic diversity.
58 Using molecular tools, we followed the dynamics of cultivar abundance of each species during
59 community assembling by a molecular method of cultivar fingerprinting (see Methods section).
60 In this experiment, the effects of cultivar frequency change (selection estimation) on ND were
61 tested. In parallel, the heights of each cultivar was characterised without competition in a
62 common garden in order to relate cultivar selection to relate species strategy in the ND process
63 (see Methods section).

64 Species distribution of vegetative height was monitored over time within each mixture to
65 characterise the shaping of the species niche^{25,26}. Vegetative height is a key plant feature widely
66 used in the literature to characterise the light-acquisition strategy⁷ to express the plant
67 competitive ability over neighbours²⁷ and to explain a species ability to perform in a grassland
68 community^{7,28-31}. It is also associated with the competition – colonization trade-off for clonal
69 plants opposing a strategy competing for vertical space to a strategy competing for horizontal
70 space^{32,33}. As observed in literature^{34,35} and in our dataset (Fig. S5), plant height covaries
71 negatively with tiller density and lateral spread at the interspecific level. Hence, we assume
72 plant height is the key candidate trait to characterise a dimension of the species niche³⁶. We
73 modelled the temporal dynamics of height niches of all species using Bayesian Generalised
74 Additive Distributional Models (GAM). We determined by model selection procedure based
75 on the Watanabe-Akaike-Information Criterion (an unbiased measure of the log posterior
76 predictive density of models, see *Methods*) if the niche dynamics differed for each species in
77 terms of both mean trajectory and of niche deformation (dilatation or contraction).

78 From an overlapped distribution of species height for all mixtures studied (Fig. 1a - year 1),
79 three distinct trajectories appeared over time (Fig. 1b), which were linked with known strategies
80 of light capture (Fig. 1b), but were independent of mixture identity (Table 1, mod_{div} does not
81 improve significantly the predictive power). Our results show that the partitioning of vegetative
82 height distribution was strongly species-specific, the model describing a trajectory for each
83 species ($\text{Mod}_{t,\mu}$) providing a far higher predictive power than Mod_t estimating a common
84 trajectory for all species (Fig. 1b, Table 1, $\Delta\text{WAIC } \text{Mod}_t - \text{Mod}_{t,\mu} = 1851 \pm 80$; Table S6). *L.*
85 *corniculatus* and *M. sativa* rose above the canopy between years one and five. Conversely, *T.*
86 *repens* and *L. perenne* clearly adopted a different strategy, spreading at a low canopy level
87 seeking for skylights. Meanwhile, *F. arundinacea* and *D. glomerata* remained at canopy level
88 during the five-year experiment, exploiting the light by their position relative to the canopy (as
89 having the highest biomass proportion in the community²²). It is worth noting that *T. pratense*
90 stayed at canopy level but was excluded by year five in line with its lower lifetime character.

91 Niche trajectories were tightly linked with niche deformation. The best model describing the
92 distribution of plant height was the one where both mean and dispersion of each species
93 depended upon a smooth time-function (Fig. 1, Table 1, $\Delta\text{WAIC } \text{Mod}_{t,\mu} - \text{Mod}_{t,\mu,\sigma} = 230 \pm 33$;
94 Table S6). Species niche deformation through time clearly reduced the general overlap of height
95 distribution and structured the exploitation of light through the canopy (Fig. S6). The species
96 that climbed above the canopy (*L. corniculatus* and *M. sativa*), exhibited loss of small

97 individuals and a clear increase in dispersion of height values with time (Fig. 2a). This niche
98 dilatation showed a relaxation of competition intensity for the species able to dominate others
99 and bypass light reduction by other species. Conversely, the diversity of height values of the
100 species spreading at ground levels for skylights (*T. repens* and *L. perenne*), drastically
101 decreased with time, indicating a contraction of their niche for species known to be poor
102 competitors for light in the presence of other species²⁴. Competitive pressures of species could
103 generate a displacement of niches either by plasticity or by selection in order to reduce light
104 competition by a displacement towards tallest values for species with vertical elongation
105 strategies and conversely towards small values for species with horizontal spreading strategies,
106 potentially linked to a resource allocation strategy³⁴. For instance, *T. repense* favours stolon
107 extension when under light competition with grass species³⁷.

108 From both the trajectory and the deformation of species height niches, we conclude that ND
109 has occurred between species during the assemblage of our temporary grassland communities
110 (Fig 1). Niche contraction occurred for some species while niche dilation occurred for others
111 along a unique resource dimension of species niches. Interestingly, the dynamics of species
112 niche, paralleled their dynamics in abundance in the community (Fig. 3), suggesting the
113 important role of ND during the community assemblage, as observed in other studies²⁰. Unlike
114 what is often expected when ND is increased between species, we did not observe a general
115 reduction of trait dispersion within species, explained by increases in total community variance
116 that strongly separate species niches without requiring their contraction. Moreover, the overlap
117 between species having similar (previously-known) light strategies was almost total.

118 Phenotypic plasticity (including ontogeny) and selection are major adaptive mechanisms that
119 contribute to niche shaping^{38,39} but their identification and relative importance in ND is unclear.
120 Using a Bayesian GAM approach, we tested if the addition of cultivar relative frequencies
121 (proportion of each cultivar) into our previous best model describing the distribution of plant
122 height (Table 1 – Mod_{t,μ,σ}; Table S6) improved the dynamics of species niche shaping.

123 Over the five-year period, cultivar dynamics within a grassland community contributed
124 significantly to the shaping of species niches. When changes in cultivar abundances were
125 included in the GAM model to modulate the mean and dispersion of plant height distribution,
126 the performance of the model was significantly improved (Table 1 Δ WAIC Mod_{t,μ,σ} - Mod_{t,prop};
127 = 82±21; Table S6). Interestingly, we observed the changes in cultivar frequencies and the
128 disappearance of height values of the initial niche of species were related to the light strategies

129 of the species. The cultivar frequencies showed significant evolution (Fig. 2) for most species
130 over the five-year period, mainly due to differential mortality between cultivars and vegetative
131 multiplication (sexual reproduction was limited in this experimental design – see the proportion
132 of individuals no-assigned in Table S2). Species with a horizontal spreading strategies and
133 showing niche contraction towards lower height values were characterised by decreases in the
134 abundance of the highest stature cultivars (V3 for *T. repens* and V5 and V6 for *L. perenne*) and
135 increases in the lowest stature cultivars (V2 for *T. repens* and V1-V2 for *L. perenne*).
136 Conversely, *M. sativa*, which has an elongation strategy, showed niche dilatation towards
137 greater height values and was characterised by the opposite response. Although contrasting
138 trends were observed (V1 for *T. repens* was expected to increase and conversely V1 for *M.*
139 *sativa* was expected to decrease but was not observed), they remained exceptions. Similar
140 results were obtained with the mixture characterised by medium genetic-complexity (see Fig.
141 S3 in Supplementary Information). This result suggests selection exists at cultivar level for most
142 species and this contributed to ND, although no change was observed for *D. glomerata* or *T.*
143 *pratense*. However, it could be that our selection estimation was not fine enough, as selection
144 within a cultivar may well exist.

145 While temporal changes in niche position and breadth, i.e. ND, were mainly the result of
146 phenotypic plasticity, we show here that selection also acted to shape the species niches along
147 the light-capture dimension. Strong similarities in species trajectories between mixtures
148 excluded genetic drift as driver of ND (see Figure S7 in supplementary information). Selection
149 was observed over the five years of experimentation. This is a very short period in relation to
150 evolutionary time and it would be interesting to study the impacts of this selection over longer
151 time scales. As the niche of species is multidimensional, other dimensions of the niche also
152 need to be investigated to better understand the cultivar selection of these species. For instance,
153 plant precocity and root preference for nitrate vs ammonium as the nitrogen resource has
154 previously been shown to structure grassland communities³⁵. Although our study focused on
155 ND at species level, similar processes could be observed at within-species level under the
156 pressure competition between genotypes belong to the same species.

157 Originally, our results experimentally demonstrated that genetic selection is related with
158 ND over a very short time scale. This offers a highly promising avenue for community ecology
159 showing for the first time that ND is truly associated with evolutionary fitness. In addition,
160 these results could be important in agro-ecology, especially to assemblages in communities in
161 the context of species diversification of agro-systems. If the limiting resources and plant traits

162 linked to the capture of this resource are known, the species and genetic composition of sown
163 grassland can be thought of as favouring niche differences between species. As ND should be
164 linked with the production stability of ecosystems²², having a good understanding of these
165 processes is key to improving the management of these⁴⁰.

166

167 **Methods**

168 **Experimental design.** The experimental design consisted of five different multispecies-
169 grassland seed mixtures, which were established in the field in September 2011. This design
170 was a subset, randomly selected, of the one in Meilhac, et al. ²² to limit logistic and financial
171 load associated with fingerprint. Seeds were sown in plots (5×1.3 m) in once time with two
172 replicates (five seed mixtures x two replicates = 10 plots). The soil was a clay-limestone, located
173 at the Jouffray Drillaud Station, Saint Sauvant, France (46° 21' 37" North, 0° 03' 25" East).
174 Plots were exposed to the local temperate climate with an average annual rainfall of 730 mm.
175 No irrigation or nitrogen were added during the five-year experimental period. The low weed
176 biomass during experiment (see figure S4 in supplementary information) and species nature
177 (*Crepis sancta* was a rosette plant form type and not in competition for light) no justified a
178 particular management. A plot comprised eight 5-m-long rows, each containing the same seed
179 mixture. Each mixture contained seven perennial species, all of them in common use in
180 temporary grasslands and are known to naturally exhibit high level of phenotypic plasticity -
181 *Lotus corniculatus*, *Dactylis glomerata*, *Festuca arundinacea*, *Trifolium pratense*, *Medicago*
182 *sativa*, *Lolium perenne* and *Trifolium repens*. The five mixtures differed in within-species
183 genetic diversity. This was achieved by varying the number of cultivars per species (see Table
184 S1, supplementary information). The range of variability of phenotypic traits was similar
185 between mixtures but the genetic structure was different. Three mixtures (M-1, M-2 and M-3)
186 were of simple genetic structure within each species (just one cultivar per species), one mixture
187 (M-4) had an intermediate genetic structure within each species (just two or three cultivars per
188 species) and one mixture (M-5) had a more complex genetic structure within each species (up
189 to six cultivars per species and containing all the cultivars used in this experiment). Each seed
190 mixture was sown with the same total seed weight and species proportions in each plot (Table
191 S1, supplementary information). Each mixture plot was replicated twice from the same seed
192 lots and plots were distributed randomly within two blocks of five plots each. Plots were
193 maintained over five years and harvested three times each year. Species were chosen to have
194 contrasting response strategies to light competition and space occupation. The first group

195 contained species having an elongation strategy - *Lotus corniculatus*, *Dactylis glomerata*,
196 *Festuca arundinacea*, *Trifolium pratense* and *Medicago sativa* – these all seek light by
197 extending their leaves or stems upwards to reach the top of the canopy. The second group
198 contained species having a spreading strategy i.e. they seek skylights in the community by
199 spreading horizontally - *Trifolium repens* (stolons) and *Lolium perenne* (tillers). The vegetative
200 height mean and variance of each cultivar was measured without competition in a common
201 garden at the INRA station in Lusignan (near Saint Sauvant), France (see cultivar
202 characterisation section).

203 **Phenotypic diversity in the mixture.** Vegetative height was measured *in situ* on 20 individuals
204 per species in each plot and each block. To limit the measure individuals from the same seed,
205 each plot was divided into four subplots. In each of its subplots, five most visible individuals
206 and most separated were measured. These measurements were carried out several times –
207 during the first, second, third and fifth years after sowing to quantify changes in phenotypic
208 diversity over time.

209 **Species biomass in a mixture.** For the five years of the experiment (2012 to 2016) the whole
210 canopy of each plot was harvested three times each year (spring, summer and autumn), limiting
211 sexual reproduction and by consequence the recruitment from seeds. Vegetative multiplication
212 was possible for some species, especially for *T. repens* and *F. arundinacea*. The annual species
213 biomass data came from the study of Meilhac, et al. ²² where all details, including harvesting
214 dates, methods and treatment procedure of samples, are described. All plots were cut at the
215 same time at 5 cm above ground level. Harvest date was decided based on a visual assessment
216 of the aboveground standing biomass. Each harvest from each plot was weighed fresh and a
217 sample of each was dried to constant weight at 60°C for 72 h. At each harvest, four quadrats
218 (0.33 x 0.15 m) were placed randomly in each plot and the species biomasses were separated.
219 These samples were dried and weighed to measure the proportion each species in the total dry
220 biomass. For each plot and each year, the annual total biomass (for all species) and annual
221 species biomass (for each species) were calculated by summation of the three biomass
222 measurements (spring, summer and autumn).

223 **Cultivar characterisation.** Simultaneously, each cultivar used in the mixtures was planted in
224 an isolated-plants nursery at INRA (2014 September). The seed was taken from the same lot as
225 used in the mixtures. Each cultivar was represented by 30 individuals and each individual was
226 cloned to realise three genetically-identical replicates. A total of 32 cultivars of the seven

227 species was planted. Each individual was harvested three times each year (spring, summer and
228 autumn). Vegetative height was measured twice a year over three years for each plant to
229 characterise each cultivar (mean height and variance) under conditions of no competition.

230 **Selection estimation by cultivar fingerprinting.** Individuals within each species were
231 sampled three times during the experiment in the mixtures (M-4 and M-5) containing within-
232 species genetic diversity - at six months, and at three and five years after sowing. The number
233 of individuals sampled per species varied according to genetic structure (the number of cultivars
234 per species in the mixture at sowing). A total of 16 individuals were collected per cultivar used,
235 i.e. 32 individuals for the species with two cultivars per species and 96 individuals for species
236 with six cultivars per species (Table S2, supplementary information). Individuals were assigned
237 to cultivars by genome fingerprinting in two steps, with a first step constructing a reference
238 source and second step comparing it to individuals profile sampled *in situ*. This reference
239 database was constructed from 96 individuals per cultivar taken from the same seed batches of
240 cultivars as used in the plots. Seeds were sowed in germination plates and individuals were
241 sampled from first leaves. Extraction of DNA employed CTAB and chloroform purification
242 (CYMMIT, 2005). The quality and concentration of each DNA sample was checked by 1%
243 agarose gel electrophoresis. The choice of the type of markers has been dependent on the
244 species ploidy level, the available markers and the polymorphism of markers. SSR markers
245 were used for *Lolium perenne* (diploid) and we developed and used AFLP markers for the other
246 species (tetraploid). For SSR markers, DNA samples were amplified by polymerase chain
247 reaction (PCR) for the six loci used to discriminate the six *Lolium perenne* cultivars used in the
248 mixture (Table S3, supplementary information). PCR was carried out in a final reaction volume
249 of 10 µl containing 1X polymerase buffer, 0.325 U of MP Biomedicals polymerase, 0.2 mM of
250 dNTP (Invitro-gen), 0.1 µM of forward primer with a M13 tail, 0.2 µM of reverse primer, 0.1
251 µM of M13 tail IRD700 or IRD800 labelled primer and 20 ng of DNA. The PCR reactions were
252 carried out in a DNA Engine Tetrad2 thermocycler (Biorad). A denaturation period of 4 min at
253 94°C was followed by 35 cycles of 30 s at 94°C, 1 min at T_m (65°C – 1°C/cycle) and 1 min at
254 72°C and then 10 min at 72°C for final extension. For AFLP markers, the protocol described
255 by Vos, et al. ⁴¹ was used. The selective amplification was carried out on the basis of the primer
256 pair generating maximum polymorphism between cultivars. The number of specific primer
257 pairs used varied between species from 2 to 10 pairs (Table S4, supplementary information). A
258 Li-Cor IR2 (Li-Cor Inc) sequencer was used to separate the labelled, amplified DNA fragments
259 on a 6.5% acrylamide gel. Marker segregation was scored using SAGA Generation 2 software

260 (Li-Cor Inc) by two different persons and the results were compared. The number of bands
261 scored to provide a cultivar assignment with an error rate of less than 5%, varied with species
262 from 78 to 380 scored bands (Table S4, supplementary information). The same protocol (SSR
263 or AFLP according to species) was carried out on individuals sampled *in situ* (multi-cultivar
264 mixture). Assignment of individuals sampled *in situ* was done by comparison of their genetic
265 profile to it of cultivars from database source. For *Lolium perenne*, individuals sampled *in situ*
266 were attributed to cultivars with GeneClass2 software⁴² from reference source and according to
267 Bayesian method of Rannala and Mountain⁴³ and with the Distance method developed by Nei,
268 et al.⁴⁴. For other species, to analyse AFLP data, we used Structure software⁴⁵, based on
269 methods for ambiguous genotype data such as dominant markers⁴⁶ (Version 2.3.4) with a
270 systematic Bayesian clustering approach applying Markov Chain Monte Carlo estimation.
271 According to species, we used admixture model with the length of burn-in period was 2.10^4
272 iterations and the number of MCMC after burn-in was 5.10^4 iterations for all species except
273 *Festuca arundinacea* (10^4 iterations) and *Medicago sativa* (2.10^4 iterations). In order to assign
274 individuals to cultivars, the means of the permuted matrices across replicates were computed
275 using CLUMPP software⁴⁷. From these assignment, the cultivar proportion was then calculated
276 for each species in each block for the medium and high-diversity mixture (M-4 and M-5) and
277 excluding ambiguous genotypes (i.e. genotypes that not clearly assigned to a cultivar - Table
278 S2 and S5) to the calculations.

279 **Statistical analyses.** Species trait distributions were modelled explicitly using a distributional
280 modelling framework (similar to the GAMLSS approach). This allowed modelling of each
281 parameter of a parametric distribution as the result of an equation containing hierarchical
282 parameters and smoothing functions. Because the complexity of such models can hardly be
283 captured by classical maximum-likelihood methods, parameters were estimated in a Bayesian
284 framework using Hamiltonian Monte-Carlo, as implemented in the *No-U-Turn* sampler
285 (NUTS) of the *Stan* software. We described the variation of species trait distribution with
286 models of increasing complexity, including time and genetic selection effects successively. We
287 compared models using Watanabe-Akaike-Information-Criterion (WAIC) (see below) to
288 identify the niches characteristics and the covariables that had an effect of them.

289 Species trait distributions were described using gamma distributions parameterised in terms of
290 two independent parameters describing mean (μ) and dispersion (ϕ). Gamma distributions have
291 the advantage of being able to describe a skewed distribution, which often arise in the case of

292 strictly positive random variables close to 0. The gamma distribution from which the height
293 value y of individual i is sampled followed the general formulation

$$\begin{aligned} 294 \quad y_i &\sim \text{Gamma}(\mu_i^2 \phi_i, \mu_i \phi_i) \\ 295 \quad \log(\mu_i) &= \beta_f X_i + \beta_r X_i + f_1(t_i) \\ 296 \quad \log(\phi_i) &= \gamma_f X_i + \gamma_r X_i + f_2(t_i) \end{aligned}$$

297 With X_i being a design matrix of covariates describing the environment of observation i , while
298 β_f and γ_f are fixed parameters, such as intercepts for block identities (all models) for mean (β_f)
299 and dispersion (γ_f). Similarly, β_r and γ_r represent hierarchical population parameters described
300 by a normal distribution with estimated standard deviation, for mean (β_r) and dispersion (γ_r).
301 In our case, the hierarchical parameters describe varying intercepts of mixture (all models),
302 species (all models except Mod_{div}) or species at different levels of genetic diversity (Mod_{div}),
303 but also varying slopes between cultivar proportion in each mixture and height distribution
304 ($\text{Mod}_{\text{t,prop}}$). f_{1s} and f_{2s} , describe cubic splines linking years to mean and dispersion of each
305 species trait distribution. Mod_t estimates a common spline for all species for both mean and
306 dispersion, while $\text{Mod}_{t,\mu}$ estimates a spline per species for mean only. $\text{Mod}_{t,\mu,\sigma}$, $\text{Mod}_{t,\mu,\sigma'}$ and
307 $\text{Mod}_{t,\text{prop}}$ estimate a spline per species for both mean and dispersion. Mod_{div} estimates a spline
308 per species for each level of within species genetic diversity (one cultivar per species, up to
309 three cultivars per species or up to six cultivars per species). Data of year 2 was excluded for
310 models Mod_0 , $\text{Mod}_{t,\mu,\sigma'}$ and $\text{Mod}_{t,\text{prop}}$ because no cultivar proportion was estimated this year.
311 We used regularising priors to optimise estimation and limit overfitting, based on student-t
312 distributions with three degrees of freedom and adjusted mean and scale.

313 The posterior of each model was sampled using the NUTS algorithm through the *brms* R
314 package (version 2.2.3), which allows easily computed predictions and provides links to the
315 model comparison package *loo* (version 2.0.0). The Stan Bayesian software provides
316 diagnostics for sampling abnormal behaviour and chain mixing. We took care to avoid
317 divergent transitions. We ensured convergence, by verifying that the scale reduction factor of
318 each parameter (indicating chain convergence), did not exceed 1.1. Posterior predictive checks
319 were carried out to ensure the model captured the key features of the data satisfactorily.

320 Model comparisons were carried out using Watanabe-Akaike-Information-Criterion (WAIC)
321 implemented in the *loo* package. This criterion can be interpreted as the Akaike-Information-
322 Criterion, with the best models are those with the lowest criterion. Both criteria provide an

323 unbiased measure of the expected log posterior predictive density. However, WAIC estimate
324 the effective number of parameters estimated during model fitting, which makes its use accurate
325 for hierarchical models. It also incorporates uncertainty arising from parameters estimation, and
326 is thus described by an approximately normal distribution with estimated standard-error⁴⁸. We
327 interpreted the magnitude of the difference of the WAIC of different models (Δ WAIC), but also
328 the uncertainty about this difference. During comparison of nested models of increasing
329 complexity, a Δ WAIC that was lower than twice its standard-error (approximately equivalent to
330 the 95% confidence interval) was considered to provide little support for the more complex
331 model. All computations were carried out using *R* version 3.4.4.

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450

451 **Acknowledgements**

452 The authors thank, Vincent Beguier, head of research at the Jouffray Drillaud Company (Saint
453 Sauvant, France) and his technical team for the installation of the experiment, the URP3F
454 technical team and particularly Dominique Dénoue and Brigitte Bonneau who provided
455 important experimental assistance. The authors thank four anonymous referees and the
456 Associate Editor for their relevant comments on the manuscript. The Agence Nationale de la
457 Recherche, France (PRAISE, ANR-13- ADAP-0015) funded this work. Julien Meilhac was
458 supported by the Region Poitou Charente and INRA (BAP division and MP EcoServ) for his
459 PhD salary. VM and LD were supported by the Natural Sciences and Engineering Research
460 Council of Canada (NSERC-Discovery-2016-05716).

461 **Author contributions**

462 I.L. initiated the research question, obtained the funds and led the working group. I.L., J.M.,
463 and S.F. collected the data and J.M. and S.F. organised the dataset and all authors coordinated
464 the analyses. J.M., I.L., V.M. and L.D. drafted the manuscript and all authors contributed to the
465 final manuscript.

466 **Author Information**

467 Supplementary information is available online. Reprints and permissions information is
468 available at www.nature.com/reprints. The authors declare no competing financial interests.
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470 chiarelli@inra.fr).

471 **Table 1 | Models describing the dynamics of species-niches, trough time and genetic**
 472 **selection**

Models	Specific mean (μ)	Specific dispersion (σ)	Time (t)	Genetic Diversity (div)	Cultivar proportion (prop)	WAIC (\pm s.e)	ΔWAIC (\pm s.e.)
Model selection - niches							
Mod ₀						27452 (\pm 84)	3392 (\pm 96)
Mod _t			X			26142 (\pm 105)	2081 (\pm 80)
Mod _{t,μ}	X		X			24290 (\pm 108)	230 (\pm 33)
Mod _{t,μ,σ}	X	X	X			24060 (\pm 101)	45 (\pm 33)
Mod _{div}	X	X	X	X		24014 (\pm 101)	0
Model selection - genetic selection							
Mod _{0'}						42178 (\pm 100)	5871 (\pm 119)
Mod _{prop}					X	42001 (\pm 102)	5694 (\pm 119)
Mod _{t,μ,σ'}	X	X	X			36389 (\pm 133)	82 (\pm 21)
Mod _{t,prop}	X	X	X		X	36306 (\pm 133)	0

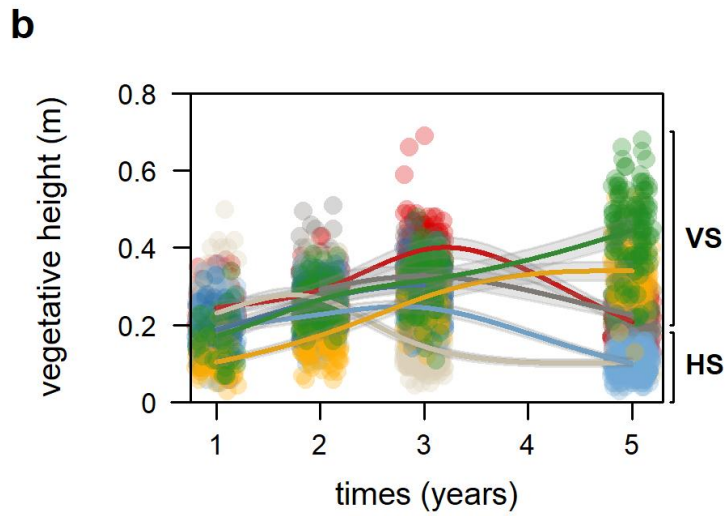
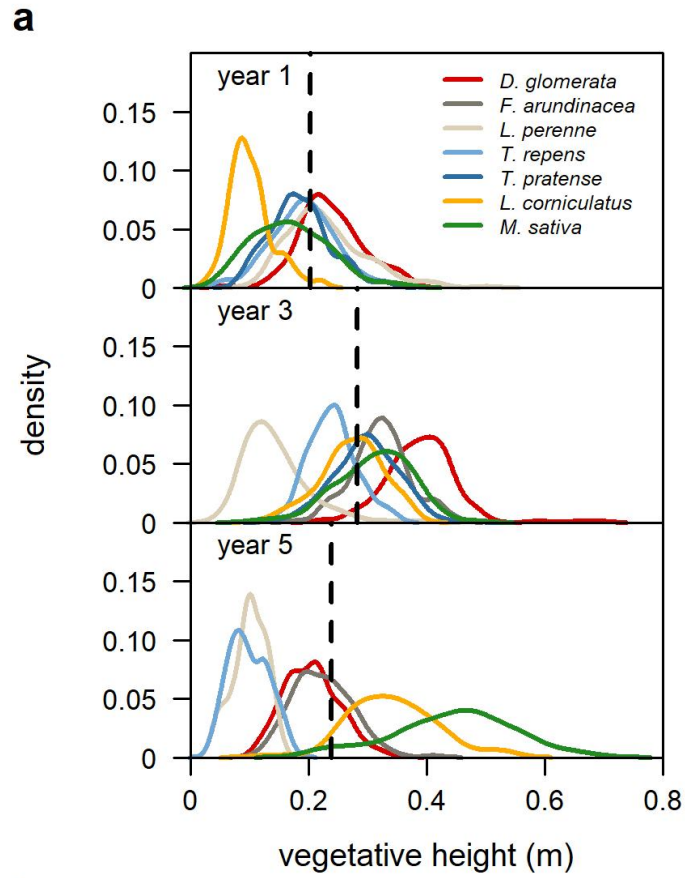
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474 **Legends of figures**

475 **Figure 1 | Niche differentiation.** **a**, Density distribution of vegetative heights between species
476 at respectively one, three, and five years after sowing the mixtures. Dotted line represents
477 average height of mixtures giving the approximate canopy height (average height of all species
478 combined). One species (*Festuca arundinacea*) is missing at the beginning as its establishment
479 took more time and *Trifolium pratense* had disappeared by the fifth year. **b**, Modelled mean
480 height of each species, with shaded area representing 95% credible interval around the mean
481 after accounting for variability between mixtures. HS indicates species with a horizontal
482 strategy and VS with a vertical strategy.

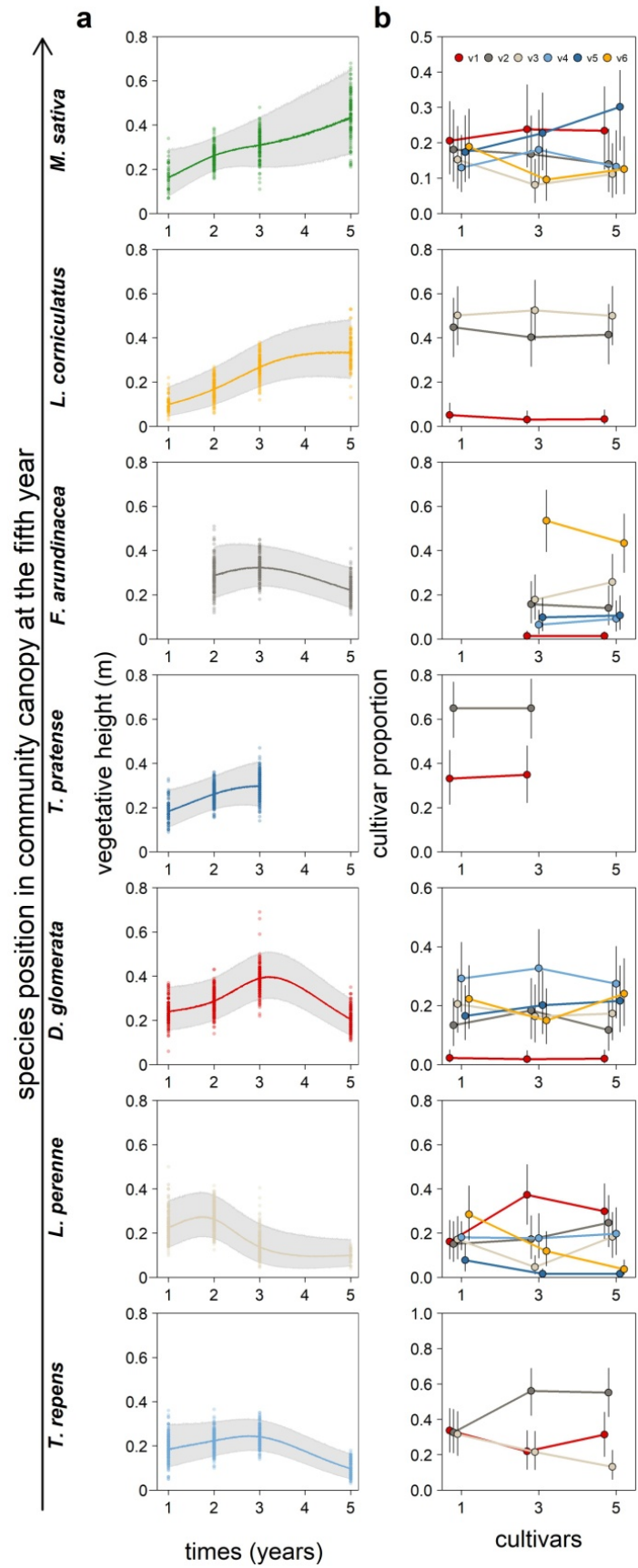
483 **Figure 2 | Phenotypic and genotypic dynamics over the five years of experimentation.** **a**,
484 Evolution of species trait distribution over time. Solid line represents the mean of each species
485 trait distribution and the shaded area the 95% predictive interval, after accounting for variability
486 between mixtures. **b**, Evolution of cultivar proportions over times for each species for the
487 mixture with high complexity of genetic structure (M-5 see supplementary method). Species
488 are sorted by their height at the fifth year and cultivars are ranked along the height values of
489 isolated plants (from shortest with v1 to tallest with v6). *Trifolium pratense* disappeared by the
490 fifth year but was still present in the third year. *Festuca arundinacea* was missing in the first
491 year because its establishment took longer than the other species. Cultivar proportion was
492 computed from individual samples which taken several weeks after phenotypic measurements
493 (*F. arundinacea* was present). Values are median \pm error (90% credible interval).

494 **Figure 3 | Species abundance.** Percentage of species dry mass per year with *Trifolium repens*
495 (white with black dots), *Lolium perenne* (light grey with black dots), *Dactylis glomerata* (dark
496 grey hatched), *Trifolium pratense* (black), *Festuca arundinacea* (light grey hatched), *Lotus*
497 *corniculatus* (white) and *Medicago sativa* (dark grey). Species are ranked by their position in
498 the canopy in the fifth year.



499

500 **Figure 1 | Niche differentiation.**



501

502 **Figure 2 | Phenotypic and genotypic dynamics over the five years of experimentation.**



503

504 **Figure 3 | Species abundance**

1 **Table S1. Proportions of species and cultivars sown for mixtures**

Species	Cultivar	Designation	Proportions (seed-mass basis)					Height cultivars (cm)	
			M-1	M-2	M-3	M-4	M-5	Mean \pm s.e.	Tukey test
<i>Dactylis glomerata</i>			0.115	0.115	0.115	0.115	0.115		
	E1V5	V1	0.000	0.000	0.000	0.000	0.166	17.4 \pm 0.5	■ a
	Accord	V2	0.000	0.000	0.000	0.333	0.166	22.8 \pm 0.4	■ b
	Lucullus	V3	0.000	0.000	0.000	0.333	0.166	24.4 \pm 0.5	■ bc
	Vaillant	V4	1.000	0.000	0.000	0.333	0.166	26.3 \pm 0.9	■ c
	Otop	V5	0.000	0.000	1.000	0.000	0.166	26.9 \pm 0.7	■ c
	President	V6	0.000	1.000	0.000	0.000	0.166	29.8 \pm 0.5	■ d
<i>Festuca arundinacea</i>			0.231	0.231	0.231	0.231	0.231		
	E3V5	V1	0.000	0.000	1.000	0.000	0.250	24.0 \pm 0.4	■ a
	Soni	V2	1.000	0.000	0.000	0.500	0.125	24.4 \pm 0.8	■ a
	Mariellendo	V3	0.000	0.000	0.000	0.000	0.125	24.5 \pm 0.4	■ a
	Elodie	V4	0.000	0.000	0.000	0.250	0.125	25.4 \pm 0.4	■ ab
	Noria	V5	0.000	0.000	0.000	0.250	0.125	26.2 \pm 0.4	■ b
	Gardian	V6	0.000	1.000	0.000	0.000	0.250	30.3 \pm 0.7	■ c
<i>Lolium perenne</i>			0.115	0.115	0.115	0.115	0.115		
	Juras	V1	0.000	0.000	0.000	0.333	0.166	19.9 \pm 0.7	■ a
	Gagny	V2	0.000	0.000	0.000	0.333	0.166	20.4 \pm 0.7	■ a
	E6V5	V3	0.000	0.000	0.000	0.000	0.166	21.8 \pm 0.8	■ b
	Aberstar	V4	1.000	0.000	0.000	0.333	0.166	21.9 \pm 0.4	■ b
	Rgmaroc	V5	0.000	0.000	1.000	0.000	0.166	23.7 \pm 0.4	■ c
	Tonnus	V6	0.000	1.000	0.000	0.000	0.166	24.9 \pm 0.1	■ d
<i>Trifolium repens</i>			0.115	0.115	0.115	0.115	0.115		
	Abervantage	V1	1.000	0.000	0.000	0.333	0.333	15.7 \pm 0.4	■ a
	Aran	V2	0.000	0.000	0.000	0.333	0.333	18.0 \pm 0.5	■ b
<i>Trifolium pratense</i>			0.115	0.115	0.115	0.115	0.115		
	Giga	V3	0.000	1.000	1.000	0.333	0.333	19.7 \pm 0.2	■ c
	Formica	V1	0.000	0.000	1.000	0.333	0.333	23.1 \pm 1.1	■ -
<i>Lotus corniculatus</i>			0.078	0.078	0.078	0.078	0.078		
	Diplo	V2	1.000	1.000	0.000	0.666	0.666	23.8 \pm 0.8	■ -
<i>Medicago sativa</i>			0.078	0.078	0.078	0.078	0.078		
	Leo	V1	1.000	0.000	0.000	0.500	0.500	15.3 \pm 0.5	■ a
	PX-ete	V2	0.000	0.000	1.000	0.000	0.250	20.2 \pm 0.9	■ b
<i>Medicago sativa</i>			0.231	0.231	0.231	0.231	0.231		
	Altus	V3	0.000	1.000	0.000	0.500	0.250	24.2 \pm 1.3	■ c
	Luzelle	V1	0.000	0.000	0.000	0.000	0.166	38.0 \pm 0.7	■ a
	Rafia	V2	0.000	0.000	1.000	0.000	0.166	52.4 \pm 1.7	■ b
	Galaxie	V3	0.000	1.000	0.000	0.333	0.166	53.3 \pm 1.3	■ b
	Kali	V4	0.000	0.000	0.000	0.333	0.166	53.6 \pm 1.2	■ b
	timbale	V5	1.000	0.000	0.000	0.333	0.166	54.0 \pm 1.7	■ b
Meldor	V6	0.000	0.000	0.000	0.000	0.166	55.0 \pm 0.7	■ b	

2 The proportion is given as a fraction of seed mass. Each cultivar used is described by a height
3 value (cm) from measurements of plants in a nursery of isolated plants (mean \pm s.e.).
4 Different letters indicate significant differences between cultivars of a species ($P < 0.05$). A
5 cultivar code is assigned for cultivars not registered in an official catalogue. "Designation"
6 refers to the cultivar code used in the paper. For all mixtures, seeds were from the same lots
7 and provided by company Jouffray-Drillaud (JD).

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1 **Table S2. Number of individuals sampled for the cultivar abundance measure by fingerprinting**

Species	Block	Mixture M-4					Mixture M-5				
		Maximum number sampled	Years 1	Year 3	Year 5	P _{NA}	Maximum number sampled	Years 1	Year 3	Year 5	P _{NA}
<i>Dactylis glomerata</i>	I	48	47	48	45	0.121	96	92	91	92	0.109
	II	48	46	44	41	0.069	96	94	91	92	0.058
<i>Festuca arundinacea</i>	I	48	37	48	48	0.053	96	39	32	92	0.104
	II	48	42	48	47	0.087	96	89	39	74	0.055
<i>Lolium perenne</i>	I	48	47	14	33	0.000	96	96	17	8	0.000
	II	48	46	14	21	0.000	96	93	13	17	0.000
<i>Trifolium repens</i>	I	48	46	37	25	0.120	48	46	36	32	0.097
	II	48	48	41	17	0.170	48	48	45	23	0.069
<i>Trifolium pratense</i>	I	32	32	14	-	0.044	32	32	20	-	0.000
	II	32	32	19	-	0.020	32	31	30	-	0.033
<i>Lotus corniculatus</i>	I	32	32	5	3	0.025	48	48	8	4	0.012
	II	32	32	3	4	0.026	48	48	8	7	0.064
<i>Medicago sativa</i>	I	48	46	12	11	0.130	96	89	34	32	0.065
	II	48	38	5	8	0.078	96	77	27	25	0.016

2 The number varies according to the species in function to the number of cultivars established, 16
3 individuals (maximum) per cultivar within species. *Trifolium pratense* had disappeared by the
4 fifth year. P_{NA} is the proportion of individuals no-assigned among the three samplings (years
5 one, three, and five).

6

7 **Table S3. Primer combinations (SSR) from Polymerase Chain Reaction for *Lolium***

8 ***Perenne***

SSR markers	5' Primer sequence	3' primer sequence
LpSSR066	GCCAGTGCCCATTCGGATAA	CCCCTCAACCAAAGCAA
LpSSR058	CGATGAACTCAAGGGGATT	GCACCGGTCTAGGGACAGAA
rv0641	TGCATAACTTCACTGCAGCATA	AGAACTCGGTAGAAGGACCTC
M15185	GGTCTGGTAGACATGCCTAC	TACCAGCACAGGCAGGTTT
B4D7op	CTGGCCTGTGCTCCGYG	TCGCCGTCCACTACCAC
LmgSSR01-08H	ATGGAACCTGGCACACCAG	GCATGGCTACATCCTCCAG

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1 **Table S4. Primer combinations per species for Amplified Fragment Length**
 2 **Polymorphism**

Species	AFLP selective primer	Number of markers
<i>Dactylis glomerata</i>		162
	E-ATT/M-CCG	60
	E-ACA/M-CGG	102
<i>Festuca arundinacea</i>		96
	E-ACA/M-CTCG	38
	E-AAG/M-CCTA	21
	E-ACC/M-CAG	37
<i>Trifolium repens</i>		116
	E-ACA/M-CCT	65
	E-AAC/M-CCA	51
<i>Trifolium pratense</i>		78
	E-ACA/M-CTT	56
	E-ATC/M-CCT	22
<i>Lotus corniculatus</i>		161
	E-AAG/M-CTG	42
	E-AAA/M-CAC	51
	E-ACT/M-CTA	39
	E-ATC/M-CAT	29
<i>Medicago sativa</i>		381
	E-ACA/M-CTG	82
	E-ACC /M-CAA	41
	E-ACA /M-CGT	53
	E-AAA /M-CGC	40
	E-ATG/M-CCG	37
	E-AGC /M-CCC	26
	E-ACA/M-CTGG	20
	E-AAA/M-CTCG	23
	E-ATG/M-CGC	24
	E-ATA/M-CGG	35

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1 **Table S5. Proportion of no-assignment (P_{NA}) in the reference source per cultivar and per species**
 2 **(mean of cultivars)**

Species	Cultivar	designation	P_{NA}
<i>Dactylis glomerata</i>			0.060
	E1V5	V1	0.022
	Accord	V2	0.022
	Lucullus	V3	0.110
	Vaillant	V4	0.076
	Otop	V5	0.098
	President	V6	0.044
<i>Festuca arundinacea</i>			0.037
	E3V5	V1	0.000
	Soni	V2	0.021
	Mariellendo	V3	0.042
	Elodie	V4	0.087
	Noria	V5	0.042
	Gardian	V6	0.031
<i>Lolium perenne</i>			0.000
	Juras	V1	0.000
	Gagny	V2	0.000
	E6V5	V3	0.000
	Aberstar	V4	0.000
	Rgmaroc	V5	0.000
	Tonnus	V6	0.000
<i>Trifolium repens</i>			0.046
	Abervantage	V1	0.064
	Aran	V2	0.054
	Giga	V3	0.021
<i>Trifolium pratense</i>			0.027
	Formica	V1	0.021
	Diplo	V2	0.032
<i>Lotus corniculatus</i>			0.041
	Leo	V1	0.000
	PX-ete	V2	0.075
	Altus	V3	0.049
<i>Medicago sativa</i>			0.065
	Luzelle	V1	0.022
	Rafia	V2	0.032
	Galaxie	V3	0.133
	Kali	V4	0.101
	timbale	V5	0.066
	Meldor	V6	0.034

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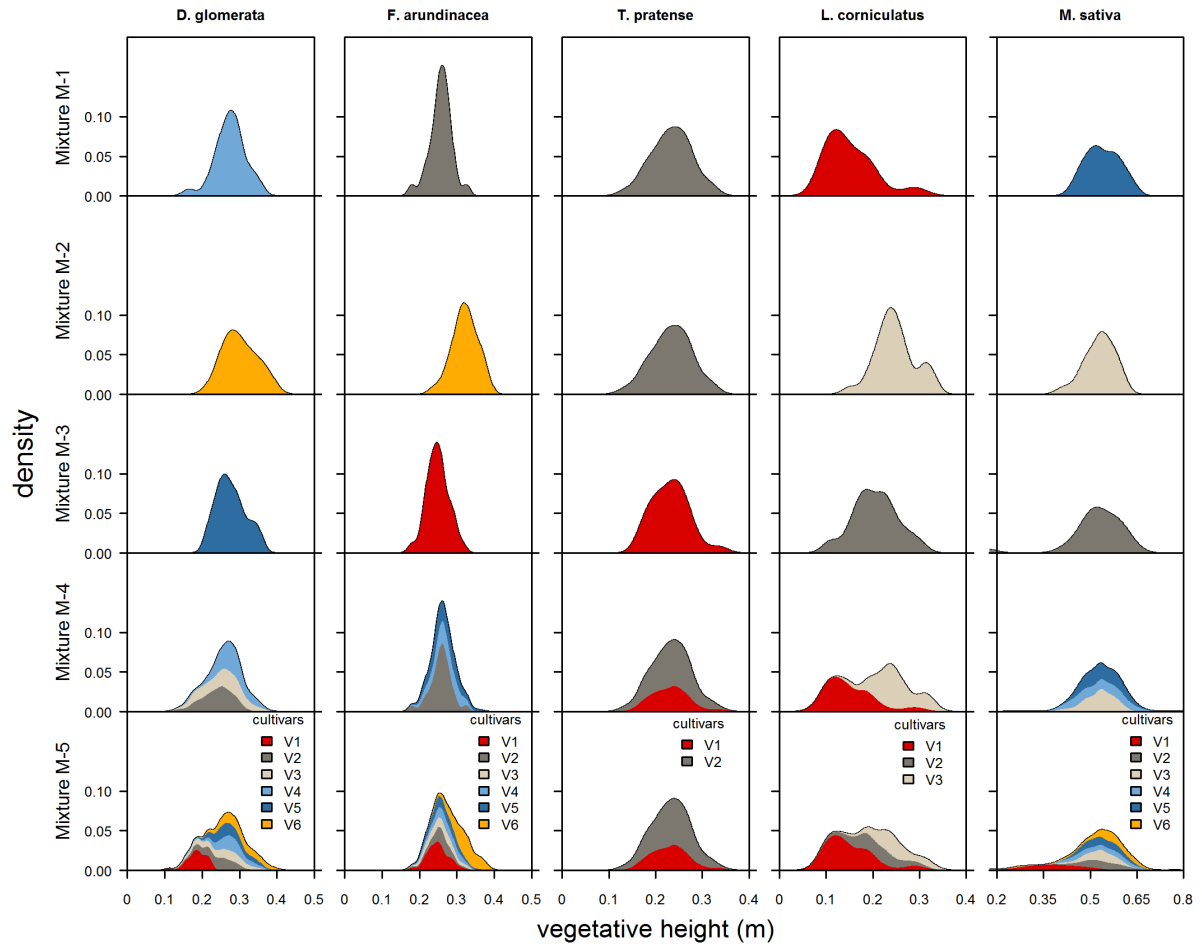
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1 **Table S6 | Models describing the dynamics of species-niches time in each block, trough**
 2 **and genetic selection.**

Models	Specific mean (μ)	Specific dispersion (σ)	Genetic Diversity (div)	Cultivar proportion (prop)	WAIC (\pm s.e)	ΔWAIC (\pm s.e.)
Model selection - niches						
Mod ₀					27443 (\pm 83)	3554 (\pm 100)
Mod _t			X		26066 (\pm 106)	2177 (\pm 86)
Mod _{t,μ}	X		X		24205 (\pm 108)	316 (\pm 50)
Mod _{t,μ,σ}	X	X	X		23951 (\pm 101)	62 (\pm 38)
Mod _{div}	X	X	X	X	23889 (\pm 103)	0
Model selection - genetic selection						
Mod _{0'}					42126 (\pm 100)	6112 (\pm 133)
Mod _{prop}				X	41938(\pm 102)	5924(\pm 122)
Mod _{t,μ,σ'}	X	X	X		36129 (\pm 133)	115 (\pm 25)
Mod _{t,prop}	X	X	X	X	36014 (\pm 133)	0

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2 **Figure S1 | Range of phenotypic variability of mixtures for species with an elongation**

3 **strategy** in relation to light competition. Each cultivar of each species used in the mixtures

4 was established in a nursery as isolated plants with 30 individuals per cultivar. Vegetative

5 height was measured on all individuals to estimate the phenotypic variability of each cultivar

6 with the value distributions estimated from the nursery. For multi-cultivar mixtures, the

7 distributions were estimated using a bootstrap method with respect to the different cultivar

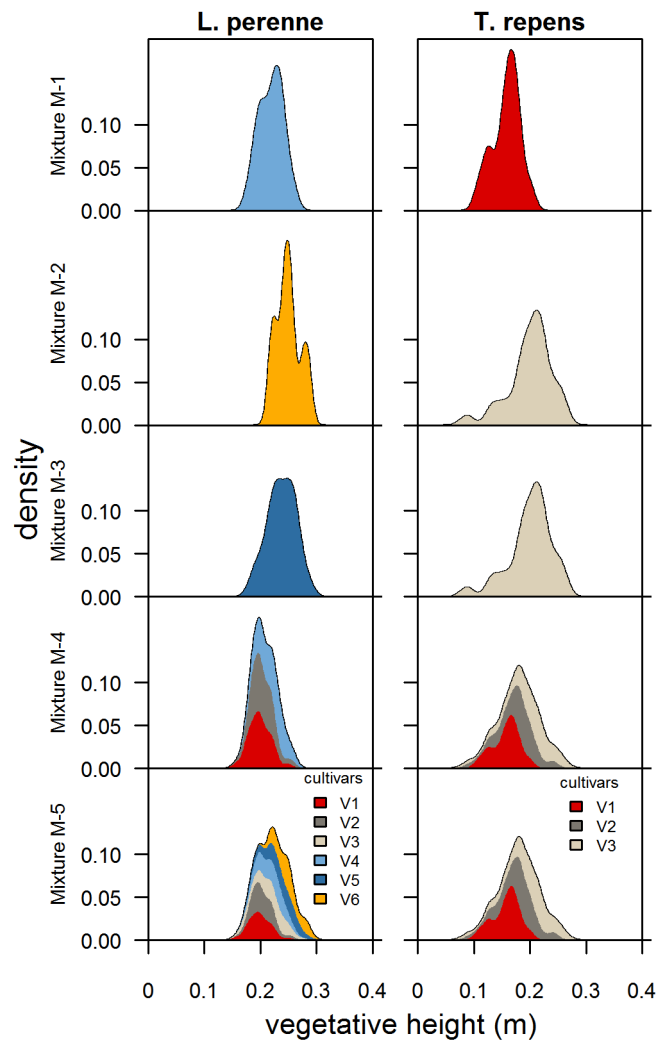
8 proportions within species and the distribution of values of each cultivar estimated from the

9 nursery.

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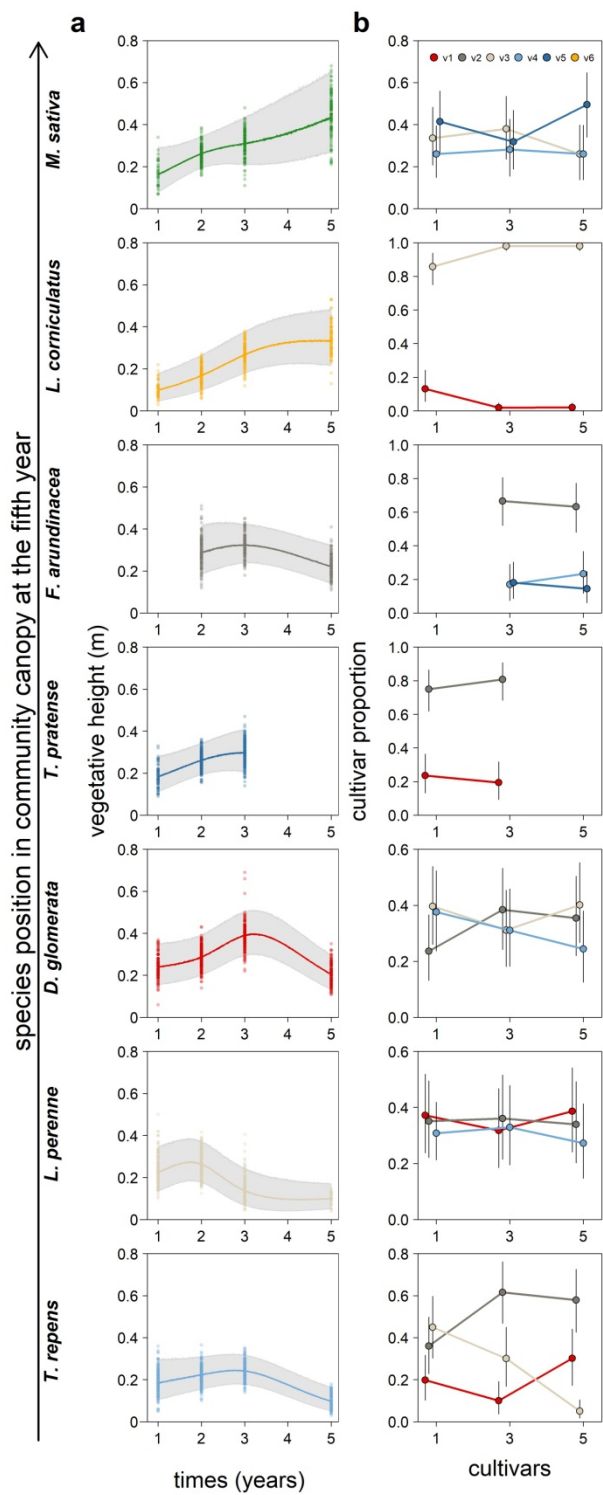
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2 **Figure S2 | Range of phenotypic variability of mixtures for species with horizontal**
 3 **spreading strategy** in relation to light competition. Each cultivar of each species used in the
 4 mixtures was established in a nursery of isolated plant with 30 individuals per cultivar.
 5 Vegetative height was measured in all individuals to estimate phenotypic variability of
 6 cultivars with the distribution values estimated from the nursery. For multi-cultivar mixtures,
 7 distribution was estimated using a bootstrap method with respect to the different cultivar
 8 proportions within species and the distribution of values of each cultivar estimated from the
 9 nursery.

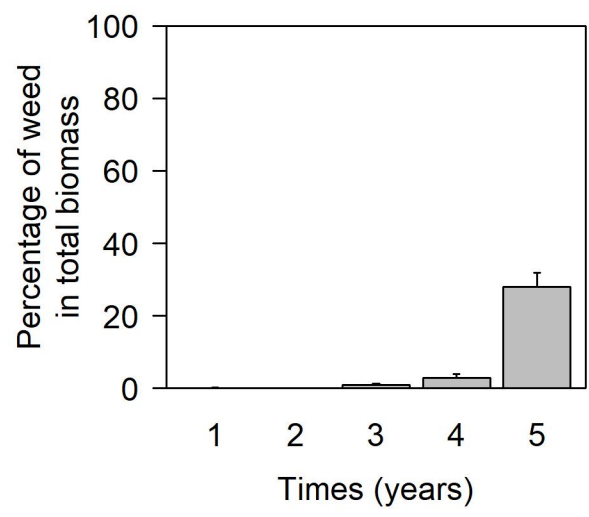


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3 **Figure S3 | Phenotypic (all mixtures) and genotypic dynamics (Mixture M-4) throughout**
 4 **the five years of the experiment. a**, Evolution of species trait distribution over time. Solid
 5 lines represent the mean of each species trait distribution and the shaded areas represent the
 6 95% predicted interval, after accounting for the variability between mixtures. **b**, Cultivar

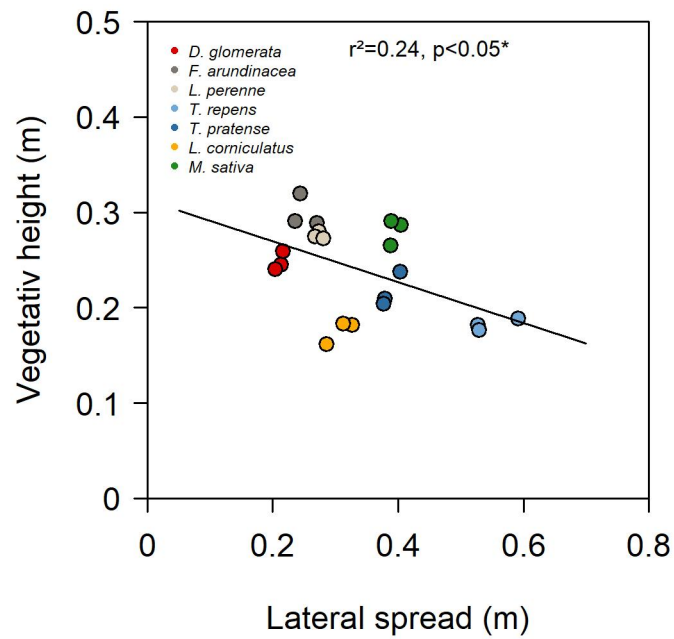
1 proportions for each species at years one, three and five after establishment (respectively
2 black, grey and white bars) for the mixture with intermediate complex structure (M-4).
3 Species are sorted by their heights at the fifth year and cultivars are ranked along their height
4 values in the nursery for isolated plants (from shortest to tallest). *Trifolium pratense* had
5 disappeared the fifth year, but was still present in the third year. *Festuca arundinacea* was
6 missing in the first year because its establishment took longer than other species. Cultivar
7 proportions were computed from individual samples which were taken several weeks after
8 phenotypic measurements (when *Festuca arundinacea* was present). Values are means \pm s.e.

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Figure S4 | Percentage of weed in total biomass production by year. The percentage corresponds to the mean of mixtures. mean + s.e.



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2 **Figure S5:** Correlation between vegetative height and lateral spread measured in common
 3 garden. Each point represents the mean of species for each block. So each species is
 4 represented by three points, the regression is significant ($p<0.05$) with $r^2=0.24$. Lateral spread
 5 corresponds to the diameter occupied by plant on the ground.

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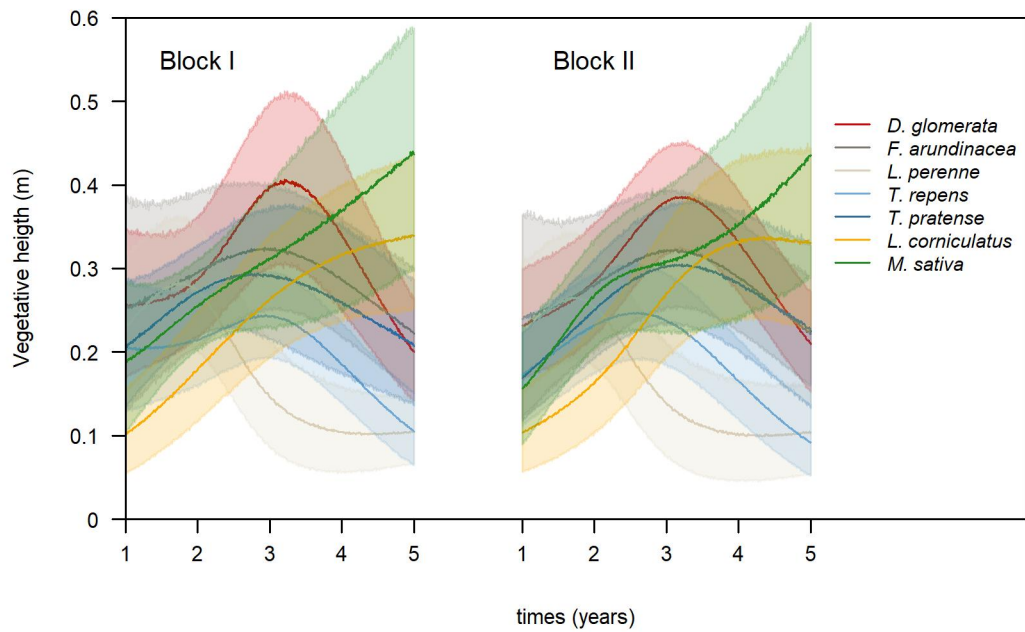
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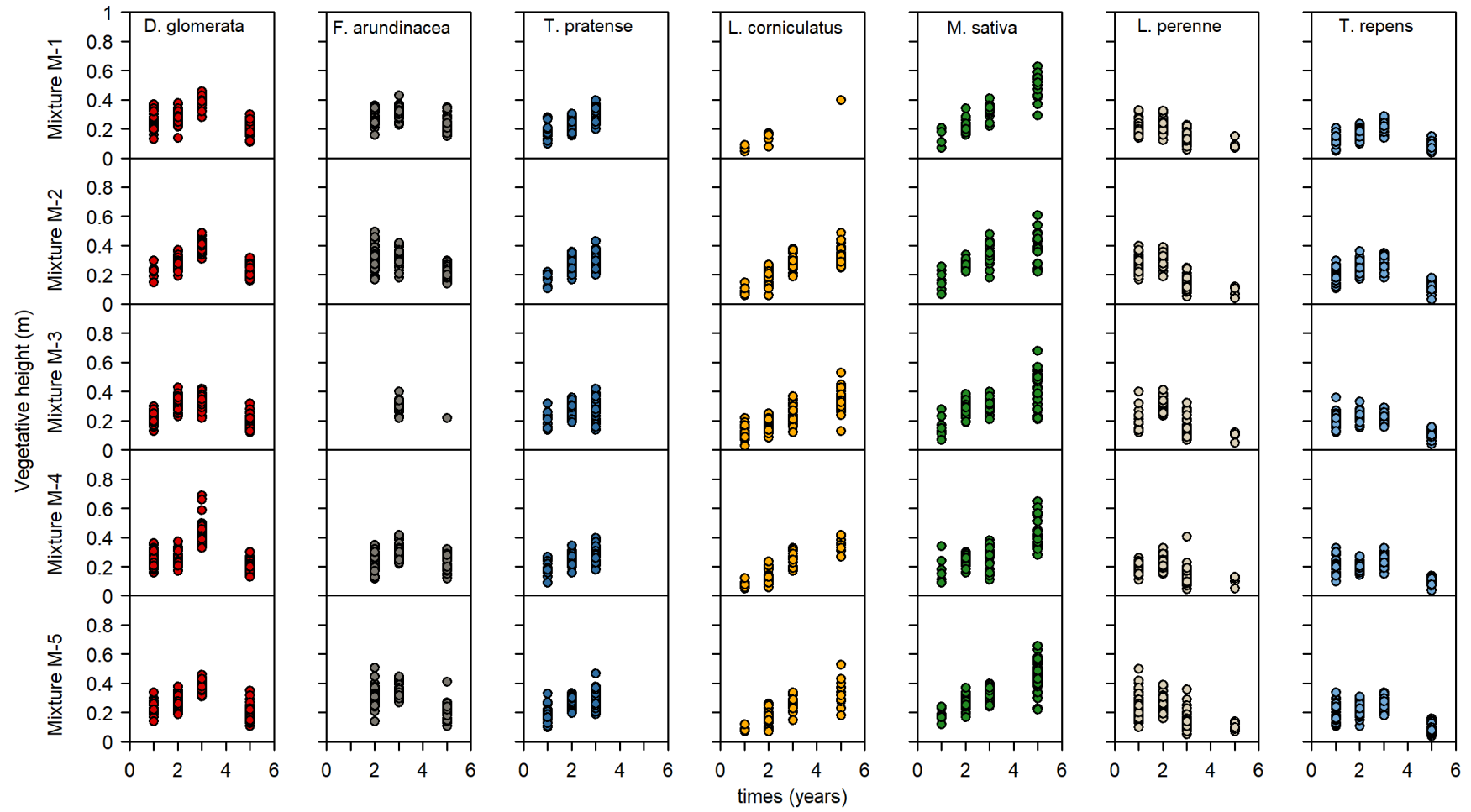
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2 **Figure S6 | Modelled vegetative height distribution of each species in each block through**
 3 **time**, with shaded area representing 90% predictive interval around the mean after accounting
 4 for variability between mixtures.



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Figure S7 | Changes of vegetative heights over time for each species, *in situ*, in each mixture (M-1 to M-5).

1 Complete description of hierarchical distributional models and their validations

2 GLM framework

3 The classical framework of the generalized linear models (GLM) allows to model any random
4 variable distributed following an exponential family distribution (such as normal, poisson,
5 gamma...). Many of these distributions are constantly bounded, implying a nonlinear
6 variation of their mean and variance close to these bounds. For example, the variation of the
7 mean of a strictly positive value, such as a count, is not linear close to zero, just as the
8 variation of a probability is nonlinear close to its bounds (zero and one). The GLM framework
9 allows to model the effects of linear predictors on a *function* of the response variable, which
10 makes the latter linear. The corresponding function is called the *link function*, $g()$. The
11 variance, which has also a non-linear behavior at the bound, is then linked to the mean by a
12 *variance function* (Smyth 1989). Thus, the variation of the mean and variance of an
13 exponential family distribution following a series of linear predictors $\mathbf{x}_i^T \boldsymbol{\beta}$ is

$$14 \quad \begin{aligned} \mu_i &= g^{-1}(\mathbf{x}_i^T \boldsymbol{\beta}) \\ \sigma_i^2 &= \phi_i w_i^{-1} v(\mu_i) \end{aligned}$$

15 Where μ_i and σ_i^2 are the mean and the variance of the distribution for the observation i ,
16 respectively, and g^{-1} the inverse of the link function. $v()$ is a non-negative variance function
17 specific to each probability distribution and w_i^{-1} are known weights. ϕ_i is an unknown
18 dispersion parameter for the observation i .

19 Distributional modelling

20 Many distributions, even if they are not properly belonging to the exponential family, might
21 be reparametrized to model conjointly mean and variance. Given the fact that we can define
22 the link between mean and variance as below, one would be able to regress both μ_i and ϕ_i as
23 the result of deterministic equations. In this framework, we can define a distributional model
24 for location and scale as follow (Rigby & Stasinopoulos 2005):

$$25 \quad \begin{aligned} \mathbf{Y} &\sim f(\boldsymbol{\mu}, \boldsymbol{\phi}) \\ g_1(\boldsymbol{\mu}) &= \mathbf{X}\boldsymbol{\beta} \\ g_2(\boldsymbol{\phi}) &= \mathbf{X}\boldsymbol{\gamma} \end{aligned}$$

26 Where Y is a column vector of the response variable, $\boldsymbol{\mu}$ and $\boldsymbol{\phi}$ are vectors of linear parameters,
27 X a matrix of predictors, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vector coefficients linking predictors to the mean
28 and the dispersion, respectively. $g_1()$ and $g_2()$ are the link function for the mean and
29 dispersion, respectively.

1 **Gamma distribution**

2 We modeled strictly positive vegetative height with a gamma distribution, with α being the
3 shape parameter and β being the rate parameter. The formulation with independent mean, μ
4 and dispersion, ϕ , is as follow:

$$5 \quad \mathbf{Y} \sim \text{Gamma}(\boldsymbol{\alpha} = \boldsymbol{\mu}^2 \boldsymbol{\phi}, \boldsymbol{\beta} = \boldsymbol{\mu} \boldsymbol{\phi})$$

$$\log(\boldsymbol{\mu}) = \mathbf{X}\boldsymbol{\beta}$$

$$\log(\boldsymbol{\phi}) = \mathbf{X}\boldsymbol{\gamma}$$

6 This parametrization is straightforward to recover, given that the first two moments of the
7 gamma distribution are defined as follow:

$$8 \quad E(Y) = \frac{\alpha}{\beta}$$

$$\text{Var}(Y) = \frac{\alpha}{\beta^2}$$

9 **Hierarchical additive model formulation**

10 Because of the structured nature of our design (individuals within species within mixtures
11 within blocks), we used hierarchical parameters for mixture and species categorical effects
12 (Gelman *et al.* 2013). Thus, intercepts for each species and each mixtures were modelled as
13 belonging to the same respective population with estimated variance. The complete
14 formulation of the model Mod_3 , which explores the adjustment of each species mean and
15 dispersion through time is:

$$y_i \sim \text{Gamma}(\mu_i, \phi_i)$$

$$\log(\mu_i) = \beta_0 + \beta_B + \beta_M + \beta_S + f_{1s}(t_i)$$

$$\log(\phi_i) = \gamma_0 + \gamma_B + \gamma_M + \gamma_S + f_{2s}(t_i)$$

$$f_{1s} = \sum_{k=1}^K \alpha_{1Sk} b_k(t_i)$$

$$f_{2s} = \sum_{k=1}^K \alpha_{2Sk} b_k(t_i)$$

$$\beta_M \sim \text{normal}(0, \sigma_{\beta_M})$$

$$\beta_S \sim \text{normal}(0, \sigma_{\beta_S})$$

$$\gamma_M \sim \text{normal}(0, \sigma_{\gamma_M})$$

$$\gamma_S \sim \text{normal}(0, \sigma_{\gamma_S})$$

$$\alpha_{1Sk} \sim \text{normal}(0, \sigma_{\alpha_{1Sk}})$$

$$\alpha_{2Sk} \sim \text{normal}(0, \sigma_{\alpha_{2Sk}})$$

16
17 Where y_i is the height value of individual i . The β and γ parameters are the coefficients for
18 mean and dispersion, respectively. Thus, β_0 and γ_0 are the intercepts, while β_B and γ_B are the
19 coefficient for the individuals harvested in the second block. β_M and γ_M are hierarchical
20 deviation parameters for each mixture m , and β_S and γ_S are hierarchical intercepts for each

1 species. f_{1s} and f_{2s} are smooth functions describing the evolution of mean and dispersion of
2 each species through each value of time t_i , respectively. f_{1s} and f_{2s} are defined as the
3 weighted sum of the $K = 4$ cubic basis b_k , with α_{1sk} and α_{2sk} being the weights of each basis
4 for each species, distributed normally with estimated variances $\sigma_{\alpha_{1sk}}$ and $\sigma_{\alpha_{2sk}}$, respectively.
5 We used weakly informative priors to optimize posterior sampling with appropriate
6 constraints and scaling, without eliciting actual knowledge. Hierarchical priors are centered
7 on 0 with relatively low scale to potentially shrink coefficient and avoid overfitting, while
8 avoiding algorithms to get lost in the posterior surface. Student-t priors with 3 degree-of-
9 freedom have thick tails, allowing algorithms to explore correctly the posterior surface even if
10 the scale is insufficiently large. Priors of Mod_3 are defined as follow, $student^+$ begin
11 positive truncated student-t distributions:

$$\begin{aligned}
& \beta_0 \sim student(3,3,3) & \gamma_0 & \sim student(3,0,3) \\
& \beta_B \sim student(3,0,1) & \gamma_B & \sim student(3,0,1) \\
12 & \sigma_{\beta_M} \sim student^+(3,0,1) & \sigma_{\gamma_M} & \sim student^+(3,0,1) \\
& \sigma_{\beta_S} \sim student^+(3,0,1) & \sigma_{\gamma_S} & \sim student^+(3,0,1) \\
& \sigma_{\alpha_{1sk}} \sim student^+(3,0,1) & \sigma_{\alpha_{2sk}} & \sim student^+(3,0,1)
\end{aligned}$$

13 The model Mod_4 , which described the adjustment of species height mean and dispersion for
14 three level of population's genetic diversity is formulated as follow:

$$\begin{aligned}
& y_i \sim Gamma(\mu_i, \phi_i) \\
& \log(\mu_i) = \beta_0 + \beta_B + \beta_M + \beta_{SD} + f_{1SD}(t_i) \\
& \log(\phi_i) = \gamma_0 + \gamma_B + \gamma_M + \gamma_{SD} + f_{2SD}(t_i) \\
& f_{1SD} = \sum_{k=1}^K \alpha_{1SDk} b_k(t_i) \\
15 & f_{2SD} = \sum_{k=1}^K \alpha_{2SDk} b_k(t_i) \\
& \beta_M \sim normal(0, \sigma_{\beta_M}) \\
& \beta_{SD} \sim normal(0, \sigma_{\beta_{SD}}) \\
& \gamma_M \sim normal(0, \sigma_{\gamma_M}) \\
& \gamma_{SD} \sim normal(0, \sigma_{\gamma_{SD}}) \\
& \alpha_{1SDk} \sim normal(0, \sigma_{\alpha_{1SDk}}) \\
& \alpha_{2SDk} \sim normal(0, \sigma_{\alpha_{2SDk}})
\end{aligned}$$

16 With β_{SD} and γ_{SD} being intercepts and f_{1SD} and f_{2SD} being smooth functions of time for each
17 species s at three level of genetic diversity, d (low, medium and high), describing the mean
18 and dispersion of height distribution, respectively.

19 The priors are as follow:

$$\begin{aligned}
& \beta_0 \sim \text{student}(7,3,3) & \gamma_0 & \sim \text{student}(7,0,3) \\
& \beta_B \sim \text{student}(7,0,1) & \gamma_B & \sim \text{student}(7,0,1) \\
1 & \sigma_{\beta_M} \sim \text{student}^+(7,0,1) & \sigma_{\gamma_M} & \sim \text{student}^+(7,0,1) \\
& \sigma_{\beta_{SD}} \sim \text{student}^+(7,0,1) & \sigma_{\gamma_{SD}} & \sim \text{student}^+(7,0,1) \\
& \sigma_{\alpha_{1SDk}} \sim \text{student}^+(7,0,1) & \sigma_{\alpha_{2SDk}} & \sim \text{student}^+(7,0,1)
\end{aligned}$$

2 The model Mod_2' , which described the adjustment of species height mean and dispersion in
3 function of time *and* in function of changes in cultivars abundances is defined as follow.
4 Because cultivar proportions have only been measured for three years, the we reduced the
5 number of cubic basis $K = 3$.

$$\begin{aligned}
& y_i \sim \text{Gamma}(\mu_i, \phi_i) \\
& \log(\mu_i) = \beta_0 + \beta_B + \beta_M + \beta_S + \beta_V + \beta_{1V} \text{frequency} + f_{1S}(t_i) \\
& \log(\phi_i) = \gamma_0 + \gamma_B + \gamma_M + \gamma_S + \gamma_V + \gamma_{1V} \text{frequency} + f_{2S}(t_i) \\
& f_{1SD} = \sum_{k=1}^K \alpha_{1SDk} b_k(t_i) \\
& f_{2SD} = \sum_{k=1}^K \alpha_{2SDk} b_k(t_i) \\
6 & \beta_M \sim \text{normal}(0, \sigma_{\beta_M}) \\
& \beta_S \sim \text{normal}(0, \sigma_{\beta_S}) \\
& \gamma_M \sim \text{normal}(0, \sigma_{\gamma_M}) \\
& \gamma_S \sim \text{normal}(0, \sigma_{\gamma_S}) \\
& \begin{bmatrix} \beta_V \\ \beta_{1V} \\ \gamma_V \\ \gamma_{1VS} \end{bmatrix} = \text{MVNormal}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, S\right) \\
& \alpha_{1Sk} \sim \text{normal}(0, \sigma_{\alpha_{1Sk}}) \\
& \alpha_{2Sk} \sim \text{normal}(0, \sigma_{\alpha_{2Sk}})
\end{aligned}$$

7 With β_V and γ_V being hierarchical intercepts describing the effect of the presence of each
8 cultivar on the height distribution of species s in the mixture m and the block b . β_{1V} and γ_{1V}
9 are hierarchical slopes describing the effect on species s height distributions of the change in
10 cultivar v abundance through time. All of these parameters where distributed multinormally
11 with S being a covariance matrix computed as follow:

$$12 \quad S = \begin{bmatrix} \sigma_{\beta_V} & 0 & 0 & 0 \\ 0 & \sigma_{\beta_{1V}} & 0 & 0 \\ 0 & 0 & \sigma_{\gamma_V} & 0 \\ 0 & 0 & 0 & \sigma_{\gamma_{1V}} \end{bmatrix} R \begin{bmatrix} \sigma_{\beta_V} & 0 & 0 & 0 \\ 0 & \sigma_{\beta_{1V}} & 0 & 0 \\ 0 & 0 & \sigma_{\gamma_V} & 0 \\ 0 & 0 & 0 & \sigma_{\gamma_{1V}} \end{bmatrix}$$

13 Where R is an estimated 4x4 correlation matrix. The priors for this model are as follow, the
14 LKJcorr distribution being a modified beta distribution to become a prior of correlation
15 matrices defined on $[-1,1]$.

$$\begin{aligned}
& \beta_0 \sim \text{student}(3,3,3) & \gamma_0 & \sim \text{student}(3,0,3) \\
& \beta_B \sim \text{student}(3,0,1) & \gamma_B & \sim \text{student}(3,0,1) \\
& \sigma_{\beta_M} \sim \text{student}^+(3,0,1) & \sigma_{\gamma_M} & \sim \text{student}^+(3,0,1) \\
1 & \sigma_{\beta_S} \sim \text{student}^+(3,0,1) & \sigma_{\gamma_S} & \sim \text{student}^+(3,0,1) R \sim \text{LKJcorr}(2) \\
& \sigma_{\beta_V} \sim \text{student}^+(3,0,1) & \sigma_{\gamma_V} & \sim \text{student}^+(3,0,1) \\
& \sigma_{\beta_{1V}} \sim \text{student}^+(3,0,1) & \sigma_{\gamma_{1V}} & \sim \text{student}^+(3,0,1) \\
& \sigma_{\alpha_{1Sk}} \sim \text{student}^+(3,0,1) & \sigma_{\alpha_{2Sk}} & \sim \text{student}^+(3,0,1)
\end{aligned}$$

2 Model diagnosis

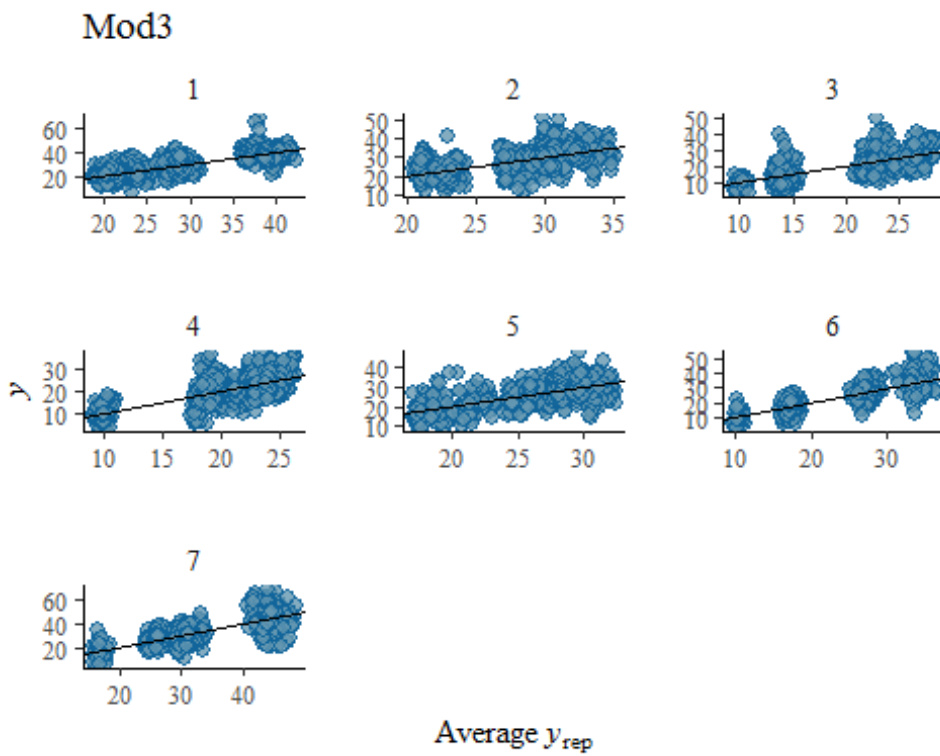
3 Sampling behaviors

4 The *No-U-Turn sampler* implemented in *stan* returned several diagnostics. For every model,
5 we ensured that there were no divergent transitions. Divergent transitions arise when the
6 curvature of an area of the posterior surface is too high to be adequately explored by the
7 sampler. This diagnostic is very important, and this situation shall be avoided, because it leads
8 to biased estimates (Gelman *et al.* 2013). Well-chosen priors and the cleverly parametrized
9 *stan* code produced by *brms* (Bürkner 2018) avoided such suboptimal sampling behavior and
10 parametrizing the step size at 0.95 in the sampler was sufficient to fit every model without
11 divergences. Once the sampler behaves correctly, the second important concern is the mixing
12 of the different chains. The chains represent independent instances of posterior surface
13 exploration, beginning at various starting points. A rule of thumb is that a Gelman-Rubin split
14 \hat{R} greater than 1.1 indicates bad mixing of chains (Gelman *et al.* 2013). Every \hat{R} in the models
15 were lower than 1.01. We also inspected each chain visually to ensure the absence of
16 problematic behaviors. Each chain were constituted of 2000 iterations including 1000 warm-
17 up iterations.

18 Posterior-Predictive checks

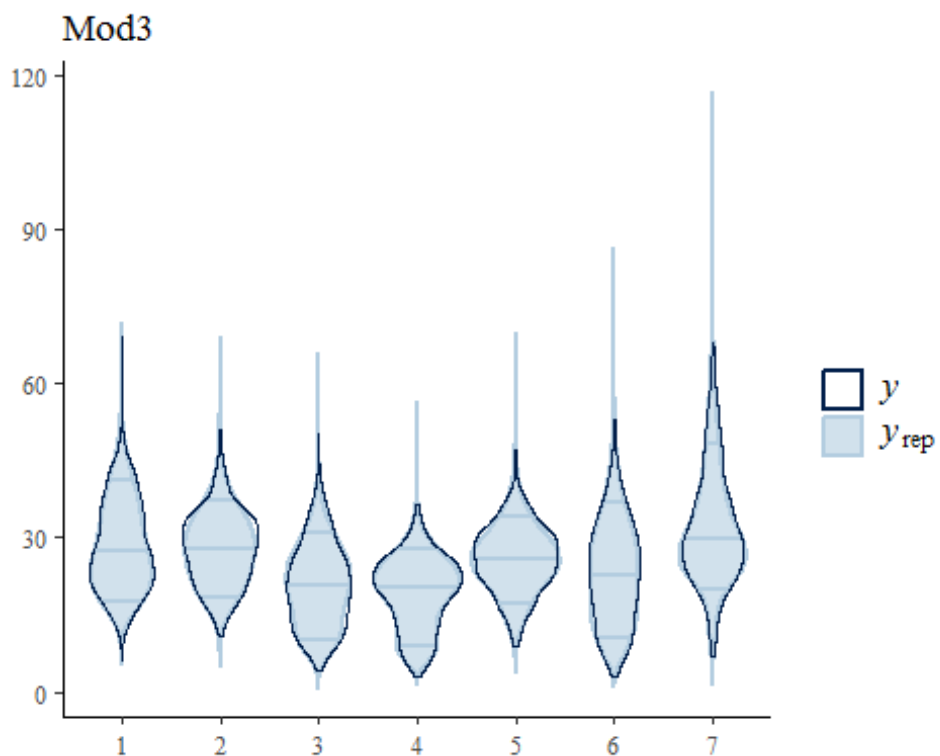
19 We checked that models recovered key features of data by confronting visually predicted and
20 observed distributions.

1 **Mod3**



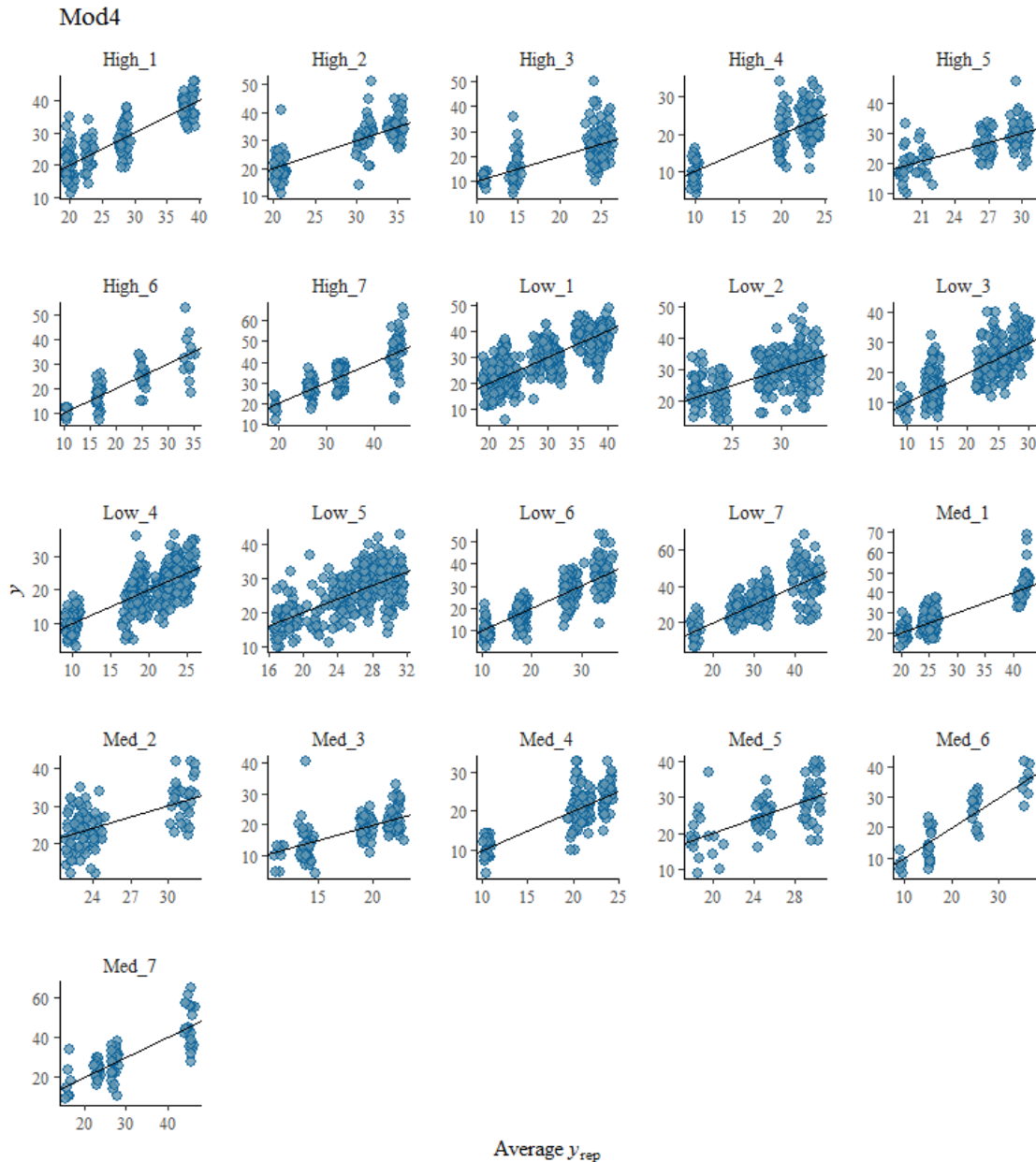
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3 Figure A 1: Scatterplots of observed individual vegetative heights in function of predicted
4 values for each species. Line represents the 1:1 relationship. Species 1: *Dactylis glomerata*, 2:
5 *Festuca arundinacea*; 3: *Lolium perenne*; 4: *Trifolium repens*, 5: *Trifolium pratense*, 6: *Lotus*
6 *corniculatus*; 7: *Medicago sativa*

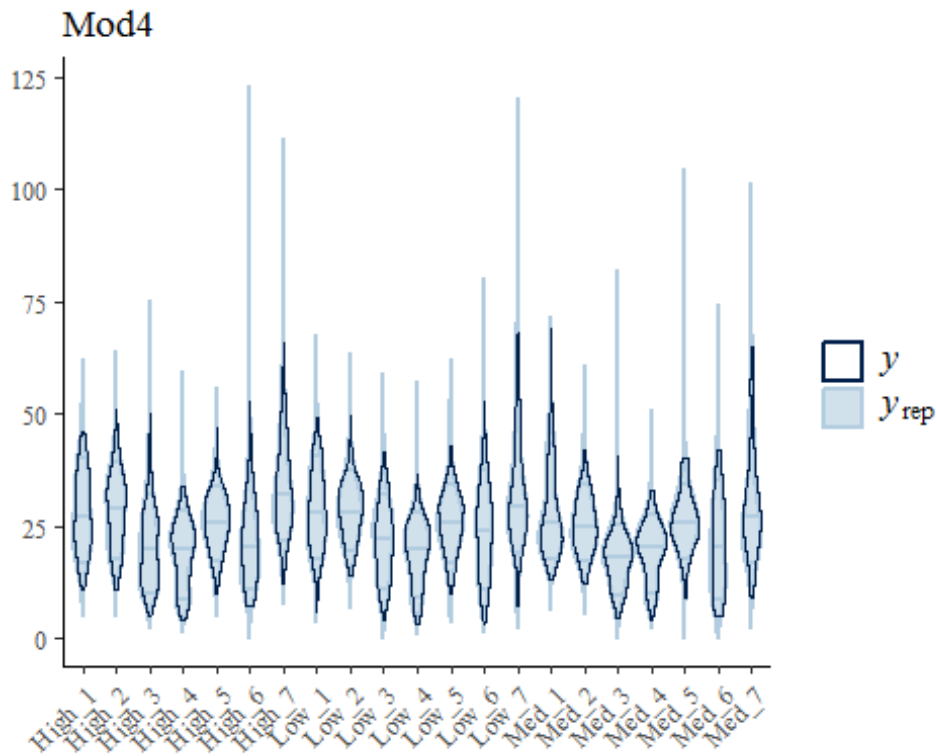


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- 1 Figure A 2: Violin plots of each species observed and predicted vegetative heights
- 2 distribution. Species 1: *Dactylis glomerata*, 2: *Festuca arundinacea*; 3: *Lolium perenne*; 4:
- 3 *Trifolium repens*, 5: *Trifolium pratense*, 6: *Lotus corniculatus*; 7: *Medicago sativa*
- 4 **Mod4**



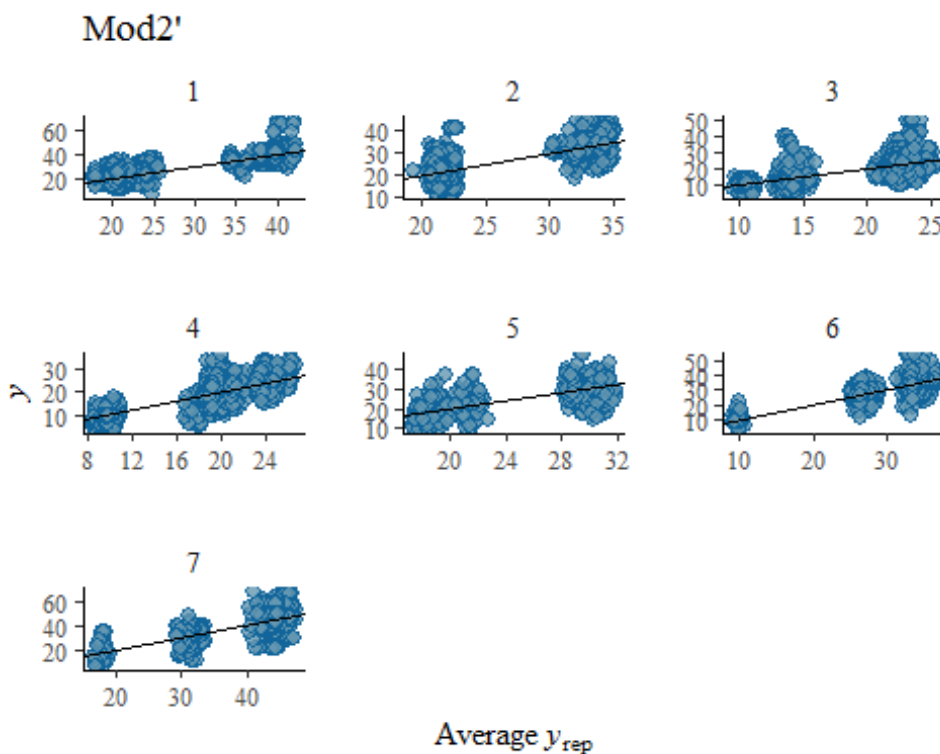
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- 6 Figure A 3: Scatterplots of observed individual vegetative heights in function of predicted
- 7 values, for each species at three level of genetic diversity. Line represents the 1:1 relationship.
- 8 Species 1: *Dactylis glomerata*, 2: *Festuca arundinacea*; 3: *Lolium perenne*; 4: *Trifolium*
- 9 *repens*, 5: *Trifolium pratense*, 6: *Lotus corniculatus*; 7: *Medicago sativa*



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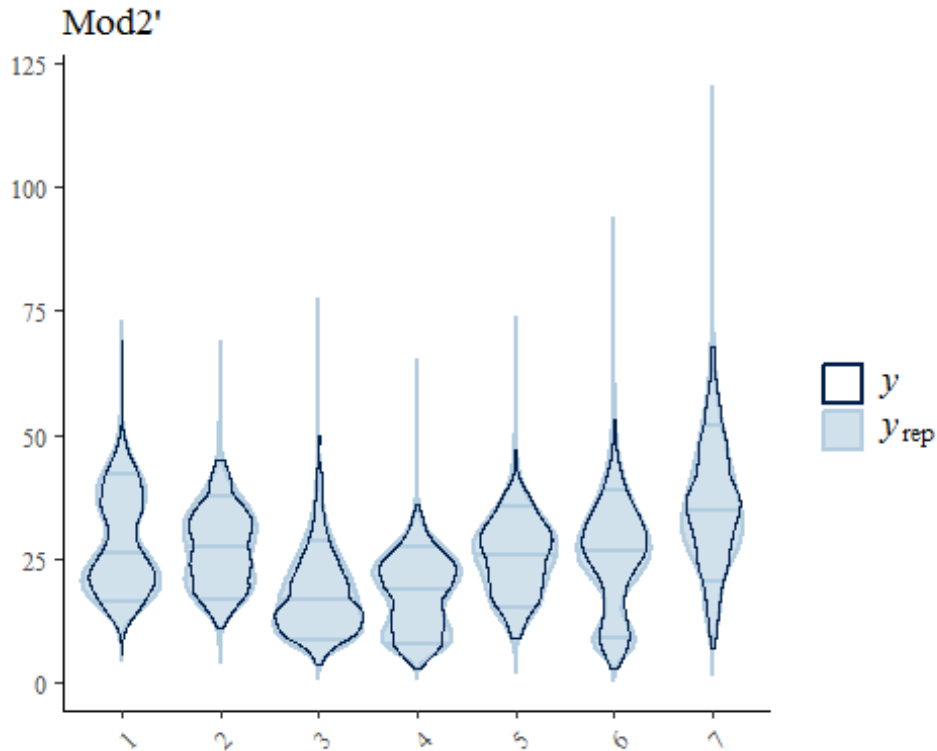
2 Figure A 4: Violin plots of each species observed and predicted vegetative height distribution,
 3 at three levels of genetic diversity. Species 1: *Dactylis glomerata*, 2: *Festuca arundinacea*; 3:
 4 *Lolium perenne*; 4: *Trifolium repens*, 5: *Trifolium pratense*, 6: *Lotus corniculatus*; 7:
 5 *Medicago sativa*

6 **Mod2'**



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1 Figure A 5: Scatterplot of observed individual vegetative heights in function of predicted
 2 values. Line represents the 1:1 relationship. Species 1: *Dactylis glomerata*, 2: *Festuca*
 3 *arundinacea*; 3: *Lolium perenne*; 4: *Trifolium repens*, 5: *Trifolium pratense*, 6: *Lotus*
 4 *corniculatus*; 7: *Medicago sativa*



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 6 Figure A 6: Violin plot of each species observed and predicted vegetative height distribution.
 7 Species 1: *Dactylis glomerata*, 2: *Festuca arundinacea*; 3: *Lolium perenne*; 4: *Trifolium*
 8 *repens*, 5: *Trifolium pratense*, 6: *Lotus corniculatus*; 7: *Medicago sativa*.

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