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# Citizen science involving farmers as a means to document temporal trends in farmland biodiversity and relate them to agricultural practices

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1 **Citizen science involving farmers as a means to document temporal trends in farmland biodiversity**  
2 **and relate them to agricultural practices.**

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10

11

12 **Abstract**

13 (1) Agricultural intensification is often recognized as a major driver of the decline of wild  
14 biodiversity in farmland. However, few studies have managed to collect relevant data to link  
15 the temporal dynamics of farmland biodiversity to the characteristics of intensive agriculture  
16 over large geographical areas.

17 (2) We used 7 years of data from a French citizen science programme, wherein 1,216 farmers  
18 monitored biodiversity in 2,382 fields encompassing field crops, meadows, vineyards or  
19 orchards, to examine the temporal trends in abundance of five taxonomic groups of  
20 invertebrates (solitary bees, earthworms, butterflies, beetles, molluscs) and their links with  
21 agronomic practices and surrounding landscape.

22 (3) We observed significant temporal trends in abundance for many taxonomic groups and in  
23 many crop types. Flying taxa (solitary bees and butterflies) were generally declining, while  
24 the trends of soil taxa were more variable. Most trends were significantly related to farming  
25 practices or landscape features. We observed a negative link between use of synthetic inputs  
26 (pesticides, mineral fertilization) and the trend in abundance of flying taxa in field crops,  
27 while in meadows organic or mineral fertilization was the main explanatory practice, with  
28 contrasting relationships across taxonomic groups. Besides, the trend in abundance of  
29 beetles and molluscs was more positive in permanent versus temporary meadows. Finally, in  
30 vineyards the trend in abundance of solitary bees was positively related to the presence of  
31 woodland in the landscape, whereas the reverse was true in meadows.

32 (4) *Synthesis and applications.* Our results provide further support for the role of citizen science  
33 as a promising source of large-scale spatial and temporal data in farmland, contributing to  
34 the identification of agronomic practices that can help mitigate biodiversity decline. Our  
35 analyses suggest that reducing chemical inputs may not only reduce the decline in bees and  
36 butterflies, but sometimes even promote their regrowth. Increasing organic fertilization may  
37 foster bee and beetle abundance in meadows but reduce mollusc abundance, while

38 preventing ploughing of meadows may promote soil invertebrate abundance. Finally, such  
39 citizen science programmes engage farmers to undertake monitoring. Whether such group  
40 engagement may also contribute to biodiversity conservation by raising farmers' awareness  
41 remains to be addressed.

42 **Keywords:** bees, beetles, butterflies, earthworms, fertilization, landscape, mollusks, pesticides

43 **Additional abstract / Résumé**

44 (1) L'intensification de l'agriculture est reconnue comme un facteur majeur du déclin de la  
45 biodiversité sauvage dans les terres agricoles. Cependant, peu d'études ont pu relier les  
46 changements temporels de la biodiversité agricole aux pratiques agricoles.

47 (2) Grâce aux données issues de l'Observatoire Agricole de la Biodiversité, un programme de science  
48 participative ayant rassemblé 1216 agriculteurs entre 2011 et 2017, pour un total de 2382 parcelles  
49 comprenant des grandes cultures, des prairies, des vignobles ou des vergers, nous avons étudié les  
50 tendances temporelles de l'abondance de cinq groupes d'invertébrés (abeilles solitaires, vers de  
51 terre, papillons, carabes, mollusques) et leurs liens avec les pratiques agronomiques et le paysage  
52 environnant.

53 (3) Nous avons observé des variations temporelles significatives de l'abondance pour plusieurs  
54 groupes taxonomiques et dans de nombreux types de cultures. Les taxons volants (abeilles solitaires  
55 et papillons) sont en général en déclin, tandis que les tendances des taxons terrestres sont plus  
56 variables. La plupart des tendances sont significativement corrélées aux pratiques agricoles ou au  
57 paysage. L'utilisation d'intrants de synthèse (pesticides et fertilisation minérale) est corrélée au  
58 déclin des taxons volants dans les grandes cultures, tandis que dans les prairies, la fertilisation  
59 organique et/ou minérale est la principale pratique explicative, avec des relations contrastées entre  
60 les groupes taxonomiques. En outre, les carabes et des mollusques sont en augmentation dans les  
61 prairies permanentes mais en déclin dans les prairies temporaires. Enfin, dans les vignobles, les

62 variations d'abondance des abeilles solitaires sont positivement reliées à la présence de bois dans le  
63 paysage, alors que l'inverse est vrai dans les prairies.

64 (4) *Synthèse et applications*. Nos résultats confortent le rôle de la science citoyenne comme source  
65 prometteuse de données à grande échelle spatiale et temporelle dans les espaces agricoles,  
66 contribuant à l'identification des pratiques agronomiques qui peuvent aider à atténuer le déclin de la  
67 biodiversité. Nos analyses suggèrent que la réduction des intrants chimiques peut non seulement  
68 réduire le déclin des abeilles et des papillons, mais parfois même favoriser leur augmentation. Une  
69 fertilisation organique plus importante peut favoriser l'abondance des abeilles et des carabes dans  
70 les prairies mais réduire l'abondance des mollusques, tandis que le non-retournement des prairies  
71 peut favoriser l'abondance des invertébrés du sol. Enfin, ces programmes de science citoyenne  
72 incitent les agriculteurs à observer la biodiversité de leurs parcelles. Reste à savoir si cet engagement  
73 collectif des agriculteurs peut également contribuer à la conservation de la biodiversité par une plus  
74 forte sensibilisation sur le sujet.

## 75 **1 | Introduction**

76 Agricultural intensification is recognized as a major driver of the current biodiversity decline for  
77 insects (Sánchez-Bayo & Wyckhuys, 2019; Seibold et al., 2019), birds (Stanton, Morrissey, & Clark,  
78 2018) or soil biota (Ponge et al., 2013). Different mechanisms may explain this agriculture-driven  
79 biodiversity loss, including non-target effects of pesticides (Zaller & Brühl, 2019), fertilization  
80 (Haddad, Haarstad, & Tilman, 2000), tillage (Roger-Estrade, Anger, Bertrand, & Richard, 2010),  
81 landscape simplification and homogenization (Gamez-Virues et al., 2015), etc. However, proving a  
82 causal link between practices and biodiversity is often challenging.

83 Several limitations of studies relating biodiversity to farming practices are responsible for this lack of  
84 conclusiveness. First, such studies are often restricted in space and time or focus on specific taxa,  
85 which hampers generalization (see Cardinale et al. 2011 for a review). In contrast, the few studies  
86 that benefit from large-scale, long-term biodiversity monitoring data have limited information on  
87 agronomic practices. For instance, Hallmann et al., (2017) could only speculate on the role of  
88 agriculture in the massive decline in insect biomass, because they lacked accurate data on  
89 agriculture. Second, most studies measuring the impacts of potential drivers assume space-for-time  
90 substitution (SFT). SFT can be relevant to study the effects of slow environmental changes, by  
91 comparing systems at different stages of development (Pickett, 1989). Such approach assumes that  
92 the temporal dynamics of the sites can be ignored and that spatial patterns are due to different  
93 ecological equilibria (Damgaard, 2019). These assumptions are true only when ecological processes  
94 are quick compared to environmental changes (Damgaard, 2019), which may not apply for  
95 biodiversity dynamics in rapidly changing agroecosystems (Jackson & Blois, 2015; Kratz, Deegan,  
96 Harmon, & Lauenroth, 2003).

97 To our knowledge, only a handful of studies addressing the impacts of agricultural practices on  
98 biodiversity included a true temporal dimension. Among them, Hallmann et al. (2014) linked the  
99 introduction of neonicotinoids to a negative trend in insectivorous bird populations by comparing

100 different periods of surveys (before/after). Berger et al. (2018) observed a relationship between  
101 changes in glyphosate application modes and amphibian migration. Finally Seibold et al. (2019)  
102 showed a general decline of arthropods driven by land-use intensification at large spatial extent.  
103 These temporal approaches to elucidate the role of agriculture in biodiversity changes are few  
104 because they require gathering temporal and spatial data at large scales, which is labor and time  
105 intensive. A way to solve this problem may be to capitalize on the recent expansion of citizen science  
106 for biodiversity monitoring, which can involve geographically dispersed observers during several  
107 years (Chandler et al., 2017).

108 In this article, we rely on a citizen science program designed for farmers to study temporal trends in  
109 abundance of several taxonomic groups (solitary bees, earthworms, molluscs, beetles and  
110 butterflies). We investigated how the temporal trends in abundance of these groups are correlated  
111 with both agronomic practices and surrounding landscape. Documenting such relations may help  
112 identify possible levers for the conservation of invertebrates in farmland, through changes in  
113 agricultural practices.

114

## 115 **2 | Materials and methods**

### 116 **2.1 | Citizen science to monitor farmland biodiversity**

117 The Farmland Biodiversity Observatory (FBO) is a French citizen science programme launched in  
118 2011, wherein 1,216 farmers monitored biodiversity in 2,382 fields, thereby ensuring a good  
119 representation of the diversity of farming practices and crop distribution across France (Fig. S1A).

120 Four types of crops are monitored: field crops (1,515 fields), meadows (705 fields), vineyards (538  
121 fields) and orchards (240 fields). We used data collected between 2011 and 2017. As in most citizen  
122 science programmes, participant turnover is high in FBO, with a mean duration of participation from  
123 1.22 to 1.39 years, depending on the taxonomic group monitored (Fig S1B). However, the number of  
124 newly involved farmers each year is relatively stable through time, such that the dataset provides a

125 “series of pictures” of biodiversity throughout France. Note S1 provides more information on FBO,  
126 the farmers involved, and ongoing research on how this programme changes farmer perceptions of  
127 biodiversity.

128

## 129 **2.2 | Biodiversity data**

130 FBO focuses on four taxonomic groups chosen for their interconnections with agriculture: solitary  
131 bees (pollination services, Potts et al., 2016; Winfree, Williams, Dushoff, & Kremen, 2007), butterflies  
132 (sensitive to changes in land use at the landscape scale, Dover & Settele, 2009; Nilsson, Franzen, &  
133 Pettersson, 2013), earthworms (soil fertility, Lemtiri et al., 2014) and soil invertebrates (pests and  
134 beneficial organisms, Kromp, 1999; Symondson, Sunderland, & Greenstone, 2002). Monitoring  
135 protocols are simple, yet standardized. Observers can access keys to identify individuals to either  
136 functional group or taxonomic rank (genus and sometimes species level). Bee monitoring uses two  
137 trap nests of 32 tubes each placed in the field edge, facing south. Observers monitor nest occupancy  
138 by counting sealed tubes (Fig. S2C). For butterflies, observers walk a 10 minutes transect (100-300m)  
139 on the field edge, recording all individuals flying in a 5x5x5m cube around them (Fig. S2A). To  
140 monitor soil invertebrates, three wooden cover-boards of 30x50 cm are laid on the ground, two at  
141 the edge and one at the center of the plot (at 50m of the two others) (Fig. S2B). The observer quickly  
142 lifts the board to count all invertebrates; identification focuses on beetles and mollusks but other  
143 invertebrates are also reported. Finally, earthworms are sampled through three 1m<sup>2</sup> replicates  
144 located 6 m apart inside the field. Each replicate is watered twice with 10L of a mustard solution (Fig.  
145 S2D). Earthworms expelled to the surface by the irritant solution are collected, counted and sorted  
146 into four functional groups: epigeic, black- and red-headed anecic and endogeic (Bouché, 1972).

147

148 In FBO, bees were monitored in 1,345 fields, butterflies in 727 fields, soil invertebrates in 807 fields  
149 and earthworms in 685 fields (Fig. S3 shows the distribution of monitoring protocols across crop  
150 types). The number of annual surveys per field varies across protocols. In theory, earthworms are

151 sampled only once in winter or early spring, bees and invertebrates are monitored once a month  
152 between February and November, and butterflies are monitored five times per year between May  
153 and September. However, some observers may skip some of the surveys. To handle this variation in  
154 the number of observations per field and year, we did not work on annual summaries of biodiversity  
155 data, but chose to use individual surveys. For each group we focused on the total abundance, since  
156 most individuals cannot be identified to species level in the monitoring protocols. Moreover,  
157 abundance is more sensitive to environmental changes than diversity (Pereira et al., 2013).

158

### 159 **2.3 | Practices and landscape data**

160 Farmers also provide information about the landscape surrounding the field and their agricultural  
161 practices (Table S1 shows all variables associated with the protocols and crops). Some information is  
162 common to all plots: pesticide use (insecticide, herbicide, fungicide, molluscicide, others),  
163 fertilization (organic and mineral) and amendment (organic and calcium), which are provided as a  
164 number of applications. The surrounding landscape is described via field edge types (wood-fringe,  
165 hedge, grassy strip, roadside, ditch, flower strip, crop, other) and neighbouring land use (meadow,  
166 wood, urban, pond, crop, other). The field edges described are those close to the trap nests and  
167 transect for bees and butterflies; all edges for earthworms and invertebrates. Other information is  
168 only relevant for some types of crops: tillage (direct sowing, shallow or deep ploughing) in field crops,  
169 management of inter-rows (bare, partly grassy, grassy) in vineyards and orchards and use (mowing,  
170 pasture, mix), type (temporary or permanent) and age in meadows. Complementary protocol-specific  
171 information includes: distance to the nearest tree for earthworms, flowers in the crop and edges for  
172 butterflies and vegetation height for bees. Soil attributes (earthworms and invertebrates) and  
173 weather (butterflies, earthworms and invertebrates) are also collected. We computed degree-day  
174 (cumulative sum of temperature over zero) for each day using data from Cornes, Schrier, Besselaar,  
175 & Jones (2018) and the R package climateExtract (Schmucki, 2020).

176

177 **2.4 | Multivariate analyses to summarize the diversity of in-field practices and surrounding**  
178 **landscape**

179 Agricultural practices, as well as landscape variables, are often correlated with one another due to  
180 the consistency of agronomic systems. To circumvent this problem, we summarized practices and  
181 landscape variables with multivariate analyses. We used a principal component analysis (PCA) on  
182 fertilization and pesticide use. We considered each crop type separately because they are associated  
183 with contrasting production systems that use different amounts and classes of pesticides and  
184 fertilization. These differences were easily seen on a PCA on all fields (Fig. 1A-B). However, regardless  
185 of crop type, we observed the same general pattern in the outputs of the PCA, with the two main  
186 axes easily interpreted as a “chemical treatment axis” (mostly pesticides and mineral fertilization)  
187 and an “organic fertilization” axis, respectively (Fig. 1C-D-E-F). In the following, we therefore used the  
188 coordinates of fields on these axes as two uncorrelated variables describing the diversity of practices  
189 (Fig. 1C-D-E-F).

190 In the same way, we applied a multiple correspondence analysis (MCA) on binary landscape variables  
191 (presence / absence of elements in the edges or neighbouring land use) to summarize landscape  
192 diversity around fields. We analysed taxonomic groups separately because protocols differ in the  
193 number of surveyed field edges (see above). Nonetheless, for all protocols, one of the two first axes  
194 was interpreted as proximity to woodland (Fig. S4-5-6-7). The meaning of the other axis was more  
195 variable. For bees, butterflies, beetles and molluscs, it singled out the category “other” of the  
196 surrounding landscape and was not easily interpretable. For earthworms, it contrasted the presence  
197 of a pond versus adjacent crops (Fig. S4-5-6-7).

198

199

200

201 **2.5 | Statistical modelling to correlate temporal trends in group abundance with practices and**  
202 **landscape**

203 To investigate the temporal trends in abundance per taxonomic group and their correlation with  
204 farming practices and landscape variables, we used generalized linear mixed models (GLMM) (Bolker  
205 et al., 2009). We assumed a negative binomial distribution of the data to take into account  
206 overdispersion. We started from a complete model with year, practice and landscape variables (the  
207 latter two being described by the first axes of the multivariate analyses), and their interactions, plus  
208 relevant additional covariates depending on the taxonomic group (hereafter “control covariates”,  
209 Table S1) and a random effect of field. Practices were represented by the two axes of the PCA plus  
210 crop type-dependent variables (Table S1). We also tested alternative models using the total number  
211 of pesticide and (organic and mineral) fertilizer applications, instead of PCA axes, as a proxy for  
212 intensification. Axes 1 and 2 of the MCA reflected the surrounding landscape (Fig. S4-5-6-7). The  
213 general structure of the model was the following:

$$\begin{aligned} 214 \quad \log(\mu_{AB}) = & \beta_0 + \beta_1 Year + \beta_2 Axis1_{PCA} + \beta_3 Axis2_{PCA} + \beta_4 Axis1_{MCA} + \beta_5 Axis2_{MCA} \\ 215 & + \beta_{6x} SpecificPractices + \beta_{7x} Covariates + \beta_8 Year: Axis1_{PCA} \\ 216 & + \beta_9 Year: Axis2_{PCA} + \beta_{10} Year: Axis1_{MCA} + \beta_{11} Year: Axis2_{MCA} \\ 217 & + \beta_{12x} Year: SpecificPractices + Field_i \end{aligned}$$

218 With  $\beta_j$  the regression coefficients and  $Field_i$  the field-specific random effect. “Specific practices”  
219 (tillage, inter-row...) and covariates (weather conditions, GPS coordinates...) varied depending on  
220 protocol and type of crops (Table S1). All numerical variables were scaled. We selected variables  
221 using backward stepwise elimination from a complete model and significance of the change in log-  
222 likelihood as a criterion. We checked that all the “control” covariates had a consistent relationship  
223 with abundance, e.g. more abundant bees in the South or more abundant butterflies with lower wind  
224 (Tables 1-5 and S2-6). As for earthworms, models were GLM since the random field effect was not  
225 significant. We used the R package buildmer (Voeten, 2020).

226 Of five taxonomic groups and four crop types, we analysed only 18 separate models out of 20  
227 because we discarded earthworm data in orchards and vineyards, which were too few (some years  
228 with fewer than 10 surveys).

229 We diagnosed the fit of the models using the DHARMA package (Hartig, 2020). Over the 18 separate  
230 models of crops and taxonomic groups, all QQ plots were acceptable upon visual inspection. No  
231 Kolmogorov-Smirnov deviation test was significant, except for bees in field crops, for which the  
232 significant deviation was visually small. The residuals were significantly but moderately spatially  
233 autocorrelated (Table S17); introducing a covariance structure in the models did not modify the  
234 results (not shown). Variance inflation factors (VIF), computed using the package performance  
235 (Lüdecke, Makowski, Waggoner, & Patil, 2020), were generally below 2 (Tables S7-16) except for  
236 artificially structured variables (e.g. degree days and squared degree days) and in models with a  
237 significant effects of meadows use or type. Removing these variables did not change the results for  
238 other variables (not shown). The models explained a fair amount of the variability in abundance, as  
239 estimated following Nakagawa, Johnson, & Schielzeth (2017), although ca. 2/3 resided in the random  
240 effect: from 0.1 to 0.35 without, and from 0.43 to 0.85 with the random field factor. Lastly, we  
241 analyzed interaction terms using the package ggeffects (Lüdecke, 2018), which computes marginal  
242 effects of each variable with all others at their mean (quantitative variables) or at representative  
243 values (qualitative variables) from statistical models (Figs. 2-4).

244

### 245 **3 | Results**

246 The 1,216 farmers provided multi-year data from their fields on five taxonomic groups and in four  
247 crop types, and the overall analysis showed that there were significant temporal trends in  
248 biodiversity abundance in 16 of the 18 analyses. Some trends are related to farming practices or  
249 surrounding landscape. Tables 1-5 display a summary of the models using the PCA axes (“chemical  
250 treatment” and “organic fertilization”) as proxy for farming practices, while Tables S2-S6 give a

251 summary of the models using the number of applications of pesticides and fertilization. For each  
252 combination of crop type and taxonomic group, these two types of model may differ slightly. In the  
253 following, we focus on results that seem most robust, i.e. significant in the two types of models, but  
254 we illustrate all significant interactions in Figures S11-14.

255

### 256 **3.1 | Solitary bees**

257 The abundance of solitary bees appeared to be declining significantly in all crops but vineyards, and  
258 these declines were related to farming intensity or landscape structure (Tables 1 and S2). Conversely,  
259 the trend was positive in vineyards. Declines were stronger in fields with more pesticide use or more  
260 mineral fertilization (effects are statistically difficult to separate) in field crops (Figs. 2 and S8). On the  
261 other hand, bee declines were less steep with more organic fertilization (field crops, meadows) as  
262 well as in vineyards closer to woodland (Figs. 4 and S10). Conversely bee decline was stronger in  
263 meadows closer to woodland.

264

### 265 **3.2 | Butterflies**

266 The abundance of butterflies declined in field crops and vineyards and increased in meadows (Tables  
267 2 and S3). Declines were related to farming intensity, but in opposite ways: as with bees, the trend in  
268 field crops was negatively correlated with the use of pesticides or mineral fertilization (Figs. 2 and  
269 S8). Conversely, the decline in vineyards was stronger in fields with fewer pesticide applications. No  
270 temporal trend was identifiable in orchards, but sample size was small ( $N=213$  for 37 fields).

271

### 272 **3.3 | Earthworms**

273 The abundance of earthworms showed a temporal decline in meadows only that did not vary with  
274 practices or landscape (no significant interactions, Tables 3 and S4, Figs. 3 and S9). However, the  
275 abundance of earthworms was significantly and positively related to a reduced tillage in field crops,  
276 as well as to organic fertilization and meadow age in meadows.

### 277 **3.4 | Beetles**

278 The abundance of beetles increased significantly in field crops and vineyards and decreased in  
279 meadows and orchards (Tables 4 and S5). Declines in meadows and orchards were stronger in fields  
280 with more mineral fertilization (or pesticides in orchards, effects are difficult to separate) (Figs. 3 and  
281 S9). Finally, the decline in meadows was detected in temporary but not in permanent grasslands,  
282 where we observed a stronger increase in fields with more organic fertilization.

283

### 284 **3.5 | Molluscs**

285 As with beetles, the abundance of molluscs increased significantly in field crops and vineyards and  
286 decreased in meadows and orchards (Tables 5 and S6). Increases in vineyards were stronger in fields  
287 with more mineral fertilization or pesticides (effects are difficult to separate) but less organic  
288 fertilization. Declines in meadows were stronger in fields with more organic fertilization and in  
289 temporary versus permanent meadows (Figs. 3 and S9).

290

### 291 **4 | Discussion**

292 In this study we documented significant correlations between temporal trends in biodiversity  
293 abundance and in-field agricultural practices or wider landscape variables, across the whole of France  
294 thanks to participation of farmers in citizen science. In the following, we first compare our results  
295 with the existing literature using professionally collected data, contrasting flying versus soil taxa, and  
296 discuss the possible limitations related to the participatory nature of the data. We then examine how  
297 citizen science engaging farmers in monitoring of biodiversity can help pinpoint possible levers for  
298 the conservation and even restoration of invertebrates in agroecosystems through modifications of  
299 farming practices.

300

301

302 **4.1 | Worrying temporal trends in abundance for several invertebrates monitored in FBO are**  
303 **related with agricultural practices**

304 Of the five groups monitored, we observed a general negative trend in abundances, in particular for  
305 the two flying taxa with relatively long-distance movements (butterflies and solitary bees). These  
306 findings are in line with recent studies showing a decline in bees and butterflies, whether on a local  
307 (Hallmann et al., 2019), regional (Habel, Trusch, Schmitt, Ochse, & Ulrich, 2019), national (Dooren,  
308 2019) or global scale (Klink et al., 2020; Sánchez-Bayo & Wyckhuys, 2019). Soil taxa, including  
309 potentially flying species but with short-distance daily movements, such as beetles, show a more  
310 mixed picture, with a temporal decline in abundance in meadows and orchards but a more surprising  
311 increase in field crops and vineyards. One major question is whether these trends reflect true  
312 variations in arthropod abundance in farmland, or are partly caused by temporal changes in the  
313 sample of fields surveyed each year, owing to the turnover of FBO participants. Two points discard  
314 the latter explanation. First, the general trend in abundance was negative, which could have been  
315 caused by a temporal increase in the fraction of fields under intensive farming in the FBO sample.  
316 Yet, if anything, the tendency in the FBO sample is that of an increase in the fraction of fields under  
317 organic farming consistent with the national trend (Note S1). Second, we did not analyze trends on  
318 raw data, but in a model including interactions with farming practices or landscape, thereby  
319 controlling for temporal changes in the latter variables.

320 Our ability to relate temporal trends in biodiversity with local agricultural practices contrasts with  
321 most previous studies. Our results are generally consistent however with numerous smaller-scale  
322 studies using the SFT assumption: stronger declines in fields with more synthetic inputs (mineral  
323 fertilization and pesticides) or in more homogeneous landscapes in most cases, but with some  
324 exceptions. Fertilization affects habitat quality via enrichment and sorting of competitive plant  
325 species. This may reduce the diversity and amounts of food for pollinating insects (e.g. bees and  
326 butterflies in field crops) and phytophagous species (e.g. molluscs in meadows). In some cases,

327 however, increased plant biomass and leaf nitrogen content associated with fertilization can result in  
328 increased invertebrate abundance, as observed e.g. by Haddad, Haarstad, & Tilman (2000) and in  
329 several instances in FBO: for molluscs with mineral fertilization in vineyards, as well as for bees and  
330 beetles with organic fertilization in meadows.

331 Pesticides often have non-target negative effects on invertebrates, demonstrated in the lab  
332 (Desneux, Decourtye, & Delpuech, 2007; Henry et al., 2012; Mulé, Sabella, Robba, & Manachini,  
333 2017) or in fields (Mulé et al., 2017), through direct mortality or multiple sublethal effects (Brittain &  
334 Potts, 2011; Desneux et al., 2007). Such effects may explain the negative relationship observed  
335 between pesticide use and trends in abundance of bees and butterflies in field crops. We found a  
336 more surprising positive correlation with butterfly abundance trends in vineyards. This is consistent  
337 with Muratet & Fontaine (2015) who observed the same positive relationship in gardens with  
338 fungicides and Bordeaux mixture - two products highly used in vineyards – on butterflies and  
339 bumblebees. A hypothesis would be that plants protected from pests allocate more resources to  
340 nectar production.

341 Finally, proximity to woodland has mixed effects on solitary bees. The positive effect in vineyards is in  
342 line with numerous studies such as Carrié, Andrieu, Ouin, & Steffan-Dewenter (2017). For some bee  
343 species, semi-natural landscape elements such as forests provide nesting sites and long-lasting food  
344 sources (Hopfenmüller, Steffan-Dewenter, & Holzschuh, 2014) as well as a high connectivity in the  
345 landscape. Decline of bee abundance in meadows close to woodland is consistent with Winfree,  
346 Griswold, & Kremen (2007) and may be explained by the lower quality of forests vs. farmland for bee  
347 species that are likely specialists of open habitats.

348 Although these results corroborate previous knowledge and go beyond by relating biodiversity  
349 trends with in-field practices, this approach suffers some limitations, some of which are inherent to  
350 citizen science. As in many studies, including professional ones, our results are correlative and do not  
351 formally demonstrate a causal relationship between agricultural practices or surrounding landscape

352 and biodiversity. For example, a positive relationship between pesticide use and abundance of soil  
353 taxa may arise because pest outbreaks trigger pesticide use, which we are not able to differentiate  
354 from a positive effect of pesticides on these groups. This limitation could be partly overcome with  
355 time and a higher fidelity of participants: with longer time series, the dataset would contain a larger  
356 number of events of changes in practices. Such events could be used to analyse in more detail the  
357 impact of changing practices on biodiversity in real time, in an experimental-like manner. Second, the  
358 effects of pesticides and mineral fertilization were often not distinguishable from each other. This is  
359 related to the first point: across farming systems, pesticide and fertilizer uses are strongly correlated  
360 with each other. This multicollinearity undermines our ability to differentiate the relative  
361 contribution of each practice, a problem that could be partly alleviated again by real-time monitoring  
362 of changes in practices. Another option would be to collect higher resolution data on chemical  
363 products used (date and mode of application, quantity...), beyond a mere number of applications.  
364 Finally, data collection by non-taxonomists implies that in most cases, specimens could not be  
365 identified to species level. This may hamper our understanding of the ecological mechanisms  
366 influencing abundance trends in broad taxonomic groups containing species with contrasting  
367 ecological preferences. For example, some groups could be dominated by a single successful species.  
368 Alternatively, landscape may matter for some large but relatively rare ground beetles, but mixing  
369 them with smaller species with limited dispersal ability masked possible correlations with landscape  
370 structure.

371

#### 372 **4.2 | Promising levers for invertebrate conservation in agricultural landscapes**

373 Our study pinpoints two key levers for invertebrate conservation in agroecosystems: i) identification  
374 of practices that may restore biodiversity ii) involvement of farmers in biodiversity monitoring;  
375 farmers are the main, albeit not the sole, social group with impacts on farmland biodiversity, and  
376 they have the agency to change practices.

377 Despite the above limitations, this study illustrates that citizen science can be a powerful tool to  
378 gather extensive ecological datasets allowing research at multiple spatio-temporal scales and the  
379 identification of levers for invertebrate conservation. Although collected via simplified sampling  
380 protocols, the data make it possible to detect temporal trends in total abundance of several  
381 understudied taxonomic groups and interactions with other variables. This confirms that well-  
382 designed participatory science adds value to large-scale biodiversity studies (Chandler et al., 2017;  
383 McKinley et al., 2017) and allows the development of indicators (Couvet, Jiguet, Julliard, Levet, &  
384 Teysseire, 2008). Such design could also be used to foster arthropod conservation in farmland,  
385 which is crucial for ethical and economic reasons (FAO, 2019). Below we show that our results  
386 converge with Habel, Samways, & Schmitt (2019) recommendations for a European strategy  
387 mitigating the decline of terrestrial insects, including the protection of high quality habitats for  
388 insects, ecological intensification of agriculture and the reduction and control of fertilizers and  
389 pesticides.

390 As discussed above, promoting participant fidelity to track the consequences of changes in farming  
391 practices should help separate the effects of pesticides versus fertilizers and identify biodiversity-  
392 friendly practices with demonstrated causative effects. Improved fidelity can be achieved by  
393 developing more user-friendly data entry interfaces, by promoting FBO in large professional  
394 networks, such as unions, or by providing more personalized feedback to participants, all of which is  
395 under way. We may also hope to see more changes in practices as a result of recent political will to  
396 reduce pesticides use or of awareness raising through participatory science (Deguines, Princé, Prévot,  
397 & Fontaine, 2020).

398 Beyond the reduction of inputs, our results also suggest that arthropod conservation can be  
399 promoted via improved habitat quality, e.g. presence of old meadows or woodland. For example, we  
400 observed that the decline of beetles and molluscs in temporary meadows could be reversed,

401 depending on management, in permanent meadows. This corroborates the recognized importance of  
402 permanent grasslands for biodiversity (Petters, 2015).

403 Finally, Habel, Samways, & Schmitt (2019) also stressed the society's relationship to insects and the  
404 need to highlight their economic and ecological importance to help raise public awareness. One of  
405 the distinctives of FBO as a citizen science object is that it is aimed at a specific socio-professional  
406 public. The involvement of farmers in farmland biodiversity monitoring may help them acknowledge  
407 the need to take biodiversity into account in their professional practice and transform their vision of  
408 their farm (Deschamps & Demeulenaere, 2015; Hampartzoumian et al., 2013). Participatory science  
409 through an experience-based knowledge and sharing through professional networks (McKinley et al.,  
410 2017) could be a driving force for change in agricultural practices at the farmers' scale. By providing  
411 data directly from their fields and practices (as opposed to experimental conditions), farmers took an  
412 active role in the demonstration of the effects of agriculture on its environment, which may elicit  
413 citizen involvement. Furthermore, engagement in citizen science could launch interactions between  
414 farmers and scientists to work together on new agricultural systems (Berthet, Barnaud, Girard,  
415 Labatut, & Martin, 2016). Finally, FBO tends to serve as an exchange platform between  
416 environmentalists/naturalists and farming professionals. The program is therefore becoming a  
417 political tool for agro-ecological transition, soon providing indicators for public management and  
418 hopefully contributing in a compelling way, as an output of citizen science, to the scientific warning  
419 messages on the biodiversity crisis.

420

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431

### 432 **Authors' contributions**

433 EP, RLV and OB conceived the ideas and designed methodology; OB analysed the data; EP and OB led  
434 the writing of the manuscript. All authors contributed critically to the drafts and gave final approval  
435 for publication.

### 436 **Data availability statement**

437 Data is available from Zenodo (Billaud, Vermeersch, & Porcher, 2020)

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601

602 **Table 1.** Results of the GLMM models on abundance of solitary bees for each crop type, using the  
603 PCA coordinates as proxy for farming practices and the MCA coordinates as proxy for landscape  
604 characteristics. PCA axis 1 stands for chemical treatment and axis 2 for organic fertilization in field  
605 crops, vineyards and orchards (Fig.1 C-D-F), while the reverse is true in meadows. The first axis of  
606 MCA represents proximity to woodland; the interpretation of the second axis is more variable (see  
607 main text and Fig. S4-5-6-7). Values are log-coefficients, followed by their significance (stars).  
608 Marginal and conditional R<sup>2</sup> give the variance explained by the model with and without the random  
609 “field” effect of the model (with variance  $\sigma^2$ ).

<i>Bees</i>	<i>Field crops</i>	<i>Meadows</i>	<i>Vineyards</i>	<i>Orchards</i>
<b>Year, landscape, practices</b>				
Year	-0.21 ***	-0.13	0.05	-0.38 **
MCA1	0.24 ***	0.19	0.07	0.34
MCA2	n/a	-0.34 ***	-0.22 *	-0.13
PCA1	-0.16 *	0.22 *	0.16	0.15
PCA2	-0.21 **	n/a	n/a	-0.67 ***
Meadows' use: Mix	n/a	0.29	n/a	n/a
Meadows' use: Pasture	n/a	-0.73 ***	n/a	n/a
Inter-rows: Partly grassy	n/a	n/a	-0.05	n/a
Inter-rows: Bare	n/a	n/a	-0.76 **	n/a
<b>Interactions</b>				
Year*PCA1	-0.28 ***	0.22 *	n/a	-0.38 **
Year*PCA2	0.15 *	n/a	n/a	n/a
Year * MCA1	n/a	-0.19 *	0.24 ***	-0.27 *
Year * MCA2	n/a	n/a	-0.16 *	0.37 **
<b>Covariates</b>				
Degree days	2.05 ***	2.54 ***	2.50 ***	2.13 ***
Degree days <sup>2</sup>	-1.26 ***	-1.74 ***	-1.63 ***	-1.57 ***
Longitude	0.40 ***	0.37 ***	0.39 **	0.57 ***
Latitude	-0.42 ***	-0.20	n/a	n/a
Vegetation height	0.26 ***	n/a	0.13 *	n/a
Installation date	-0.11 *	-0.32 ***	-0.19 *	-0.26
$\sigma^2$	3.73	2.68	2.79	2.98
Marginal R <sup>2</sup> / Conditional R <sup>2</sup>	0.223 / 0.839	0.289 / 0.829	0.238 / 0.801	0.306 / 0.829

\*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

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611

612

613 **Table 2.** Results of the GLMM models on abundance of butterflies for each crop type, using the PCA  
 614 coordinates as proxy for farming practices. PCA, MCA axes and all symbols as in Table 1.

<i>Butterflies</i>	<i>Field crops</i>	<i>Meadows</i>	<i>Vineyards</i>	<i>Orchards</i>
<b>Year, landscape, practices</b>				
Year	-0.05	0.19 ***	-0.14 *	n/a
MCA1	n/a	-0.18 **	n/a	n/a
MCA2	n/a	-0.13	n/a	n/a
PCA1	0.01	n/a	n/a	n/a
Inter-rows: Partly grassy	n/a	n/a	-0.16	n/a
Inter-rows: Bare	n/a	n/a	-0.79 ***	n/a
<b>Interactions</b>				
Year*PCA1	-0.09 *	n/a	n/a	n/a
Year *MCA2	n/a	0.14 **	n/a	n/a
<b>Covariates</b>				
Degree days	1.69 ***	1.31 ***	0.94 ***	1.80 ***
Degree days <sup>2</sup>	-1.51 ***	-1.23 ***	-1.02 ***	-1.77 ***
Latitude	-0.18 ***	-0.29 ***	-0.38 ***	n/a
Longitude	n/a	n/a	0.24 **	n/a
Cloud cover: Sunny	0.59 ***	0.70 ***	0.4	n/a
Cloud cover: Slightly cloudy	0.53 ***	0.45 *	0.54	n/a
Cloud cover: Thin overcast	0.43 **	0.94 ***	0.58	n/a
Cloud cover: Cloudy	0.35 **	0.47 *	0.13	n/a
Cloud cover: Very cloudy	0.08	-0.18	-0.64	n/a
Wind: Light	0.56 ***	0.46 **	n/a	n/a
Wind: No	0.67 ***	0.26	n/a	n/a
$\sigma^2$	0.46	0.43	0.67	0.4
Marginal R <sup>2</sup> / Conditional R <sup>2</sup>	0.262 / 0.601	0.252 / 0.566	0.243 / 0.707	0.188 / 0.529

\*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

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617 **Table 3.** Results of the GLM models on abundance of earthworms for each crop type, using the PCA  
 618 coordinates as proxy for farming practices. PCA, MCA axes and all symbols as in Table 1.

<i>Earthworms</i>	<i>Field crops</i>	<i>Meadows</i>
<b>Year, landscape, practices</b>		
Year	n/a	-0.26 ***
PCA1	n/a	0.18 **
Tillage: Deep ploughing	-0.28 *	n/a
Tillage: Direct sowing	0.81 ***	n/a
Meadow's age	n/a	0.26 ***
<b>Covariates</b>		
Degree days	-0.13 *	-0.13 *
Soil humidity: Waterlogged	0.56	-1.58 **
Soil humidity: Wet	-0.09	-0.67
Soil humidity: Dried	0.06	0.27
Soil humidity: Dry	-0.69 *	-0.35

\*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

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621 **Table 4.** Results of the GLMM models on abundance of beetles for each crop type, using the PCA  
 622 coordinates as proxy for farming practices. PCA, MCA axes and all symbols as in Table 1.

<i>Beetles</i>	<i>Field crops</i>	<i>Meadows</i>	<i>Vineyards</i>	<i>Orchards</i>
<b>Year, landscape, practices</b>				
Year	0.24 ***	-0.28 *	0.29 ***	-0.93 ***
PCA1	0.18 ***	0.58 ***	0.20 *	0.88 ***
PCA2	-0.04	0.34 *	n/a	n/a
Meadows' type: Permanent	n/a	-0.15	n/a	n/a
<b>Interactions</b>				
Year*PCA1	n/a	-0.37 **	n/a	-0.49 ***
Year*PCA2	0.17 ***	0.30 *	n/a	n/a
Year*(Meadows' type: Permanent)	n/a	0.80 ***	n/a	n/a
<b>Covariates</b>				
Degree days	n/a	-0.14 ***	-0.25 ***	-0.20 ***
Degree days <sup>2</sup>	-0.10 ***	n/a	n/a	n/a
Latitude	0.22 ***	n/a	0.62 ***	n/a
Installation date	n/a	-0.34 **	0.22 *	n/a
Board humidity: Dried	-0.36 ***	n/a	0.61 ***	-0.20
Board humidity: Dry	-0.45 ***	n/a	0.68 ***	0.47 *
$\sigma^2$	1.21	1.83	1.70	1.60
Marginal R <sup>2</sup> / Conditional R <sup>2</sup>	0.069 / 0.594	0.124 / 0.711	0.127 / 0.472	0.169 / 0.750

\*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

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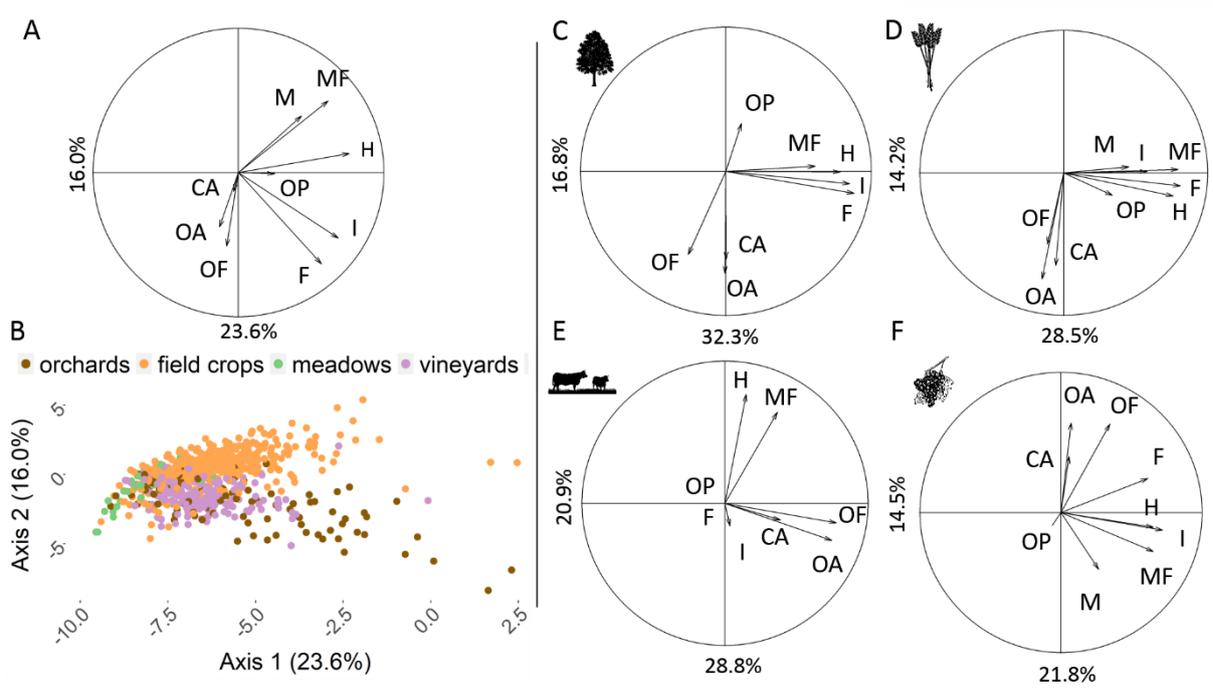
626 **Table 5.** Results of the GLMM models on abundance of molluscs for each crop type, using the PCA  
 627 coordinates as proxy for farming practices. PCA, MCA axes and all symbols as in Table 1.

<i>Mollusks</i>	<i>Field crops</i>	<i>Meadows</i>	<i>Vineyards</i>	<i>Orchards</i>
<b>Year, landscape, practices</b>				
Year	0.50 ***	-0.43 ***	0.15 *	-0.14 *
MCA2	0.09 ***	n/a	n/a	n/a
PCA1	-0.01	0.09	0.18	0.34 *
PCA2	0.07	0.17	-0.14	-0.17 **
Tillage: Deep ploughing	-0.04	n/a	n/a	n/a
Tillage: Direct sowing	0.52 **	n/a	n/a	n/a
Inter-rows: Partly grassy	n/a	n/a	0.29	0.29
Inter-rows: Bare	n/a	n/a	-0.85 **	-1.13 ***
Meadows' type: Permanent	n/a	0.11	n/a	n/a
Meadows' use: Mix	n/a	-0.45 **	n/a	n/a
Meadows' use: Pasture	n/a	0.32	n/a	n/a
<b>Interactions</b>				
Year*PCA1	0.10 *	-0.67 ***	0.22 **	-0.17 *
Year*PCA2	-0.27 ***	0.35 ***	-0.35 ***	n/a
Year*(Tillage: Deep ploughing)	-0.19 *	n/a	n/a	n/a
Year*(Tillage: Direct sowing)	0.12	n/a	n/a	n/a
Year*(Meadows' use: Mix)	n/a	0.32 *	n/a	n/a
Year*(Meadows' use: Pasture)	n/a	0.03	n/a	n/a
Year*(Meadows' type: Permanent)	n/a	0.91 ***	n/a	n/a
<b>Covariates</b>				
Degree days	-0.70 ***	-1.06 ***	-0.48 ***	-0.75 ***
Degree days <sup>2</sup>	0.60 ***	0.84 ***	0.45 ***	0.52 ***
Longitude	n/a	n/a	0.42 **	n/a
Board humidity: Dried	-0.05	-0.30 ***	0.15	n/a
Board humidity: Dry	-0.46 ***	-0.42 ***	-0.30 **	n/a
Board soil: Grassy	0.19 **	n/a	0.29 **	n/a
$\sigma^2$	1.12	0.82	1.03	0.80
Marginal R <sup>2</sup> / Conditional R <sup>2</sup>	0.163 / 0.641	0.227 / 0.769	0.116 / 0.728	0.112 / 0.745

\*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

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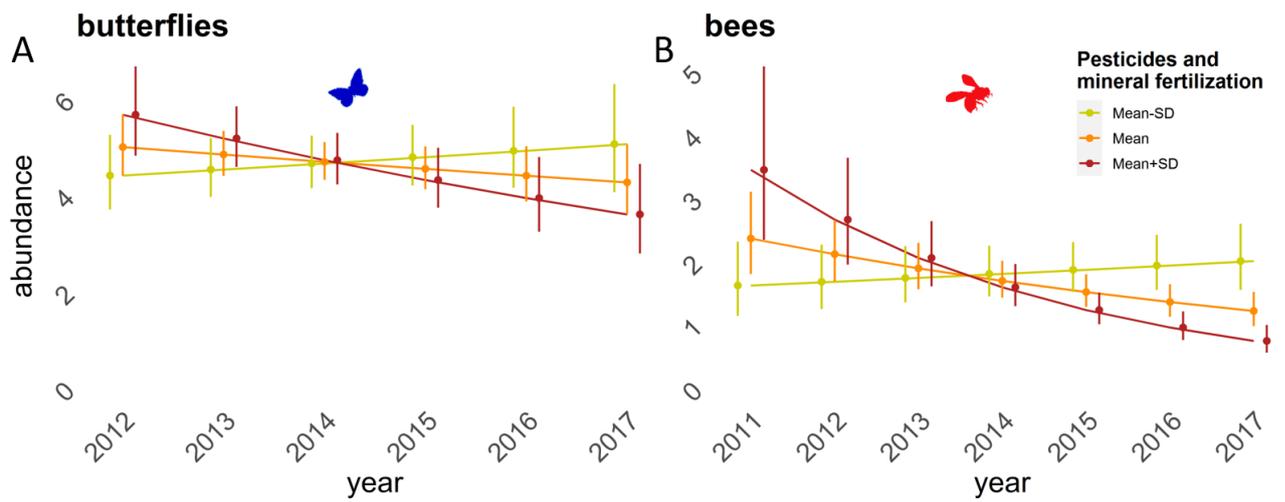
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631 **Figure 1.** Principal Component Analysis on farming practices over all crop types (A-B) or within crop  
 632 types (C orchards, D field crops, E meadows, F vineyards). Panels A and C-F show the correlation  
 633 circles, with the fraction of variance explained by the first two axes. Abbreviations: H herbicide, F  
 634 fungicide, I insecticide, M molluscicide, OP other pesticides, MF mineral fertilization, OF organic  
 635 fertilization, OA organic amendment, CA calcium amendment. Panel B shows the distribution of the  
 636 fields with different crop types along the two axes.

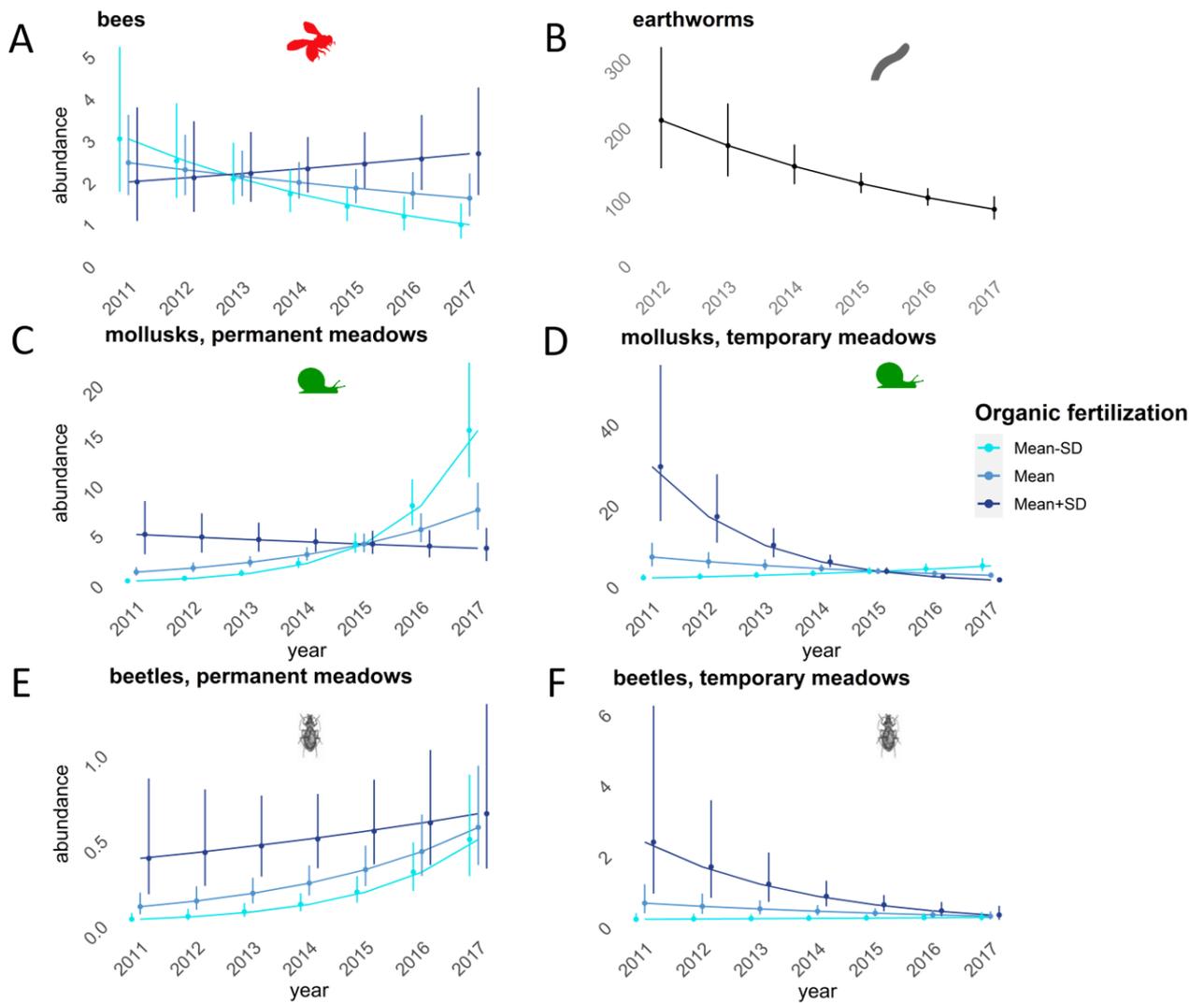
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639 **Figure 2.** Relationship between synthetic inputs (pesticide and mineral fertilization use) and temporal  
 640 trends in butterfly (A) and bee (B) abundance in field crops. Use of synthetic inputs is characterized  
 641 here by the coordinates of the first PCA axis (Fig. 1D), from high levels (red line: mean plus one  
 642 standard deviation), through medium levels (orange line: mean) to low values (yellow line: mean  
 643 minus one standard deviation). Other variables are at their mean (quantitative terms) or  
 644 representative levels (qualitative terms).

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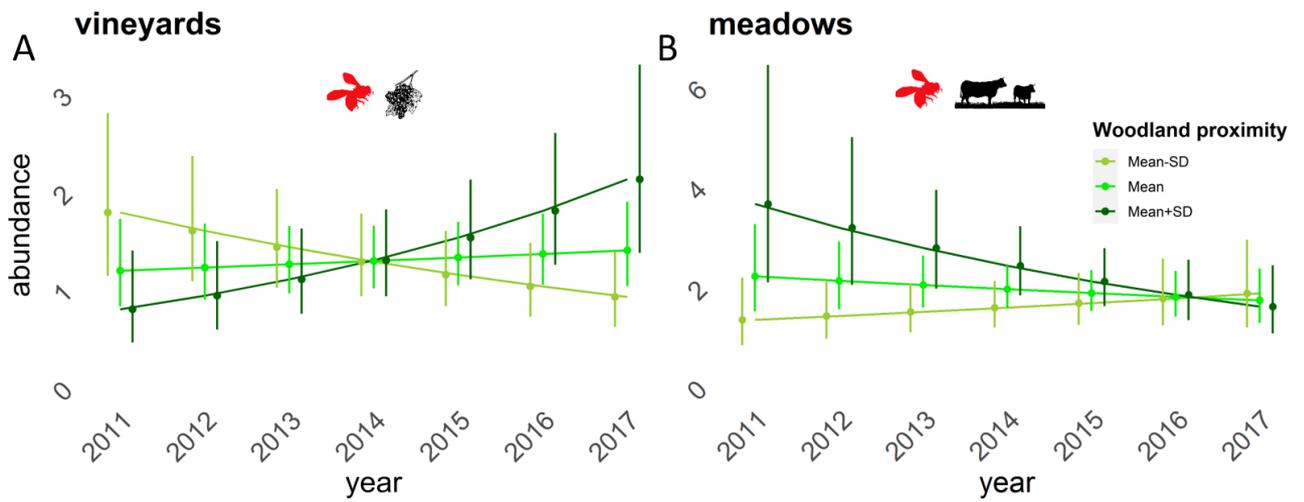


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647 **Figure 3.** Relationship between organic fertilization and temporal trends in meadows. Organic  
 648 fertilization is characterized here by the coordinates of the first PCA axis (Fig. 1E), from high levels  
 649 (dark blue line: mean plus one standard deviation), through medium levels (blue line: mean) to low  
 650 values (light blue line: mean minus one standard deviation). Other variables are at their mean  
 651 (quantitative terms) or representative levels (qualitative terms). Beetle and mollusk abundance are  
 652 predicted in permanent (C-E) and temporary meadows (D-F).

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**Figure 4.** Relationship between landscape (woodland proximity) and temporal trends in bee

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abundance in vineyards (A) and meadows (B). Woodland proximity is characterized here by the

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coordinates of the first MCA axis (Fig. S4), from high levels (dark green line: mean plus one standard

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deviation), through medium levels (green line: mean) to low values (light green line: mean minus one

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standard deviation). Other variables are at their mean (quantitative terms) or representative levels

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(qualitative terms). Predicts are computed from models using the PCA as proxy for practices.