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1 **Agricultural practices in olive groves modify weeds**  
2 **floral traits and resources throughout the year**

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21

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## 26 **Authors' contributions**

27 LG, AM, EK and KB conceived the idea and designed the experiment. LG, AM and EK  
28 collected the data. LG analysed the data and led the writing of the manuscript. All authors  
29 contributed critically to the drafts and gave their final approval for publication.

## 30 **Data availability statement**

31 Data available on UMR ABSYS Dataverse: <https://doi.org/10.18167/DVN1/B9HXLE>

32 (temporary link:

33 [https://dataverse.cirad.fr/dataset.xhtml?jsessionid=d1fe6f791a3566c0ca444ff52930?persistentId=doi%  
34 3A10.18167%2FDVN1%2FB9HXLE&version=DRAFT \)](https://dataverse.cirad.fr/dataset.xhtml?jsessionid=d1fe6f791a3566c0ca444ff52930?persistentId=doi%3A10.18167%2FDVN1%2FB9HXLE&version=DRAFT)

## 35 **Declaration of competing interest**

36 The authors declare no conflict of interest.

37

## 38 **Abstract**

39 Lack of floral resources is suspected to be one of the factors involved in flower-visiting insect  
40 declines. Because agricultural landscapes are often poor in flowers, it seems crucial to assess  
41 weeds as floral resources to feed flower-visiting insects and to identify the factors that drive  
42 floral productivity, defined as floral biomass produced by the weed community. We monitored  
43 floral presence, productivity and traits in 16 olive groves from September 2021 to June 2022.  
44 The objectives were to understand to which extent abiotic factors, among agricultural practices,  
45 pedoclimate and weather, determine floral productivity and to analyse the relationships between  
46 floral traits, floral presence and productivity. We found mowing frequency (2 to 3 per year on  
47 average) increased mean floral area and height, advanced flowering onset, and increased floral  
48 functional diversity and flowering species richness, which in turn increased floral presence and  
49 productivity.

## 50 **Keywords**

51 Floral productivity; floral resources; floral traits; woody agroecosystem; mowing

52

# 53 **1. Introduction**

54 Since nectar and pollen are the main food resources for pollinating insects (Roulston and  
55 Goodell, 2011), the lack of floral resources is one of the major causes of decreasing pollinating  
56 insect populations (Goulson et al., 2015; Potts et al., 2010; Scheper et al., 2014). In  
57 agroecosystems, species-rich weed communities support populations of insect natural enemies  
58 and pollinators (Aviron et al., 2023), thereby contributing to biodiversity conservation,  
59 biological control and entomophilous pollination. Insect visitation depends on traits linked to  
60 floral resources (nectar, pollen) or morphology (flower area height, number of flowers etc.) ,  
61 driving the quality of plants as floral resources (Fornoff et al., 2017; Hatt et al., 2019; Hegland  
62 & Totland, 2005; Rowe et al., 2020). Besides, weed communities with high taxonomic and  
63 functional diversity enhance diversity across trophic levels (Lefcheck et al. 2015). High  
64 functional diversity in weed communities should support more populous and diverse insect  
65 communities by multiplying ecological niches for the first trophic level of consumers with  
66 various ecological requirements (Potts et al., 2010). However, intensive agricultural practices  
67 in Europe since 1945 curtailed weed diversity and abundance (Andreasen et al., 1996; Baessler  
68 & Klotz, 2006; Meyer et al., 2013), and hence floral resources in landscapes (Bretagnolle &  
69 Gaba, 2015; Richner et al., 2015).

70 In woody agroecosystems, weeds are a biodiversity component contributing to inter-  
71 row ground cover and can be managed in a biodiversity-friendly way by cover cropping or  
72 mowing, which maintain higher plant and insect richness and abundance than tillage or  
73 herbicide spraying (Carpio et al., 2019 ; Kratschmer et al., 2019 ; Kazakou et al., 2016). Low-  
74 intensity management such as moderate mowing (once or twice a year) maintain soil cover and  
75 insect-pollinated weeds throughout the year (Tarifa et al., 2021), especially when fewer flowers

76 are available in surrounding semi-natural environments and insects need food resources  
77 (Rundlöf et al., 2014).

78 Few studies have evaluated the potential of weeds for providing floral resources to  
79 insects in woody agroecosystems, by assessing their floral traits or their floral productivity, that  
80 we defined as floral biomass produced by the weed community, and even fewer have monitored  
81 weed floral resources diachronically over the year. Weeds are unstable communities mostly  
82 composed of annual species, and change considerably within one year, both taxonomically and  
83 functionally. Because floral traits vary significantly among weed species, floral resources in  
84 agroecosystems are very diverse. Common weed species can be very attractive to insects, such  
85 as *Picris hieracioides* L., *Taraxacum sp* or *Echium vulgare* L. (Balfour & Ratnieks, 2022;  
86 Hernández-Villa et al., 2020; Kuppler et al., 2023), unlike others such as *Chenopodium album*  
87 L., *Amaranthus spp.* or *Rumex spp.*, (Kuppler et al. 2023). In addition, the timing of flowering  
88 is crucial for many insects, whose requirements peak at specific periods of the year depending  
89 on their life cycle. Previous studies have shown that anthesis occurs earlier and lasts longer in  
90 weeds (Bourgeois et al., 2019). However, the impacts of agricultural practices on the floral  
91 traits and productivity of weeds are poorly known because weed studies have mostly focused  
92 on resource-use ecological strategies and effects on crops.

93 Floral traits are mostly studied as determinants of insect presence as they drive insect  
94 visitation and richness at the community scale (Fornoff et al., 2017; Rowe et al., 2020).  
95 However, their community-scale responses to environmental factors are rarely investigated  
96 (Vojtko et al., 2020), and only in grasslands or semi-natural environments., A previous study  
97 showed that floral functional diversity responds to soil characteristics in French grasslands  
98 (Goulnik et al. 2021). Another recent work investigates the effects of water deficit on floral  
99 traits, which reduces flower size and number, and nectar volume (Kuppler & Kotowska, 2021).  
100 Dry Mediterranean conditions select for mostly small or short-lived flowers (Teixido and

101 Valladares, 2014) so as to maintain a positive water balance at the flower scale (Roddy et al.,  
102 2023). However, weed floral traits response to the environment, pedoclimatic conditions or  
103 agricultural practices, are almost unknown. At the species level, weed floral traits are linked to  
104 Grime's CSR strategies (Genty et al., 2023), suggesting that they could be sensitive to  
105 management and disturbance. One recent study showed that organic farming increases  
106 functional richness and the number of red and zygomorphic flowers in weed communities  
107 (Rotchés-Ribalta et al., 2023), but how other floral traits linked to insects respond to agricultural  
108 practices is not known.

109 Flower abundance, usually measured as the flower cover, is another factor of insect  
110 visitation (Hegland and Boeke, 2006; Wray et al., 2014). However, which practices determine  
111 floral resources abundance, composition, and above all, dynamics, in agroecosystems is  
112 scarcely studied. We suppose that low-disturbance practices should allow greater weed flower  
113 production than intensive practices (Kratschmer et al., 2019). In addition, species richness,  
114 especially of flowering species, should increase flower abundance and productivity. The  
115 relationships between plant traits (Pontes et al., 2007) and productivity of vegetative biomass,  
116 as well as those between diversity and -productivity (Lehman and Tillman, 2000) are well  
117 studied. They indicate that more diverse plant communities with specific values for vegetative  
118 traits are also more productive, however, these relationships this remains largely unexplored  
119 for floral productivity.

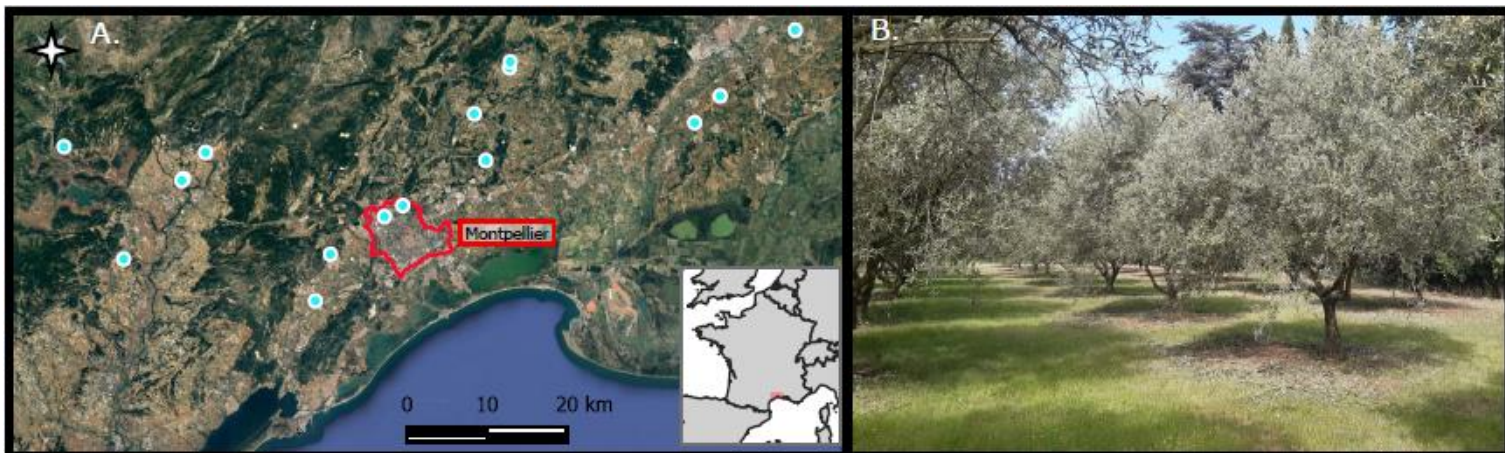
120 In this study, we explored how agricultural practices, weather and pedoclimatic  
121 conditions affected weed communities and flowers over one agricultural year in extensive olive  
122 groves in southern France, focusing on optimising weed floral resources for insects. Our  
123 hypotheses were that species richness and functional structure of weed communities (1) are  
124 affected both by agricultural and pedoclimatic variables, in particular that low-disturbance  
125 inter-row management practices (e.g. mowing), water availability and soil fertility would

126 enhance species richness and floral trait diversity, and (2) have a positive effect on floral  
127 productivity *via* their effects on traits and richness that could drive temporal niche partitioning.  
128 Weeds flowering earlier can be visited by different insects than those flowering later, thus  
129 decreasing competition to attract pollinators and improving flower production. Greater diversity  
130 in morphological floral traits in the community could increase flower-visiting insect richness  
131 because different floral morphologies attract different insects. More flowers per plant on  
132 average and longer mean flowering duration should increase floral productivity over the entire  
133 year by extending the period during which flowers are present.

## 134 **2. Material and methods**

### 135 **2.1. Sampled fields**

136



137 *Figure 1. A. Locations of the sampled olive groves (Google©, 2022) in the Mediterranean*  
138 *part of the Occitanie region, France. B. One example of surveyed grove in Spring 2022.*

139

140 We surveyed 16 olive groves in the hinterland of Montpellier, southern France, in a  
141 Mediterranean climatic area (Figure 1). Agricultural practices were assessed by interviewing  
142 farmers in 2021 and 2022, focusing on inter-row management (Genty et al., 2023). Mowing



143 was the only management practice used to control weeds and was described using the mean  
144 number of mowing interventions per year (1-5) (‘mowing’). We also recorded the yearly  
145 amount of water used for irrigation (‘irrig’)(0-190 mm) and inorganic and organic nitrogen (N)  
146 applied for fertilisation and amendments (0-641 kg of N/ha) (‘N fertilization’),.

## 147 **2.2. Pedoclimatic conditions**

148 We used the data from six weather stations of the national meteorological network (Météo  
149 France), located 0.5-19.7 km from the 16 surveyed olive groves, to describe the long-term  
150 climatic trends (1980-2021). We calculated six climatic variables describing seasonal trends  
151 using the ‘biovars’ function from the R package *dismo* (Hijmans et al., 2017): mean annual  
152 temperature ( $15.3 \pm 0.33^\circ\text{C}$ , mean $\pm$ SD), annual rainfall ( $704 \pm 124\text{mm}$ ), rainfall in the driest  
153 month ( $6.06 \pm 1.84\text{mm}$ ), maximum temperature of the warmest month ( $36.8 \pm 1.1^\circ\text{C}$ ), annual  
154 temperature range ( $41.8 \pm 15.8^\circ\text{C}$ ) and rainfall coefficient of variation ( $89.6 \pm 2.25\text{mm}$ ). In  
155 addition, we recorded rainfalls (‘Rainfalls<sub>sample</sub>’) and mean temperature (‘Mean Temp<sub>sample</sub>’)  
156 between successive sampling dates to assess short-term weather effects at the monthly scale.  
157 We also calculated the rainfall over the agricultural year (‘Rainfalls<sub>year</sub>’) and the annual  
158 minimum temperature (‘Temp min<sub>year</sub>’) to describe weather effects at the yearly scale (Table  
159 S5). Soil pH (NF ISO10390), nitrogen content, total organic matter content (NF ISO 14235),  
160 cation-exchange capacity (CEC) and texture (NF X 31-107 method) were determined for each  
161 olive grove on a 20-cm-deep composite soil sample. More informations on the soil analyses can  
162 be found in Genty et al. (2022).

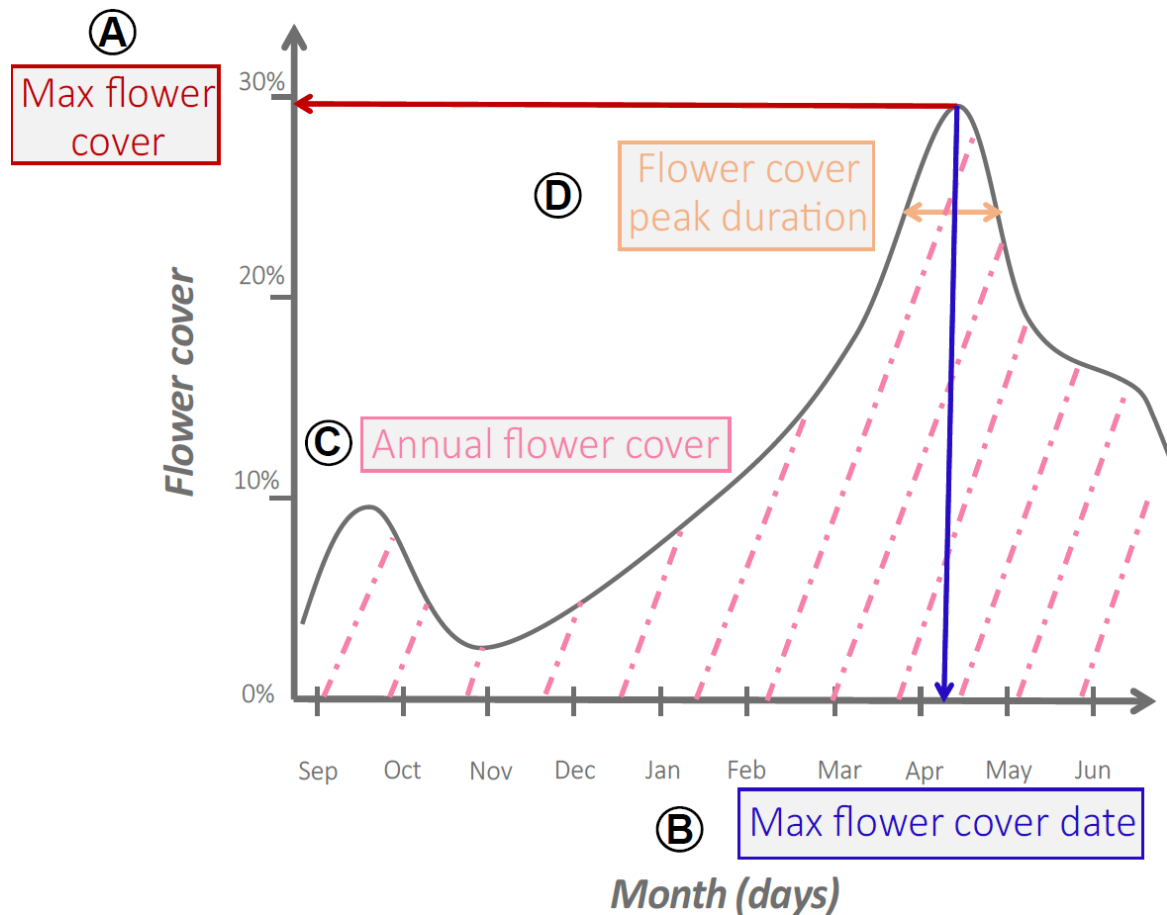
## 163 **2.3. Botanical survey of flower cover**

164 Five permanent quadrats of  $0.25\text{ m}^2$  were randomly placed in the inter-rows of each olive grove  
165 ( $n = 80$  quadrats), keeping a minimum distance of two metres from the field edge. We sampled  
166 each quadrat seven times over the entire agricultural year 2021-2022 ( $n = 560$  surveys: 17-09-

167 2021; 14-10-2021; 27-01-2022; 01-03-2022; 04-04-2022; 04-05-2022; 06-06-2022). On each  
168 date and for each quadrat we recorded the latest mowing date ('last mowing') and visually  
169 recorded the phenological stage and flower cover per species as the total percentage of the  
170 ground covered by open flowers and flower buds in each quadrat. We also recorded the number  
171 of species at the flowering stage ('floral richness') in each quadrat, and the total species richness  
172 of each field based on sampling from Genty et al., 2023. Recorded data concerned insect-  
173 pollinated species exclusively.

#### 174 **2.4. Indicators of floral productivity at the year scale**

175 We used a loess regression to model flower cover dynamics over the year (Cleveland & Devlin,  
176 1988) for each quadrat based on the seven samplings. We extracted four indicators of floral  
177 productivity (Figures 2 and 3): (1) annual flower cover, calculated as the normalised integral of  
178 the regression curve ('annual flower cover'); (2) flower cover maximum value in % of surface  
179 ('max flower cover'); (3) date of the flower cover maximum ('max flower cover date'),  
180 expressed as the number of days since the beginning of the sampling (17<sup>th</sup> of September 2021);  
181 and (4) number of days during which the flower cover reached or exceeded 80% of its flower  
182 cover maximum, representing the period of abundant flower presence in the field ('flower cover  
183 peak duration'). For flower cover peak duration, we excluded nine quadrats in which 80% of  
184 the max flower cover was under 1% (Table S1). The four indicators were measured at the year  
185 scale (n = 80) by pooling the data of the seven surveys, considering each quadrat survey as one  
186 community composed of all the sampled species proportionally. We recorded the species  
187 richness of flowering weeds in each community over the full season.



188

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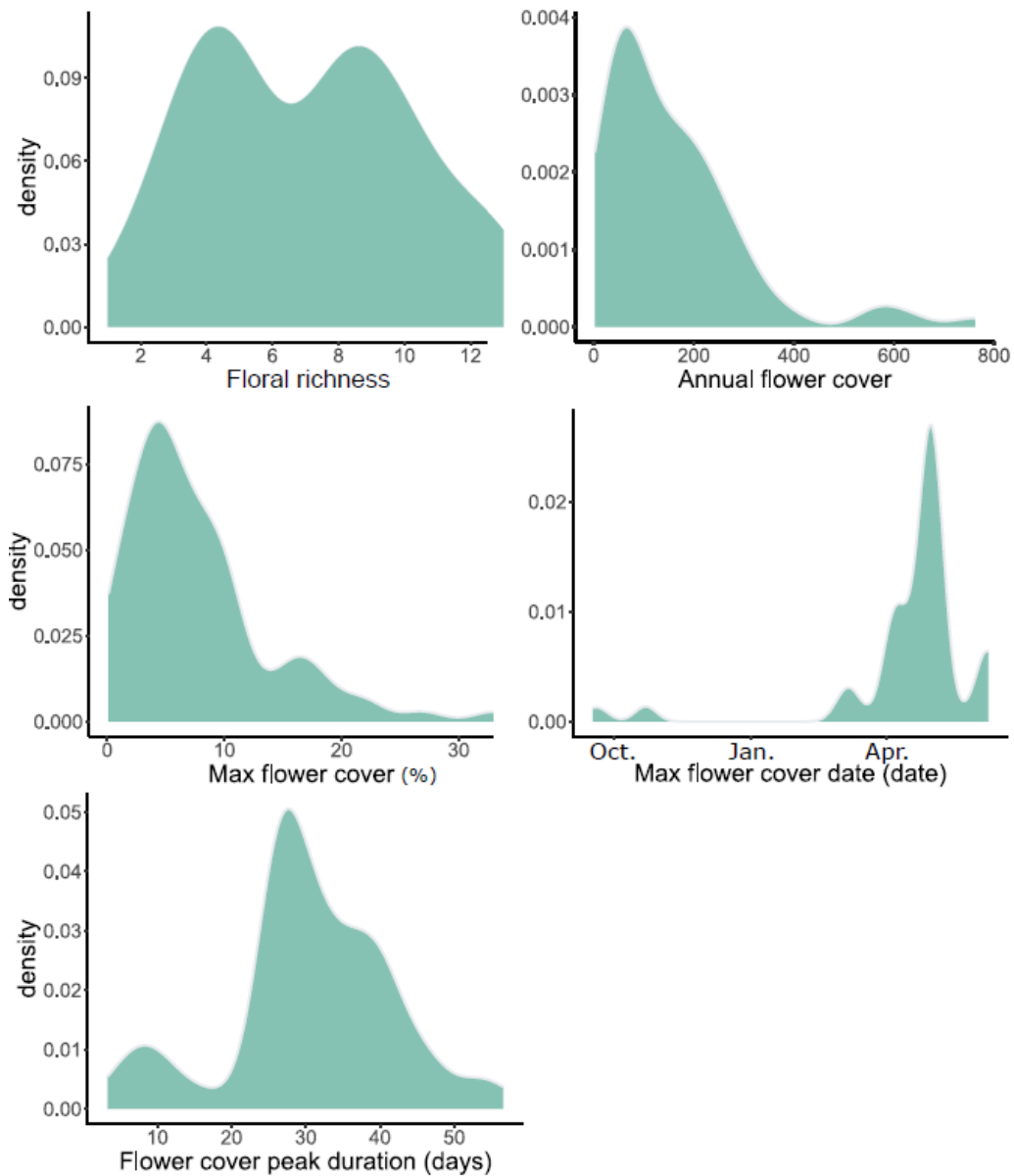
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194

*Figure 2. Dynamics of flower cover throughout the year, presenting the four floral productivity indicators: A. Max flower cover (flower cover maximum value in %), B. Max flower cover date (number of days since the start of the sampling, on 17-09-2021), C. Annual flower cover (% calculated as the normalised integral of the regression curve), and D. Flower cover peak duration (number of days with flower cover  $\geq 80\%$  of flower cover maximum).*



196

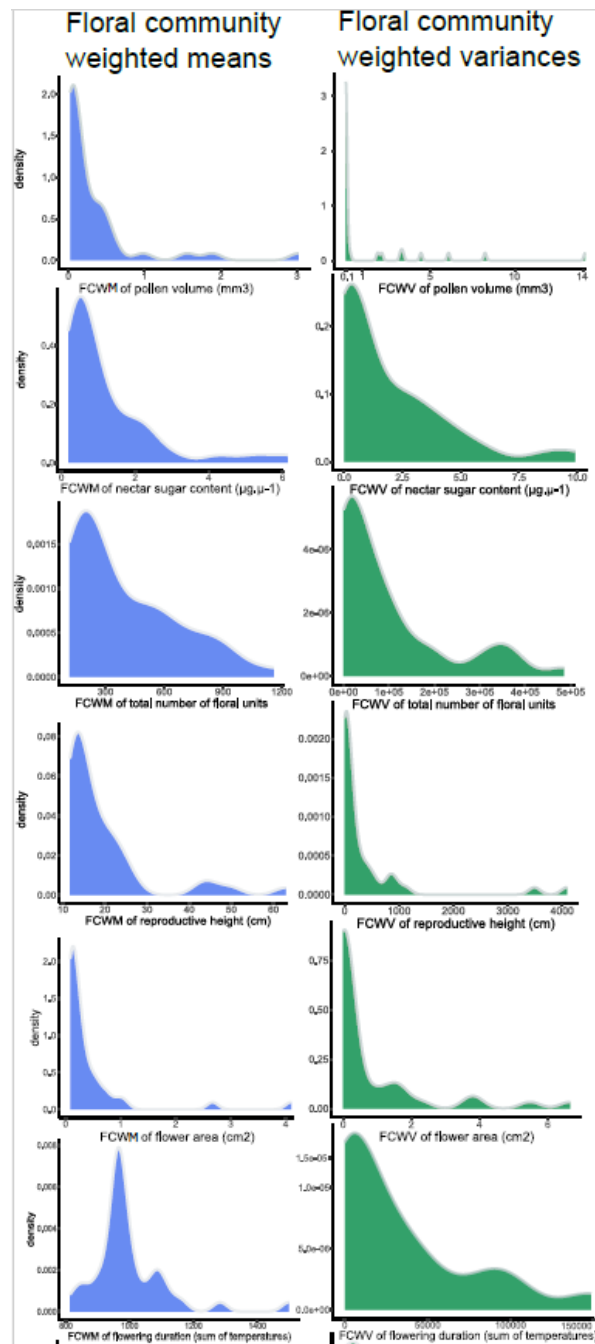
197 *Figure 3. Distribution of floral richness, annual flower cover, max flower cover, max flower*  
 198 *cover date and flower cover peak duration among weed communities (n=80).*

199

## 200 **2.5. Trait measurements and functional indices at the community level**

201 Seven floral traits linked to insect attraction (Table S2) were measured for 17 common weed  
 202 species in olive grove (Table S3) in a greenhouse experiment during the spring and summer of  
 203 2022 (Genty et al., 2023b): pollen volume ('pollen'), nectar sugar content ('nectar'), number of

204 floral units per plant ('floral unit number'), reproductive height ('height'), flower area ('area'),  
 205 flowering duration ('duration') and flowering onset ('onset').



206  
 207 *Figure 4. Distribution of community weighted means and variances of floral traits: pollen*  
 208 *volume, nectar sugar content, total number of floral units, reproductive height, flower area,*  
 209 *flowering duration and onset among weed communities (n=40).*

210

211 We calculated the floral community-weighted mean and variance of each floral trait in  
212 all the communities (n = 40) composed of at least 60% of these species, at the year scale (Table  
213 S4), using the ‘dbFD’ function of the FD package. Community weighted mean is the average  
214 floral trait value of each species at the flowering stage weighted by its relative flower cover  
215 (Garnier et al., 2004). Community weighted variance quantifies the variability of each floral  
216 trait value around the average value within the floral community (Sonnier et al., 2010) (Figure  
217 4). Because floral traits are phylogenetically conserved (Vojtko et al., 2022), we pooled trait  
218 values at the genus level for three unstudied abundant species: *Geranium molle* L., *Medicago*  
219 *polymorpha* L. and *Medicago rigidula* (L.) All. *G. molle* belongs to the same subgenus as  
220 *Geranium rotundifolium* L. and *Geranium dissectum* L. (Aedo et al., 1998), and *M. polymorpha*  
221 and *M. rigidula* to that of *Medicago minima* (L.) L. and *Medicago arabica* (L.) Hudson (Steele  
222 et al., 2010).

## 223 **2.6. Data analysis**

224 All statistical analyses were run using R version 4.3.1 (R Core Team, 2022), and in particular  
225 the packages *lme4* (Bates et al., 2015), *vegan* (Oksanen et al., 2007), *FD* (Villéger et al., 2008),  
226 *FactoMineR* (Lê et al., 2008), *MuMIn* (Barton, 2009), *car* (Fox et al., 2012) and *piecewiseSEM*  
227 (Lefcheck, 2016).

228 We ran Kruskal-Wallis’ tests and pairwise Wilcoxon’s tests as post-hoc analyses to test  
229 whether flowering species richness and flower cover differed between months and determine  
230 the periods of flower presence.

231 To summarise soil and climatic characteristics of the study sites we ran a PCA with all  
232 the pedoclimatic variables. The coordinates of each individual on the first two components were  
233 extracted and used as explanatory variables (pedoclim1 and pedoclim2).

234 To test whether agricultural practices and weather affected monthly flowering species  
235 richness and flower cover, we ran linear mixed models with ‘last mowing’, ‘Rainfalls<sub>sampl</sub>’ and  
236 ‘Mean Temp<sub>sampl</sub>’ as fixed effects and ‘month’ and ‘field’ as random effects. To test whether  
237 they influenced annual flowering species richness, floral productivity indicators, floral  
238 community weighted means and variances, we ran linear mixed models with ‘pedoclim1’,  
239 ‘pedoclim2’, ‘mowing’, ‘irrig’, ‘N fertilization’, ‘Rainfalls<sub>year</sub>’ and ‘Temp min<sub>year</sub>’ as fixed  
240 effects, and ‘field’ as random effect. Before model selection and evaluation, correlation of fixed  
241 effects was tested using variance inflation (VIF). VIF values of 5 or higher are interpreted as  
242 revealing multicollinearity issues (Hair, 2009). We performed model stepwise comparisons  
243 comparing full, reduced and ‘null’ models built by combining all fixed effects, several fixed  
244 effects or only random effects. We selected the model with the lowest second-order Akaike  
245 Information Criterion value (AICc) corrected for small sample sizes (Burnham & Anderson,  
246 2004). Two models were considered different if  $\Delta AICc > 2$  (Burnham & Anderson, 2004).  
247 When more than one model had the lowest AICc we selected the most parsimonious, with the  
248 lowest number of fixed effects. We used likelihood ratio tests to evaluate the selected models,  
249 and calculated the marginal and conditional  $R^2$  (Nakagawa & Schielzeth, 2013).

250 The relation between floral traits and indicators of floral productivity was tested with a  
251 PCA (‘community structure’ PCA) with the community weighted means of the seven floral  
252 traits and flowering species richness, followed by a hierarchical ascendant classification to  
253 create three clusters based on the first two components. To test whether the four indicators of  
254 floral productivity differed among clusters, we ran Kruskal-Wallis’ and pairwise Wilcoxon’s  
255 tests as *post hoc* analyses.

## 256 **3. Results**

### 257 **3.1. Effects of pedoclimate, weather and agricultural practices on flowering** 258 **species richness, floral productivity and floral traits**

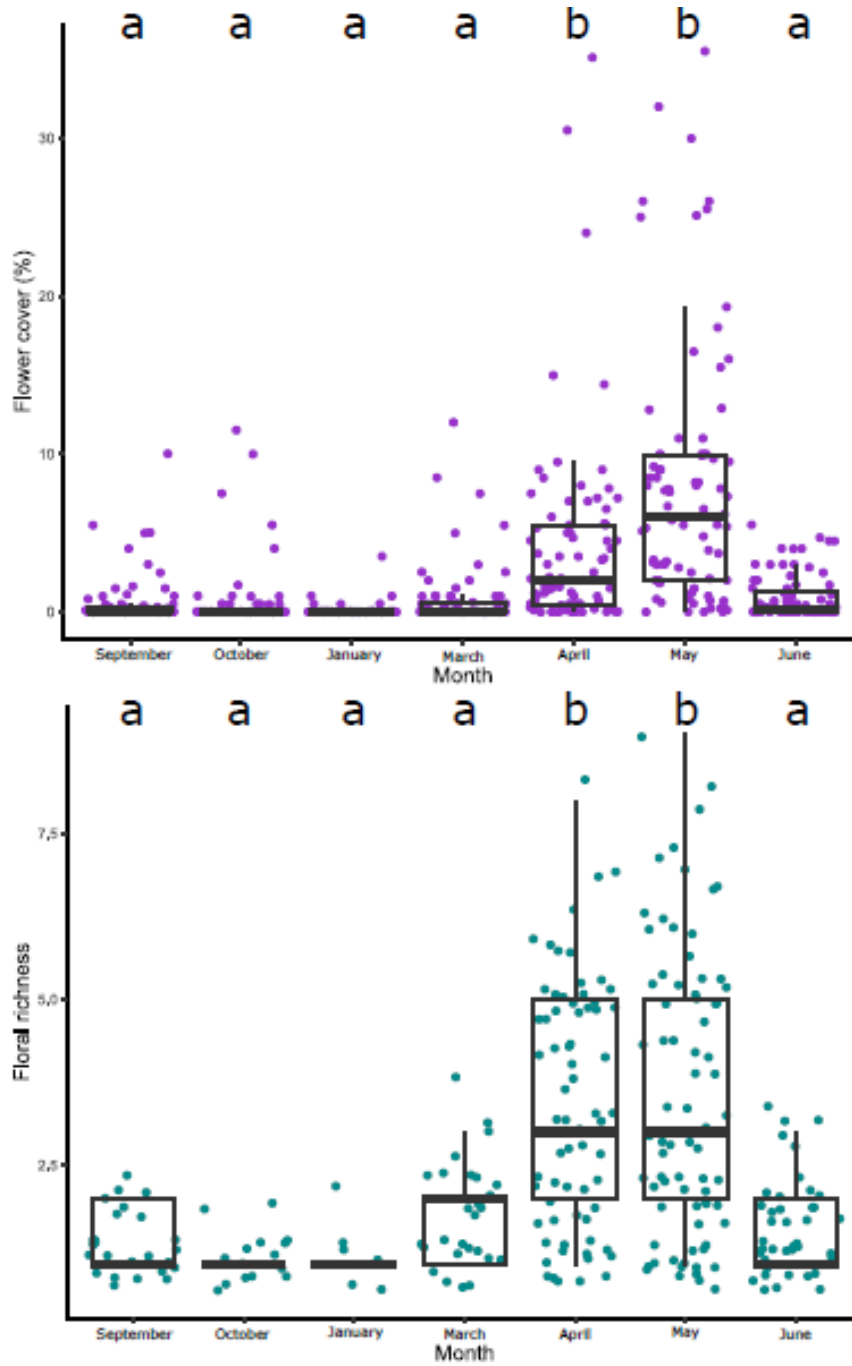
259 ‘Pedoclimatic’ PCA explained 62% of the total variance of pedoclimatic variables (Table S5).  
260 The coordinates of each field on the first two components were used as composite explanatory  
261 variables. The first component (‘pedoclim1’) explained 38% of the total variance and was  
262 positively linked to soil clay content (0.79), cation-exchange capacity (0.79), mean annual  
263 temperature (0.78) and soil nitrogen content (0.66), and negatively to annual temperature range  
264 (-0.85), soil sand content (-0.73) and maximum temperature of the warmest month (-0.68). The  
265 second component (‘pedoclim2’) explained 24% of the total variance and was positively linked  
266 to rainfall in the driest month (0.88) and annual rainfall (0.85), and negatively to rainfall  
267 coefficient of variation (-0.76).

268 Flower cover (Figure 5A) and species richness of flowering weeds (‘floral richness’)  
269 (Figure 5B) were significantly higher in April and May than in the other months. The five most  
270 abundant species in terms of flower cover at the year scale were *Medicago minima* L., *Crepis*  
271 *sancta* L., *Arenaria serpyllifolia* L., *Sherardia arvensis* L. and *Medicago arabica* L. (Table S6).

272 At the month scale, flower cover was positively correlated with time since the last  
273 mowing and floral richness with rainfall (Table 1). At the year scale, floral richness was  
274 positively affected by pedoclim2 and by the mean number of mowing interventions per year,  
275 while max flower cover date was the only indicator of floral productivity impacted by abiotic  
276 variables: it was postponed by N fertilization and advanced by pedoclim2.



277 At the year scale mowing, N fertilization, irrigation, Pedoclim1 and 2, and Temp Min<sub>year</sub>  
278 affected community weighted means and variances of all floral traits (see detailed results in  
279 Table 2).



280 *Figure 5. Flower cover (A), and number of flowering species (B) in each quadrat on each*  
281 *visit (%). Letters represent the results of pairwise Wilcoxon's tests.*

282

283 *Table 1. Individual effect of pedoclimatic characteristics and agricultural practices on floral*  
 284 *richness, indicators of flower productivity and flower cover at a monthly and yearly scale.*  
 285 *Field and month are random effects for the models at the month scale. Field is a random*  
 286 *effect for models at the year scale. Marginal R2 (R2m) represents the proportion of variance*  
 287 *explained by fixed effects in the model. Conditional R2 (R2c) includes random effects.*  
 288 *Significance stars are from the type II ANOVA's Chi<sup>2</sup>.*  
 289

Temporal scale	Response variable	Explanatory variable	Estimate	R2m	R2c
Month	Flower cover	last mowing	0.005*	0.01	0.37
	Floral richness	Rainfalls <sub>sampl</sub>	-0.005*	0.04	0.49
Year	Floral richness	pedoclim2 mowing	0.730* 1.021*	0.23	0.56
	Annual flower cover	ns	-	-	-
	Max flower cover	ns	-	-	-
	Max flower cover date	pedoclim2 N fertilization	-3.754* 0.009-	0.13	0.20
	Flower cover peak duration	ns	-	-	-

Notes: ns, not significant; -  $p < 0.1$ , \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .

*Last mowing* : number of days since the last mowing event, *Rainfalls<sub>sampl</sub>* : quantity of rainfalls between two samplings, *pedoclim2* : second axis of 'pedoclimatic' PCA, *mowing* : mean number of mowing events per year, *N fertilization* : mean N dose applied per year, *irrig* : mean quantity of irrigation per year, *Temp min<sub>year</sub>* : mean minimal temperature during the sampling period, *Rainfalls<sub>year</sub>* : total quantity of rainfalls during the sampling period

290

291 *Table 2. Individual effect of pedoclimatic characteristics and agricultural practices on*

292 *community weighted means (CWM) and variances (CWV) of floral traits at the year scale*

293

*with field as random effect.*

Functional indicator	Trait (response variable)	Explanatory variable	Estimate	R2m	R2c	
CWM	Area	mowing	0.306***	0.27	0.27	
	Pollen	pedoclim2	0.106*	0.12	0.14	
	Nectar	irrig	0.014**	0.32	0.64	
	Height	mowing	3.117*	0.12	0.17	
	Floral units number		N fertilization	0.884***		
			irrig	2.064**	0.6	0.6
	Duration		Temp min <sub>year</sub>	91.063**		
			N fertilization	-0.284**	0.27	0.27
	Onset		irrig	0.794*		
			N fertilization	-0.648***	0.66	0.68
irrig			1.483***			
		Temp	-49.732**			

		min <sub>year</sub> mowing	-44.292**		
CWV	Area	mowing N fertilization	72.360*** -0.280*	0.39	0.39
	Pollen	Rainfalls <sub>year</sub>	1.628***	0.26	0.26
	Nectar	mowing	75.102*	0.14	0.30
	Height	-	ns	ns	ns
	Floral units number	pedoclim2	3 490 184**	0.28	0.43
	Duration	-	ns	ns	ns
	Onset	pedoclim1 irrig mowing Temp min <sub>year</sub>	-736 813*** -29 414** 1 374 079*** 2 894 065***	0.44	0.44

Notes: ns, not significant; -  $p < 0.1$ , \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .

*Last mowing* : number of days since the last mowing event, *Rainfalls<sub>sampl</sub>* : quantity of rainfalls between two samplings, *pedoclim2* : second axis of 'pedoclimatic' PCA, *mowing* : mean number of mowing events per year, *N fertilization* : mean N dose applied per year, *irrig* : mean quantity of irrigation per year, *Temp min<sub>year</sub>* : mean minimal temperature during the sampling period, *Rainfalls<sub>year</sub>*: total quantity of rainfalls during the sampling period

295 **3.2. Relationships between floral productivity, richness and traits**

296 Annual flower cover, max flower cover and flower cover peak duration positively correlated  
 297 with floral richness, but not with total species richness. Only max flower cover date was  
 298 uncorrelated with floral richness (Table 3).

299 *Table 3. Individual effects of floral richness on indicators of flower productivity with field as*  
 300 *random effect.*

301

Indicator (response variable)	Explanatory variable	Estimate	R2m	R2c
Annual flower cover	Floral richness	22.56***	0.26	0.53
Max flower cover	Floral richness	0.751***	0.15	0.53
Max flower cover date	ns	-	-	-
Flower cover peak duration	Floral richness	1.158**	0.10	0.27

*Notes: ns, not significant; -  $p < 0.1$ , \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .*

302

303 Mean and variances of floral traits were related to max flower cover, max flower cover  
 304 date and flower cover peak duration: the composition of communities, affected both functional  
 305 structure and flower productivity indicators, demonstrating that quality, quantity and  
 306 temporality of floral resources are strongly linked (see details in Table 4).

307           The ‘community structure’ PCA explained 64.2% of the variability (Figure 6A). The  
308 first component (35.1% of explained variability) was positively correlated with the community  
309 weighted means of floral height (0.91), area (0.73), duration (0.71), pollen (0.67) and floral  
310 richness (0.62) ; high values on this component indicate that the species invest in more costly  
311 flowers while lower values indicate cheaper flowers (Roddy et al., 2021). The second  
312 component (29.1% of explained variability) was positively correlated with the community  
313 weighted mean of floral units number (0.84) and floral specific richness (0.56), and negatively  
314 with the community weighted means of flowering onset (-0.70) and duration (-0.57). The  
315 ascending hierarchical classification (Figure 6B) identified three clusters: cluster 1 ‘cheap, few  
316 and late-flowering flowers’, composed of 23 communities and linked to low scores on both  
317 components, cluster 2 ‘cheap, numerous and early-flowering flowers’ (13 communities) linked  
318 to low scores on the first component and high scores on the second, and cluster 3 ‘costly  
319 flowers’ (4 communities) linked to high scores on the first component. ‘Few and late-flowering  
320 flowers’ communities were more often mown (1,5 vs 2,5) and irrigated than ‘numerous and  
321 early-flowering flowers’ communities (Figure 7A), and their flower cover peak duration was 6  
322 days longer (Figure 7B).

323

324 *Table 4. Individual effects of community weighted means (CWM) and variances (CWV) of*  
 325 *floral traits on indicators of flower productivity with field as random effect.*

326

Indicator (response variable)	Functional indicator	Trait	Estimate	R2m	R2c
Annual flower cover	CWM	Nectar	50.992**	0.29	0.68
Max flower cover	CWM	Nectar	2.599***	0.27	0.76
Max flower cover date	CWM	Area	5*	0.26	0.34
		Nectar	-3.481**		
Flower cover peak duration	CWM	Onset	-0.022**	0.32	0.67
		Nectar	2.784**		
Annual flower cover	CWV	-	ns	ns	ns
Max flower cover	CWV	Nectar	1.025*	0.16	0.52
		Duration	-0.535**		
Max flower cover date	CWV	-	ns	ns	ns
Flower cover peak duration	CWV	Height	1.657**	0.20	0.63
		Area	-6.283*		

*Notes: ns, not significant; -  $p < 0.1$ , \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .*

327

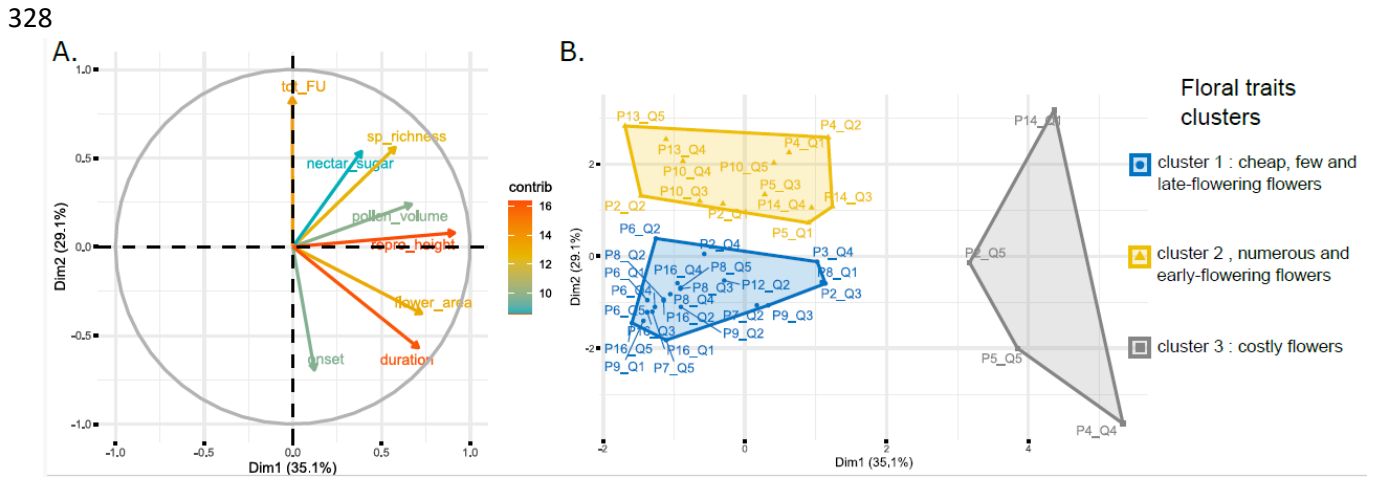


Figure 6. A. First two components of the 'community structure' PCA. The individuals are the 40 quadrats at the year scale in which at least 60% of the community was composed of species with documented floral traits. B. The three clusters created with the hierarchical ascending classification.

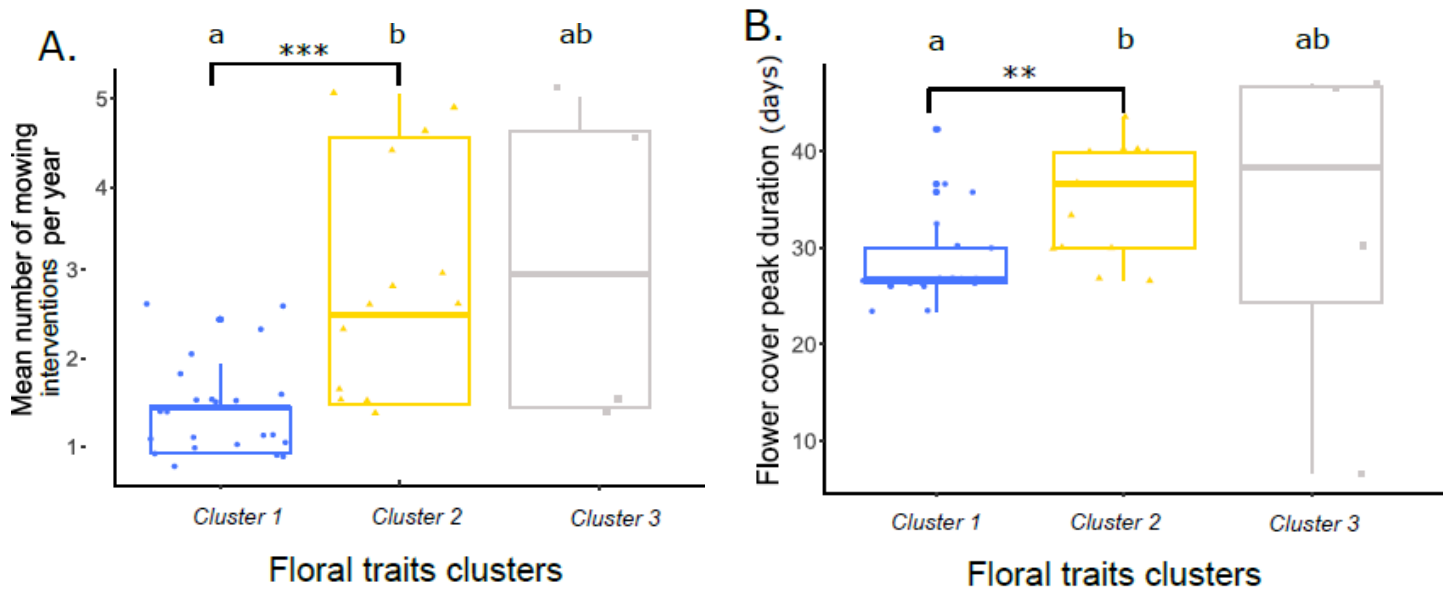


Figure 7. A. Mean yearly number of mowing interventions. B. Flower cover peak duration, according to the floral traits clusters. Letters reflect the results of pairwise Wilcoxon's tests.



## 339 **4. Discussion**

### 340 **4.1. Weed floral traits and richness are affected by pedoclimate and** 341 **agricultural practices**

342 Our results indicate that agricultural practices affect the floral functional structure of weed  
343 communities in Mediterranean olive groves. More mowing interventions (min : 0, max : 5 in  
344 the network) increased floral richness (Table 1), functional heterogeneity (i.e. wider community  
345 weighted variances) of floral area, nectar sugar content and flowering onset, postponed mean  
346 flowering onset, and resulted in communities with larger and taller flowers (Table 2),  
347 supposedly more attractive to insects (Lundin et al., 2019; Rowe et al., 2020). The diversifying  
348 effect can be explained by the positive effect of low-to-intermediate disturbance of mowing on  
349 species diversity and trait variance in the community, as predicted by the intermediate  
350 disturbance hypothesis (Wilkinson et al., 1999). The number of mowing interventions ranged  
351 from 1 to 5 per year, with a mean of 2.19, which is considered fairly low but disturbing enough  
352 to curb the dominance of the most competitive species. However, this relationship may not hold  
353 when mowing is more frequent.

354 In contrast, irrigation and fertilisation had a homogenising effect, reducing community  
355 weighted variances of floral area and flowering onset (Table 2), perhaps because high levels of  
356 resources benefited the most competitive species. For example, flowering onset was earlier in  
357 more frequently mown, fertilised but unirrigated olive groves, which is logical because more  
358 disturbed communities are traditionally composed of species flowering earlier (Fried et al.,  
359 2012). Higher levels of resources (N fertilization, irrigation) also selected for species producing  
360 more floral units that flower for a longer period, which is allowed by the available resources,  
361 as showed in vinetards by Guerra et al. (2021). Managing the regularity of mowing seems

362 efficient to regulate phenology so as to provide more diversified and abundant floral resources  
363 for flower-visiting insects (Yvoz et al., 2021).

364 Even though agricultural practices are considered the main driver of trait variability in  
365 weed communities at the regional scale (Bourgeois et al., 2021), pedoclimatic and weather  
366 variables also matter, especially for trait variance (Poinas et al., 2023). In our study, the  
367 homogenising effect of greater soil fertility, e.g. higher levels of organic matter and clay  
368 contents (pedoclim1), may be due to selection of the most competitive species (Fried et al.,  
369 2022) that develop earlier and exclude later species by pre-empting light resources (Grime,  
370 1974). Higher temperatures allowed some cold-tolerant and sensitive species to survive, thus  
371 diversifying functional structure, but also decreased community weighted mean of flowering  
372 onset, advantaging competitive species that flower early. Rainfall also had a diversifying effect  
373 leading to greater FCWVs of total floral unit number and pollen: water deficit may force weeds  
374 to allocate less resources to flowers or pollen production (Kuppler & Kotowska, 2021). As  
375 found by Bourgeois et al. (2021) for weeds in annual agroecosystems, pedoclimate affected the  
376 variance more than the mean of floral traits.

#### 377 **4.2. Floral productivity is linked to community floral richness and traits**

378 Not all floral traits were linked to floral productivity, indicating that communities with any  
379 floral strategy could potentially provide floral resources. However four floral traits were found  
380 to be positively correlated with floral productivity: mean nectar sugar content (Table 4), number  
381 of flowers, onset of flowering (Figures 5 and 6) and floral richness (Table 3), the last increasing  
382 all the indicators of floral productivity.

383 Weed richness enhanced floral productivity and thereby provided a diversity of food  
384 resources for insects (Balfour & Ratnieks, 2022). The most abundant species, e.g. *M. minima*  
385 and *S. arvensis*, had ruderal floral strategies and produced many small flowers (Genty et al.,

386 2023b) excluded by wild bees (Kuppler et al., 2023) but preferentially visited by other important  
387 pollinators such as Diptera and Coleoptera (Lanuza et al., 2023). However, the great floral  
388 richness found in the olive groves (99 flowering species) enhanced their potential for hosting  
389 plants visited by all types of pollinator, among which *E. vulgare* and *P. hieracioides*, favoured  
390 by wild bees (Kuppler et al., 2023). Regarding year-round flower presence, which is important  
391 for flower-visiting insects, we found that floral resources in olive groves peaked in mid-April  
392 overall, with local variations from March to June. This means that flowers were present early  
393 in the season, supplying food at a critical time for insects (Pelletier and MacNeil, 2003),  
394 however very few resources were available late in the season, which is another critical period  
395 for foraging.

### 396 **4.3. Mowing is a promising practice for enhancing floral productivity**

397 Since floral richness, mean traits and trait variances were directly affected by agricultural  
398 practices (Tables 1 and 2), and were linked to floral resources productivity, we conclude that  
399 agricultural practices affect floral productivity in olive groves. Indeed, the most regularly mown  
400 communities were composed of species flowering earlier and with more flowers per individual  
401 produced flowers for a longer period (Fig. 6, 7). The intermediate level of disturbance caused  
402 by two or three mowing interventions per year increased weed floral richness and trait diversity,  
403 as in grasslands (Piseddu et al., 2021). This finding suggests that the impact of agricultural  
404 practices on floral richness can rival that of environmental drivers (Pittarello et al., 2020). This  
405 may be due to the greater instability of weed communities compared with grasslands: because  
406 weeds are mostly annual species, they are more responsive to intra-annual events like  
407 management practices than communities of perennial species.

408 Mowing two to three times a year appears to be a beneficial practice for weed species  
409 richness and related ecosystem services in woody agroecosystems (Winter et al., 2020). In our  
410 work, we found that regular mowing frequency favors higher floral productivity over the year

411 in olive groves. We conclude as other studies for different services (Bopp et al., 2022b;  
412 Kavvadias and Koubouris, 2019), that mowing is a biodiversity-friendly weed management  
413 practice able to both deliver ecosystem services and ensure satisfactory yield in Mediterranean  
414 woody agroecosystems (Guerra et al., 2022).

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