



Interaction network structure predicts species temporal persistence in empirical plant-pollinator communities

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1 **Pollinators and their mutualistic interactions estab-**
 2 **lished with plants are key components of our ecosys-**
 3 **tems because they sustain terrestrial biodiversity¹ and**
 4 **human food security². Currently, the clear evidence**
 5 **of pollinator declines caused by human-induced rapid**
 6 **environmental changes (e.g. landscape fragmentation³**
 7 **or climate change⁴) clashes with our poor ability to**
 8 **predict pollinator communities prone to collapse or**
 9 **species at risk of local extinction. It is therefore urgent**
 10 **to develop mechanistic models depicting the probabil-**
 11 **ity of pollinators to persist that allow drawing sound**
 12 **predictions that can be used by conservationists⁵. To**
 13 **that end, the structuralist approach⁶ provides a solid**
 14 **theoretical framework suited to ecological communi-**
 15 **ties. Specifically, this approach is readily available to**
 16 **evaluate how the observed structure of mutualistic in-**
 17 **teractions defines the range of potential environmental**
 18 **changes in which species can persist^{7,8}. However, de-**
 19 **spite its potential predictive power, empirical valida-**
 20 **tions remain elusive. Here, using high-resolution data**
 21 **from a 6-year study following 12 independent plant-**
 22 **pollinator communities, we confirm that pollinator**
 23 **species with more persistent populations in the field**
 24 **are those theoretically predicted to tolerate a larger**
 25 **range of environmental changes. These communities,**
 26 **generally located in larger habitat patches, have a**
 27 **more cohesive structure. By showing that the struc-**
 28 **ture of ecological interactions directly informs about**
 29 **the ability of pollinators to persist, we legitimate the**
 30 **use of theoretically informed models to predict species'**
 31 **fate within the ongoing global change, unlocking our**
 32 **capacity to anticipate conservation actions.**

33 Pollinators are key components of ecological systems that provide
 34 a wide variety of ecosystem functions and services critical
 35 for human well-being, such as plant reproduction¹ and food security².
 36 However, the maintenance of these functions is at risk

due to the ongoing negative effects of global change drivers
 on pollinator abundance and diversity^{3,4,9}. There have been
 several calls to face the global crisis of pollinator decline by
 providing tools that accurately predict their population dynamics,
 and therefore their probability of extinction⁵, however our ability
 to achieve a predictive ecology is still limited¹⁰⁻¹⁴. The need to
 predict, and hence to understand, how ecological communities
 respond to ongoing environmental changes has historically fueled
 intense research on ecological stability¹⁵⁻¹⁸. Yet, this research
 has been hampered by both a profound divide between the theo-
 retical and the empirical studies¹⁸⁻²⁰, and an unclear defini-
 tion of the concept of ecological stability itself^{18,21}. This still
 ongoing debate has not given a clear link between the structure
 of ecological communities, their stability, and the persistence of
 the species constituting these communities⁷. As a potential solu-
 tion, the structuralist approach⁶ and its recent application to
 ecology have shown to provide a parsimonious theoretical bench-
 mark to understand and predict the persistence of empirical
 ecological communities in changing environments^{7,8}.

The main prediction of the structuralist approach is that the
 network of biotic interactions among species composing an
 ecological community determines their opportunities to coexist²².
 Communities with larger opportunities, which in natural
 plant-pollinator communities correspond to more cohesive
 (i.e. nested) structures of biotic interactions⁷, are predicted
 to be more likely to persist under changing environments be-
 cause they can tolerate in turn a larger difference in perfor-
 mance among species²³. The degree of structural stability of
 an ecological community can be rigorously assessed by cou-
 pling mathematical theory to population models that describe
 the dynamics of the species in terms of biotic interactions and
 intrinsic growth rates, which are a good measure of species'
 performance. However, for many communities such as pollina-
 tors, information on such performance is not available. In that
 case, the structuralist approach is still valid because it allows

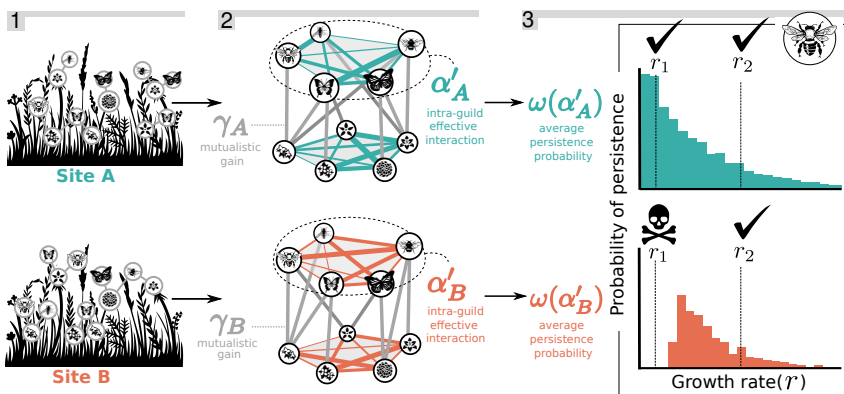


Figure 1: Species' persistence probability in model communities: 1) Empirical observations determine the mutualistic interactions of our dynamical model (γ). 2) This results in different effective biotic interaction matrices between the species (α'). 3) Quantification of their structural stability (see methods) gives the average probability that any species in the community persists ($\omega(\alpha')$). At the species level, the different distribution of reproductive rates compatible with a given species persistence (*Anthophora bimaculata* in this example) in sites A and B (colour coded) will translate as less likely persistence of that species in site B when reproductive rates are sampled randomly (r_1, r_2) as fewer values of r are compatible with species persistence in site B (i.e. it has a lower predicted persistence probability, ω_i).

73 taking a probabilistic view to ask which communities are more
 74 likely to be observed given the unknown effect of environmental
 75 conditions on species' performance^{7,8,24,25}.

76 Despite this theoretical framework providing a set of clear
 77 predictions and associated tools to assess the persistence of
 78 pollinator communities, direct empirical tests are still lacking.
 79 These tests are of fundamental importance to ensure that
 80 the transfer of basic ecological knowledge to conservation
 81 planning is relevant in the real world. Part of this lack of
 82 progress comes from the fact that very few studies follow
 83 plant-pollinator communities over long periods of time^{8,26,27},
 84 and hence most of the empirical plant-pollinator networks
 85 are a snapshot of a particular state of the community. This
 86 lack of data collected over multiple years prevents validating
 87 theoretical predictions with observed changes in population
 88 abundances under natural conditions, even for short-term
 89 predictions.

91 Here, we use a well-resolved data set on abundances and
 92 interactions between plants and pollinators in a long-term
 93 study carried out on twelve independent sites exposed to
 94 changing environmental conditions over 6 years (adding up to
 95 179 pollinator species and 1470 plant-pollinator interactions).
 96 Following the structuralist approach, we investigated whether
 97 empirical observation of species persistence is predicted by the
 98 structural stability of the plant-pollinator communities. In
 99 its probabilistic interpretation, structural stability represents
 100 the average probability that a randomly chosen species of the
 101 community persist given its internal constraints²³ (see Fig.1).
 102 Therefore, we predict that larger values of structural stability
 103 promote higher persistence of a pollinator community. To test
 104 our main prediction across levels of biological organization
 105 (both community- and species-level) we recorded, on the one
 106 hand, abundances of pollinator species over time with which
 107 we quantified empirical persistence, and on the other hand,
 108 we simultaneously documented the mutualistic network of
 109 plant-pollinator interactions with which we quantified the
 110 degree of structural stability (i.e. the average persistence
 111 probability, ω) among the 12 independent communities. To
 112 quantify the average predicted persistence of a species in a
 113 given community (ω), we need to parameterize a model that
 114 describes reasonably well the population dynamics of plants
 115 and pollinators in terms of their biotic interactions. For
 116 this, we used a standard mutualistic dynamic model^{7,23,28,29}
 117 where the mutualistic interactions are parameterized with
 118 the observed plant-pollinator networks (see Methods and
 119 Fig.1). Moreover, the model accounts for the intra-guild
 120 effective interaction matrices describing biotic interactions
 121 among plants (α'_P), and among pollinators (α'_A). We inferred
 122 these matrices following previous methodologies, which take
 123 into consideration both the intra-guild competition and the
 124 effect of the mutualistic interactions (see Methods and SI.F).
 125 Taken together, they constitute the internal constraints of the
 126 community that determine the range of species' growth rate
 127 values (r) compatible with its persistence⁷. In what follows
 128 we center our results on pollinators, but we advance that the
 129 framework also works to describe and predict which are the
 130 more persistent plant species (see Fig.S1-S2).

132 Although our analyses indicate a moderate change in the
 133 predicted average persistence probability (ω) across all 12
 134 independent sites (ranging from 0.45 to 0.55), we find that this

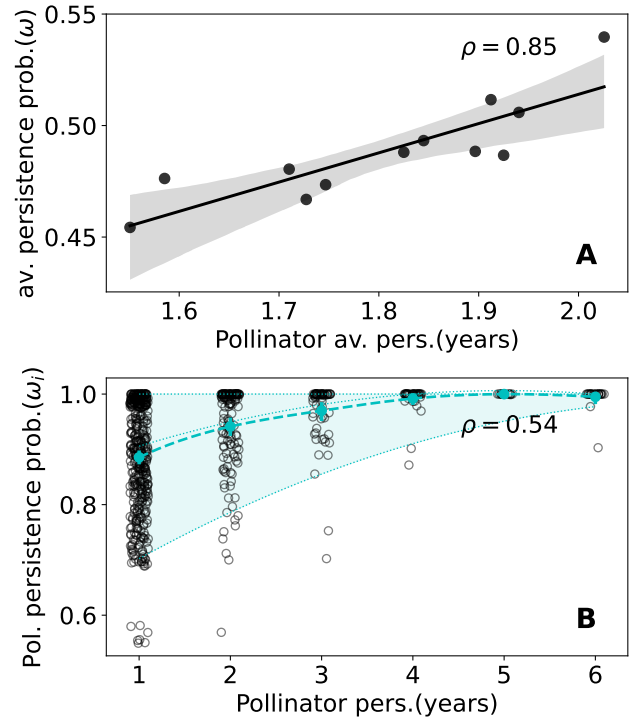


Figure 2: A, Predicted average persistence probability of pollinators (ω) versus mean persistence in the field for the 12 sites in the study. B, Predicted pollinator persistence probability (ω_i) versus the number of years the pollinator is present in the field. Each point represents one pollinator in one site, and all sites are plotted together. The shaded regions represent the 5-95 quantile regression, and the round points with error bars indicate the average value with the standard deviation. The dotted line is a help to the eye. Both figures include Spearman's rank correlation coefficient (ρ).

135 variation was sensitive enough to capture differences in empiri-
 136 cal persistence between pollinator communities. Note that we
 137 studied natural communities within a single habitat type and
 138 for which the main drivers of environmental change are related
 139 to its fragmentation degree and weather variability. Hence, we
 140 do not expect large changes in species persistence, in contrast
 141 to comparisons across habitats, or in situations where most of
 142 the focal habitat has been destroyed³. According to our main
 143 hypothesis, we observe that those pollinator communities with
 144 higher opportunities for species to coexist (i.e., with higher
 145 average persistence probability, ω) strongly correspond with
 146 higher mean pollinator persistence in the field (Spearman
 147 correlation coefficient, henceforth called ρ , of 0.85) as shown
 148 in Fig.2.A. This result indicates that the structure of species
 149 interactions in the studied communities contains information
 150 on how easily can species, on average, persist under changing
 151 environments (a result that holds when excluding species
 152 only observed once, see Fig.S3). Interestingly, our results
 153 additionally suggest that landscape intensification matters for
 154 determining the observed variation in predicted persistence
 155 probability (correlation $\rho \approx 0.6$) with communities in larger
 156 habitat patches tending to exhibit higher persistence and a
 157 more cohesive structure (i.e. nestedness) than those in smaller
 158 patches (Fig.S4). This means that landscape fragmentation,
 159 one of the consequences of more intensive agricultural prac-
 160 tices, can have a negative impact on the ability of the species

161 to withstand other changes, such as climate change. While
 162 these results can give us information on the whole community,
 163 from a conservation point of view is often important to also
 164 study the persistence of the individual species. For that, we
 165 quantified the predicted probability of persistence for each
 166 species in the 12 studied communities (ω_i)^{8,25}, and compared
 167 such probabilities with the number of years each species is
 168 present in the field (Fig.2.B). In agreement with our main
 169 prediction, we also find a positive relationship between the
 170 predicted pollinator persistence probability in the model
 171 (ω_i) and the number of years that a pollinator is found
 172 in the field ($\rho=0.54$), meaning that species that are more
 173 frequently expected to be locally extinct in the theoretical
 174 models also tend to have lower observed persistence in real
 175 communities. Some of the species more frequently predicted
 176 to be extinct are comparatively rare species (Fig.S5). Prior
 177 work suggests that the link between rare species and their
 178 lower probability to persist occurs when species are under
 179 a process of extinction debt³⁰, or, in open systems like our
 180 empirical communities, they represent transient species just
 181 “passing through”, subject to source and sink dynamics^{31,32}.
 182 Regardless of whether both situations are occurring in our
 183 system or not, our results highlight that the structuralist
 184 approach is a useful theoretical framework to progress our
 185 mechanistic understating of two interrelated problems in
 186 ecology: the identification of dynamically stable species that
 187 persist despite environmental fluctuations³³, and how such
 188 stability permeates from species to communities¹⁸.

190 Species might persist despite presenting strong tempo-
 191 ral fluctuations in their abundances³⁴. Thus, a natural next
 192 question to ask is whether this framework can not only identify
 193 persisting species, but also more stable species in terms of
 194 changes in temporal abundance. We found no correlation
 195 between the predicted average persistence probability (ω) and
 196 the temporal stability of the aggregated pollinator population
 197 (S) ($\rho = 0.30$, not statistically significant), suggesting that
 198 structural stability is not a good predictor of the temporal
 199 stability at the community level. If the structuralist approach
 200 is not a strong predictor of temporal stability, it opens the
 201 question of which are instead their predictors. To answer this
 202 point, we performed a linear regression accounting for the
 203 three main variables known to determine temporal stability
 204 in plant and pollinator communities: species richness³⁵,
 205 temporal stability of species’ populations³⁶, and population
 206 asynchrony³⁷. Among these predictors, both pollinator
 207 richness (Fig.3.A), and temporal stability of pollinators’

208 populations (Fig.3.B) were weakly correlated with the tempo-
 209 ral stability of the community. Instead, more temporally
 210 stable communities are composed of pollinators with strong
 211 asynchronous responses (Fig.3.C), a result that we recover also
 212 with plants (Fig.S2). This negative relationship, which is a
 213 common phenomenon observed in empirical studies including
 214 pollinators³⁸, is known as biodiversity insurance or portfolio
 215 effect^{39,40}, and it indicates that the persistence dynamics that
 216 capture the structuralist approach are independent of those
 217 captured by the temporal stability of the community. While
 218 the structural stability informs of the average persistence of
 219 communities and species, the temporal stability informs of
 220 the asynchronous temporal fluctuation. At the species level,
 221 however, we found a weak but significant positive correlation
 222 between structural and temporal stability, caused by a subset
 223 of species that sustain stable populations with a high predicted
 224 probability of persistence (Fig. S6).

226 Ecology is entering an exciting phase where models based on
 227 solid theory are being used to simultaneously understand eco-
 228 logical processes and predict the fate of ecological communi-
 229 ties under global change¹⁰⁻¹³. Under these circumstances, the
 230 resurgence of monitoring programs, including ambitious polli-
 231 nator ones^{41,42}, holds great potential to seek the perfect em-
 232 pirical and theoretical marriage to rigorously describe and pre-
 233 dict temporal changes in pollinator populations, which can di-
 234 rectly allow to better inform conservation and management de-
 235 cisions. Building on prior work that highlights the importance
 236 of applying the structuralist approach to the network of bi-
 237 otic interactions to understand the species’ demographic conse-
 238 quences^{7,8}, we show here that interaction networks contain pre-
 239 dictive power to describe the temporal dynamics across levels
 240 of biological organization. That is, we can clearly distinguish
 241 which communities and which particular species will persist or
 242 will die out in the face of ever-present environmental variation,
 243 thus providing promising tools for management which allow
 244 anticipating actions to combat pollinator loss. Taken together,
 245 our results show the power to couple detailed empirical data
 246 with mathematical theory and associated modelling tools to
 247 understand and anticipate pollination declines, opening new
 248 avenues of study and at the same time, reinforcing previous
 249 theoretical results.

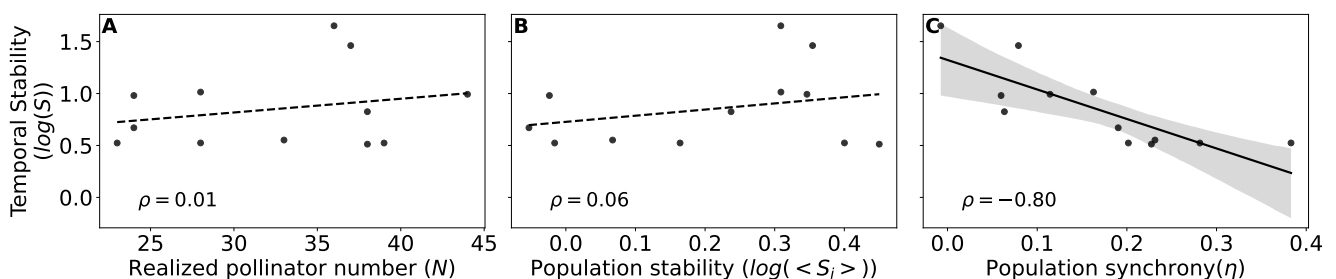


Figure 3: Dependence of temporal stability of the aggregated pollinator population ($\log(S)$) on A, realized pollinator species number (N), B average pollinator population stability ($\log(\langle S_i \rangle)$), and C, synchrony of pollinator populations (η). Each figure includes Spearman’s rank correlation coefficient (ρ) and the regression line (dashed when not statistically significant).

250 Methods

251 **Dataset:** Data on species population and interaction
 252 strength has been gathered during empirical observations
 253 through six years (2015-2020) along the spring season. Each
 254 year we sampled at least seven rounds across 12 different
 255 sites situated in a landscape fragmentation gradient in the
 256 southwest of the Iberian peninsula (Huelva and Seville),
 257 gathering data on plant-pollinator interaction frequency and
 258 flower abundance. In each site, and during each round, we
 259 walked a 100 m straight line for 30 minutes in which we wrote
 260 down every plant-pollinator interaction seen (resulting in a
 261 total of more than 250h of field observations). In addition, we
 262 measured the abundance of plants by recording the number
 263 of flowers of each plant species in ten $1m^2$ subplots placed
 264 along the transect. Bees and plants that we were unable
 265 to identify *in situ* were collected for later identification.
 266 We preserved bees in a freezer at $-20^{\circ}C$ until they could
 267 be pinned and labeled in the lab. Bees were caught by
 268 hand-netting and plants were preserved using plant presses.
 269 Later F.P. Molina identified them using a binocular loupe
 270 and determination keys. Those specimens that he was not
 271 able to identify to species level were sent to taxonomic experts.
 272

273 **Empirical measures of persistence and temporal stabil-**
 274 **ity:** We obtained the yearly floral abundance of plant species
 275 in each site by aggregating the abundance of all rounds in the
 276 year. We measured pollinators' yearly abundance by aggregating
 277 through each year the number of times each pollinator
 278 species had interacted with any plant. Note that we recorded
 279 both the number of individuals and the number of visits per indi-
 280 vidual, and abundance metrics were always derived from indi-
 281 vidual counts, not visitation frequencies, to avoid confounding
 282 pollinator activity with its frequency. In both cases, we nor-
 283 malized the abundances with the sampling effort of that year
 284 (i.e. the number of rounds).

285 To quantify the **persistence** of each species in each site, we
 286 measured the number of years the species was present in the
 287 field, and then obtained the mean persistence of plants and
 288 pollinators in each site as the average persistence of the species
 289 present in the site.

290 We quantified **temporal stability** of plant and pollinator pop-
 291 ulations at two scales. At the community scale, we first ob-
 292 tained the total abundance of flowers and pollinators for each
 293 year by aggregating the abundance of all the species in the site,
 294 and then we measured the inverse of the coefficient of variation
 295 (σ/μ)³⁵ of such aggregated abundances. At the species scale,
 296 we measured for each species in each site the inverse of the co-
 297 efficient of variation (σ_i/μ_i) of the species abundance through
 298 the 6 years.

We quantified species average **synchrony** (η) as the mean cor-
 relation coefficient between the field abundances A_i of each
 species i versus the rest of the community (all A_j except i)
 following³⁷:

$$\eta = (1/N) \sum_i r(A_i, \sum_{j \neq i} A_j)$$

299 **Empirical interaction networks:** We obtained the net-
 300 work of pollinator interactions in each site by aggregating
 301 through all the years the frequency of the interactions recorded
 302 between plants and pollinators. To build a model as parsimo-
 303 nious as possible we only used unweighted interactions in the
 304 mutualistic model (i.e. $M_{ij} = 1$ if species i and j interacted

in the field and 0 otherwise) as is usually done in this type of
 models^{7,23,28,29}.

307 **The mutualistic model:** To quantify the average persis-
 308 tence probability (ω) we used a standard mutualistic dynamics
 309 model^{7,23,28,29}, using the empirical networks as the skeleton
 310 (see below). The equations describing the abundance of plants
 311 (P_i) and animal (A_i) species are of the form:

$$\begin{bmatrix} \frac{dP}{dt} \\ \frac{dA}{dt} \end{bmatrix} = \text{diag} \left(\begin{bmatrix} P \\ A \end{bmatrix} \right) \times \left(\begin{bmatrix} r_P \\ r_A \end{bmatrix} - \underbrace{\begin{bmatrix} \alpha_P & -\gamma_P \\ -\gamma_A & \alpha_A \end{bmatrix}}_A \begin{bmatrix} P \\ A \end{bmatrix} \right) \quad (1)$$

with parameters accounting for intrinsic growth rate (r),
 intraguild competition (α) and mutualistic benefit (γ). We
 considered mean field intra-guild competition ($\alpha_{ii}^P = \alpha_{ii}^A = 1$,
 $\alpha_{ij}^P = \alpha_{ij}^A = \rho$), and used the empirical networks to parametrize
 the mutualistic benefit as follows: $\gamma_{ij} = \gamma_0 M_{ij}$, where $M_{ij} = 1$
 if we recorded a plant-pollinator interaction between species i
 and j in the field and zero otherwise, and γ_0 represents the
 overall level of mutualistic strength. The results in the main
 text correspond to $\rho=0.005$ and $\gamma_0=0.1$, but we checked the
 robustness of the results in SI.G using values of γ_0 below the
 critical threshold to ensure that all our simulated communities
 where linearly stable²⁹. While improvements can be made
 (e.g. empirically based competition instead of mean field), we
 chose this model for simplicity and because it is used in many
 previous theoretical studies.

In order to treat pollinators and plants separately, we worked
 in an **effective interaction framework**⁷, where the mean-
 field competition between plants and animals is modified by the
 mutualistic interactions. Diagonalizing the interaction matrix
 (\mathbf{A}) per block, allows going from a set of $N_P + N_A$ entangled
 equations for the abundances of plants and pollinators in the
 steady state (eq.2), to two sets of equations, one for plants (N_P
 species) and one for pollinators (N_A species), with only intra-
 guild interactions (eq.3). This is achieved by multiplying by
 the matrix $T = 1 + \Gamma C^{-1}$ both left sides of equation 2:

$$\begin{bmatrix} r_P \\ r_A \end{bmatrix} = \left(\underbrace{\begin{bmatrix} \alpha^P & 0 \\ 0 & \alpha^A \end{bmatrix}}_C - \underbrace{\begin{bmatrix} 0 & \gamma_P \\ \gamma_A & 0 \end{bmatrix}}_A \right) \begin{bmatrix} P \\ A \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} r'_P \\ r'_A \end{bmatrix} = \begin{bmatrix} \alpha'_P & 0 \\ 0 & \alpha'_A \end{bmatrix} \begin{bmatrix} P \\ A \end{bmatrix} \quad (3)$$

We quantified the predicted average persistence probability
 (ω) using matrices α'_A and α'_P in equation 3 with the code
 provided in a previous study²⁹.

To calculate the persistence probability of a particular species
 in the model community (ω_i), we used the **structural fore-**
casting framework^{8,25}. We randomly sampled 3000 direc-
 tions of r -vectors uniformly inside the full parameter space
 and solved the systems of equations 3 to determine the pro-
 portion of cases in which each species was present in the
 community ($P_i, A_i > 0$).

339 **Data and code availability:** Dataset of species interaction
340 and abundances, together with the code used in this study can
341 be downloaded [here](#) and will be accessible via Zenodo upon
342 publication acceptance.

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351 search; F.P.M did field work and identified species; V.D.-G. de-
352 veloped code and analyzed data; V.D.-G. and I.B. performed
353 research; V.D.-G., O.G. and I.B wrote the paper.

354 **Competing interests** The authors declare no competing in-
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Supplementary information for

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Interaction network structure predicts species temporal persistence in empirical plant-pollinator communities

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This pdf includes:

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- Supplementary text
- Figures S1 to S8
- Table S1

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505 **Supporting information text**

506 **A Results for plant species**

507 While in the main text we only show results for pollinators, we find that the results for plant species are similar, as shown
 508 below.

509 **A.1 Predicted persistence probabilities**

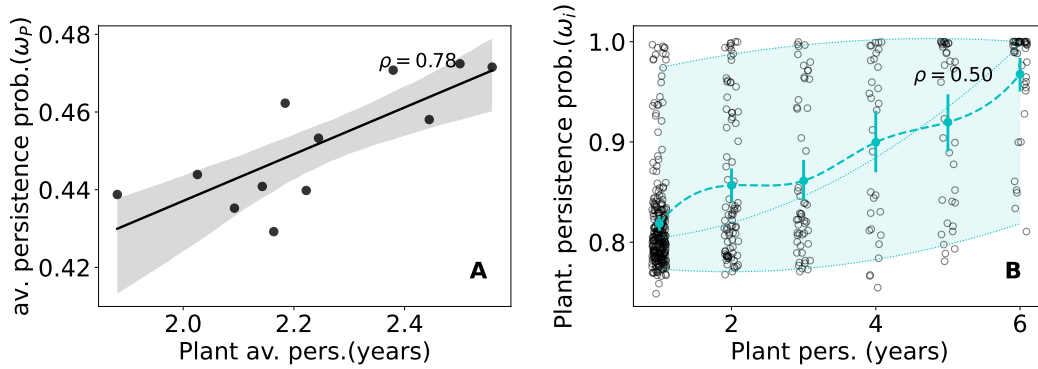


Figure S1: A, Predicted average persistence probability of plants (ω_P) versus plant mean persistence in the field for the 12 sites in the study. B, Predicted plant persistence probability in the model (ω_i) versus number of years the plant is present in the field. Each point represents one plant species in one site, and all sites are plot together. The shaded regions represent the 5-95 quantile regression, and the round points with error bars indicate the average value with the standard deviation. The dotted line is a help to the eye. Both figures include Spearman rank correlation coefficient (ρ).

510 **A.2 Temporal stability of plant abundance**

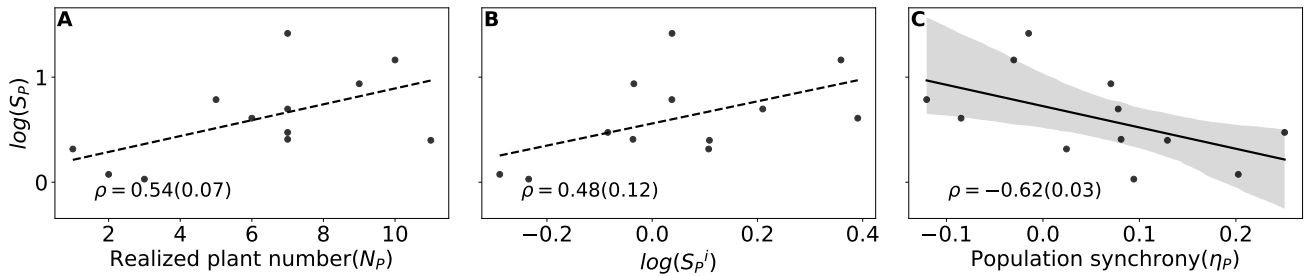


Figure S2: Dependence of temporal stability of plant abundance($\log(S_P)$) on A, realized plant species number(N_P), B average plant population stability($\log(\langle S_P^i \rangle)$), and C, synchrony of plant abundances(η_P). Each figure includes Spearman rank correlation coefficient(ρ) and the regression line (dashed when not statistically significant).

B Ignoring singleton species

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In order to study how much of the correlation between the predicted average persistence probability (ω) and the empirical persistence that we exposed in the main text was driven by rare species we decided to check this relationship when rare pollinator species are not considered (Fig. S3). To do that, we first ignored the pollinator species that only appear once in our study by removing them from the empirical measures of mean persistence and from the model to quantify persistence probability (Fig. S3.B). We also decided to go further and ignore species that have been only recorded at most once during each year, by removing them both from the empirical observations when measuring mean pollinator persistence, and from the model used to quantify persistence probability (Fig.S3.C). While removing singleton species reduces the correlation between mean pollinator persistence in the field and predicted average persistence probability, the correlation remains relatively high and significant in all scenarios.

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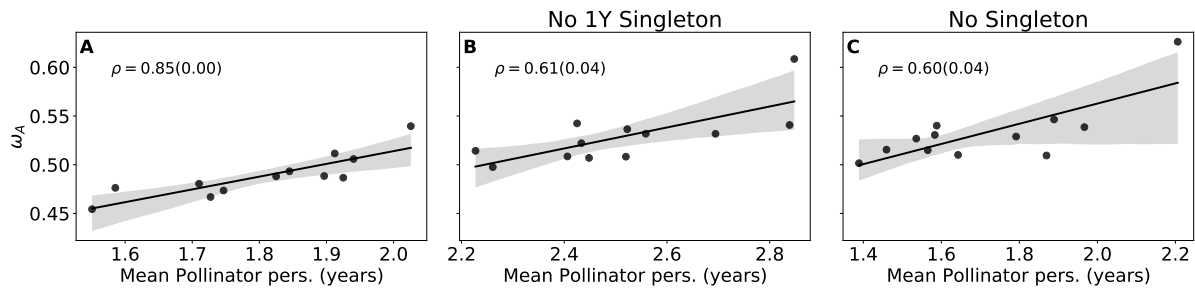


Figure S3: Predicted average persistence probability (ω) vs mean pollinator persistence in the field when A) all pollinator species are considered (as in main text), B) when pollinator that only appear once in the data-set are ignored, and C) when pollinators that only appear once per year are ignored. Each figure includes Spearman rank correlation coefficient(ρ) and p-value.

C Patch size affects structural stability

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The patch size, measured as the area of the focal habitat patch where the transect was located, is positively correlated with the predicted average persistence probability of the pollinator communities (ω)(Fig.S4 left). We also observe that communities in larger patches tend to have a more cohesive (i.e. nested) structure of mutualistic interactions (Fig.S4 right). This means that landscape fragmentation, one of the consequences of more intensive agricultural practices, can have a negative impact on the ability of the species to withstand other global change drivers, such as climate change.

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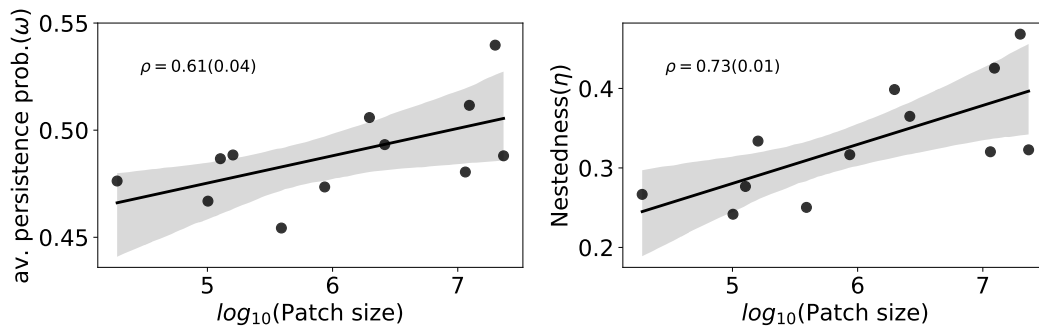


Figure S4: Left: Predicted average persistence (ω) vs Patch size. Right: Nestedness of the mutualistic interaction network vs Patch size. Both figures include the Spearman's rank correlation (ρ) and p-value (in brackets).

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527 **D Species' persistence probability and abundance**

528 Comparing species abundance in the field (quantified as the % of abundance each species represents in the community) with its
 529 expected persistence probability in the model (ω_i), shows that species with lower predicted persistence probabilities are always
 530 the least abundant. Said otherwise, it is evident that more abundant species are always predicted to survive in the model
 communities.

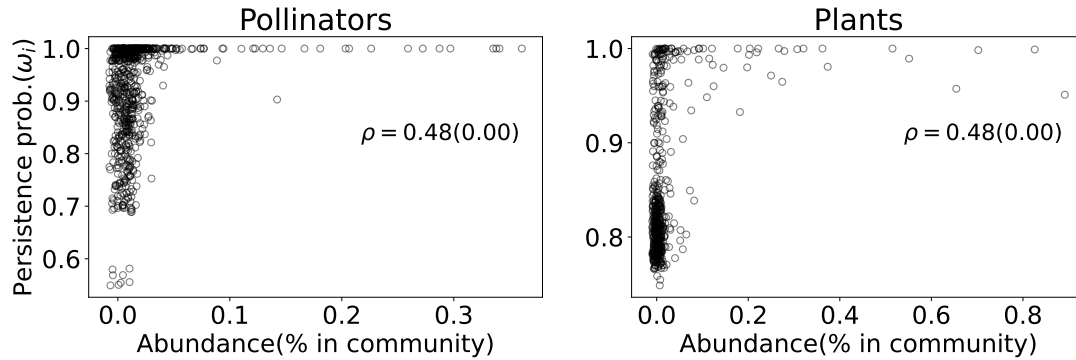


Figure S5: Species' probability of survival in the model (ω_i) vs. its abundance in the field for pollinators (left) and plants (right). Each figure includes Spearman rank correlation coefficient(ρ) and p-value in brackets.

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532 **E Species' temporal stability, predicted persistence probability and persistence**

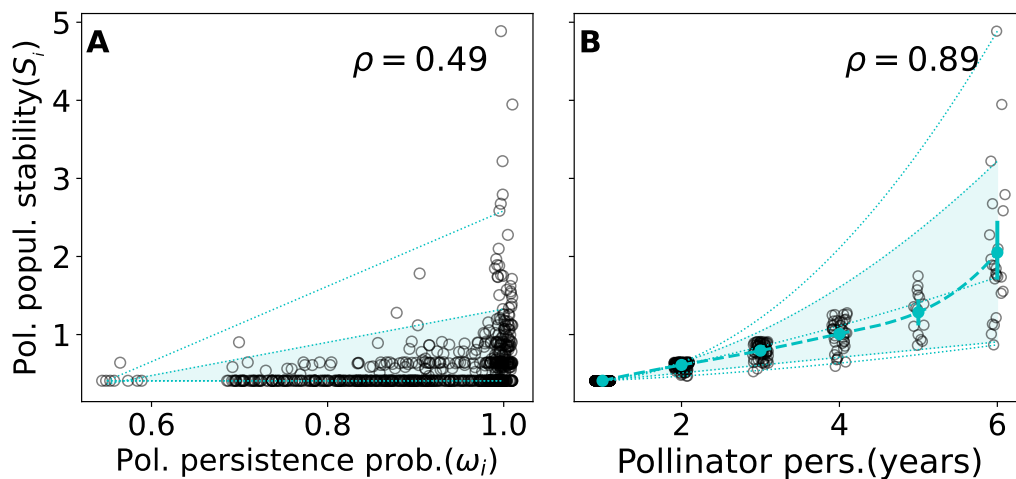


Figure S6: Observed temporal stability of pollinator abundances (S_i) versus A, pollinator persistence probability predicted by the mutualistic model (ω_i), and B, the number of years the pollinator is present in the field. The round points with error bars indicate the average value with the standard deviation, and the dotted line is a help to the eye. Shadow areas represent the 5-95 quantile, and the area inside the blue line is the 1-99 quantile. Both figures include Spearman rank correlation coefficient (ρ).

533 While at the community level we found no significant correlation between the predicted average persistence probability (ω)
 534 and the temporal stability of the aggregated pollinator population (S), at the species's scale we found a weak but significant
 535 positive correlation between pollinator's predicted persistence probabilities (ω_i) and its population temporal stability (S_i)
 536 ($\rho=0.49$, Fig.S6.A). This correlation coefficient could suggest that pollinators predicted to persist tend to present more stable
 537 populations, but the spread on the y-axis values for pollinators with high persistence probability shows that these pollinators
 538 do not necessarily present stable populations. Pollinators with more stable populations are always predicted to survive, but not
 539 all pollinators predicted to survive necessarily sustain stable populations in time. In effect, looking at the temporal stability of
 540 population populations (S_i) vs their persistence in the field (Fig.S6.B) also shows that more persistent pollinators exhibit larger
 541 variations in their population stability. As for the strong positive correlation in the figure, the result is not too surprising given
 542 how temporal stability is defined, yet it clearly indicates that pollinators with lower observed persistence (i.e., those that are
 543 observed fewer number of years in the community) tend to have more variable populations, while pollinators that are repeatedly

observed in the community one year after another, show larger variation in their population stability, but overall present more stable population over time. Again, we find a similar result for plants (Fig.S7).

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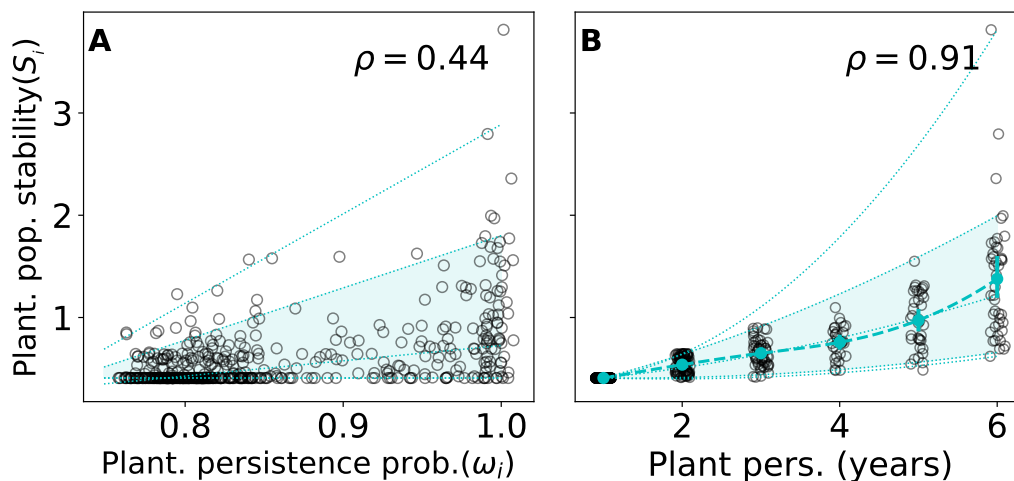


Figure S7: Observed temporal stability of plant abundances (S_i) versus A, plant persistence probability predicted by the mutualistic model (ω_i), and B, number of years the plant is present in the field. The round points with error bars indicate the average value with the standard deviation, and the dotted line is a help to the eye. Shadow areas represent the 5-95 quantile, and the area inside the blue line the 1-99 quantile. Both figures include Spearman rank correlation coefficient (ρ).

547 **F Deriving effective biotic interaction matrices**

In order to disentangle plant and pollinator systems we apply the transformation presented in [7], multiplying both left sides of equation 4 by $T = 1 + \Gamma C^{-1}$. The transformations allow going from this system where plants and pollinators are entangled ($N_P + N_A$ equations)

$$\begin{bmatrix} r^P \\ r^A \end{bmatrix} = \left(\underbrace{\begin{bmatrix} \alpha^P & 0 \\ 0 & \alpha^A \end{bmatrix}}_C - \underbrace{\begin{bmatrix} 0 & \gamma^P \\ \gamma^A & 0 \end{bmatrix}}_r \right) \begin{bmatrix} P \\ A \end{bmatrix} = -\hat{A} \begin{bmatrix} P \\ A \end{bmatrix} \quad (4)$$

548 to these two disentangled systems, one for plants (with N_P equations) and another for pollinators (with N_A equations)

$$\begin{bmatrix} r^P + \gamma^P (\alpha^A)^{-1} r^A \\ r^A + \gamma^A (\alpha^P)^{-1} r^P \end{bmatrix} = \begin{bmatrix} \alpha^P - \gamma^P (\alpha^A)^{-1} \gamma^A & 0 \\ 0 & \alpha^A - \gamma^A (\alpha^P)^{-1} \gamma^P \end{bmatrix} \begin{bmatrix} P \\ A \end{bmatrix} \quad (5)$$

549 that represents the effective intra-guild interaction once the competition and mutualistic effects have been taken into account

$$\begin{bmatrix} r'_P \\ r'_A \end{bmatrix} = \begin{bmatrix} \alpha'_P & 0 \\ 0 & \alpha'_A \end{bmatrix} \begin{bmatrix} P \\ A \end{bmatrix} \quad (6)$$

550 In this new framework r'_P and r'_A are called effective intrinsic growth rates and α'_A and α'_P effective interaction. These two
551 matrices are the ones we use to quantify the structural stability of the pollinator community and of the plant community.

552 **F.1 Reconstructing persistence probability of the full plant-pollinator communities**

553 Since we are working with the effective interaction matrices instead of the original representation, we studied to what extent
554 the predicted persistence probability of the effective interaction systems was representative of the original community with
555 mutualism and mean field competition. Here we show that we can recover almost perfectly (up to 97%) the persistence
556 probability of the whole community (ω_C) as a combination of the persistence probability of plants and pollinators (ω_P and ω_A).

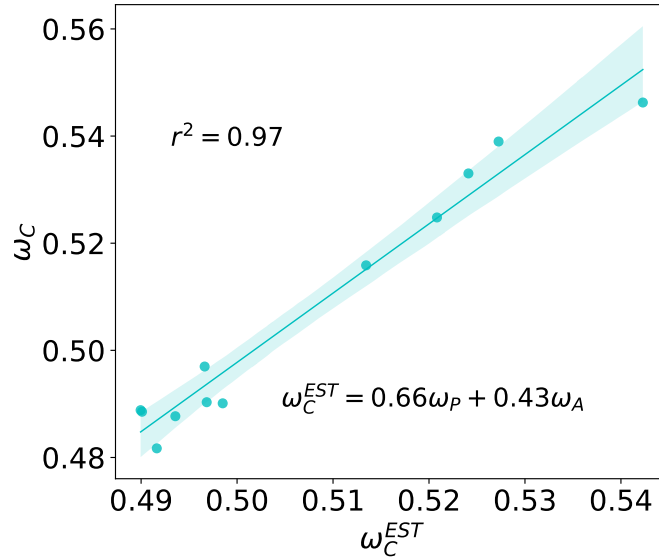


Figure S8: Average persistence probability of the full plant-pollinator mutualistic communities (ω_C) vs the estimated average persistence probability of the plant-pollinator community (ω_C^{EST}). The text shows the best estimation for average persistence probability (ω_C^{EST}) as a combination of the average persistence probability of the effective biotic matrix interaction of plants (ω_P) and pollinators (ω_A), as well as the goodness of the reconstruction (r^2).

G Parameter robustness

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In order to check the robustness of our results, we repeated the first analysis (correlation of empirical persistence versus average predicted persistence probability (ω)) with different values for the dynamical parameters of intra-guild competition (α) and average mutualistic gain (γ_0). The different values of γ_0 explored are those compatible with the linear stability of the least stable system (i.e., those below the minimum γ_0 threshold)²⁹. The results are summed up in Table 1. In the main text we used $\alpha=0.005$ and $\gamma_0=0.1$, similarly as in previous studies²⁹, but looking at the table we can see that as long as the mutualistic strength is large enough for a given competition strength, the correlation appears. In the cases where competition is higher, we did not check larger values of γ_0 because we choose the same value for all the networks in the database, and hence we were limited by the threshold value of the least stable network, but we guess that if the increase the mutualistic gain value for the networks that are stable we will recover that high empirical persistence is associated with a high predicted average probability of persistence.

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α	γ_0	ρ (Plants)	ρ (Pollinators)
		0.001	0.10
	0.11	0.79	0.63
0.002	0.10	0.83	0.71
	0.11	0.82	0.67
0.003	0.10	0.83	0.77
	0.11	0.83	0.71
0.005	0.10	0.79	0.85
	0.11	0.80	0.81
	0.12	0.80	0.74
0.010	0.10	0.68	0.57
	0.11	0.70	0.73
	0.12	0.72	0.83
	0.13	0.67	0.86
0.020	0.10	0.59	0.12
	0.11	0.62	0.22
	0.12	0.60	0.29
	0.13	0.63	0.39
	0.14	0.57	0.45

Table 1: Correlation between empirical persistence and average predicted persistence probability (ρ), for plants and pollinators, as a function of the dynamical parameters of the mutualistic model: intra-guild mean-field competition (α) and average mutualistic gain(γ_0).

H Data availability

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The database of species interactions and abundances, together with the code used for generating the results presented in this study are available in [this](#) compressed file. Upon publication of the manuscript they will be uploaded to Zenodo in accordance with open data and open science guidelines.

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