Trade-offs among plant reproductive traits determine interactions with floral visitors

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Plant life strategies are constrained by cost-benefit trade-offs that determine plant form and function. However, despite recent advances in the understanding of tradeoffs for vegetative and physiological traits, little is known about plant reproductive economics and how they constrain plant life strategies and shape interactions with floral visitors. Here, we investigate plant reproductive trade-offs and how these drive interactions with floral visitors using a dataset of 17 reproductive traits for 1,506 plant species from 28 plant-pollinator studies across 18 countries. We tested whether 12 a plant's reproductive strategy predicts its interactions with floral visitors and if the different reproductive traits predict the plant's role within the pollination network. We found that over half of all plant reproductive trait variation was explained by two independent axes that encompassed plant form and function. Specifically, the first axis indicated the presence of a trade-off between flower number and flower size, while the second axis indicated a pollinator dependency trade-off. Plant reproductive 18 trade-offs helped explain partly the presence or absence of interactions with floral 19 visitors, but not differences in visitation rate. However, we did find important differences in the interaction level among floral visitor guilds on the different axes of trait variation. Finally, we found that plant size and floral rewards were the most important traits in the understanding of the plant species network role. Our results highlight the importance of plant reproductive trade-offs in determining plant life strategies and plant-pollinator interactions in a global context. 25

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Despite the astonishing diversity of floral structures among flowering plants^{1,2} and their importance in shaping plant-pollinator interactions^{3,4}, a unified framework that explores plant reproductive compromises is currently lacking⁵. In addition, macroecological studies that investigate plant reproductive traits are scarce^{6–9} and consequently, there is poor understanding of how reproductive traits drive interactions with floral visitors at large scales^{10–13}. Linking the plant's position in the trait-space with the different pollinator groups could help to improve our understanding of plant-pollinator

associations¹⁴. Further, there is increasing interest in understanding drivers of plant-pollinator interactions using trait-based approaches^{3,15} and trait-matching analyses^{16,17}. However, reproductive traits have been overlooked beyond highly specialised pollination systems⁴ despite the generalist nature of plant-pollinator interactions^{18,19}. Overall, it is unclear how specific plant reproductive biology traits shape plant-pollinator interactions^{20,21}.

Species can optimise their fitness through various life-history traits, yet trade-offs among those traits constrain the range of potential strategies that a species can use. With the recent availability of large trait databases (e.g., TRY²² and COMPADRE²³), plant ecological strategies are being increasingly examined, and are facilitating the identification of global patterns and constraints in plant form and function 12,24-26. However, most studies have focused on vegetative traits such as leaf²⁷, wood²⁸, or root²⁹ trade-offs with little or no attention given to reproductive traits^{5,30} which are critical to plant life strategies that shape interactions with pollinators and ultimately determine plant reproductive success. For instance, short lived versus perennial species tend to have low versus high levels of outcrossing, respectively, 931 and outcrossing levels are positively correlated with flower size³². In addition, the presence of costly rewards (e.g., pollen or nectar) and showy flowers or floral displays can only be understood through consideration of plant species' reliance upon animal pollination (pollinator dependence) and its role in attracting pollinators^{33,34}. However, it is still unknown to what extent these different reproductive compromises determine plantpollinator interactions.

Several studies have identified links between plant traits and plant-pollinator network properties^{35–37}. Moreover, plant traits can define species' network roles (e.g., specialists vs generalists)^{20,38}. For example, plant species that occupy reproductive trait space extremes are more likely to exhibit higher levels of specialisation and be more reliant on the trait-matching with pollinators^{39,40}. Morphological matching between plant and floral visitors often determines plant-pollinator interactions, and can thus strongly influence interaction network structure^{16,41}. Remarkably, the combination of traits

have shown to increase the predictive power of the network interactions⁴². Therefore, considering the different plant reproductive trade-offs which represent the species reproductive strategy within the network¹⁴ could progress our understanding of plant-pollinator interactions. Further, we know little if those patterns generally studied at the community level are representative at wider macroecological scales.

Here, we aim to explore the potential trade-offs among reproductive traits and how these influence plant-pollinator interactions. First, we identify the major axes of reproductive trait variation and trade-offs that determine plant form and function. Second, we investigate how plant species' position in trait-space influence interactions with floral visitors. Finally, we investigate how both the main axes of trait variation, and individual traits, influence plant species' roles within networks using a set of complementary interaction network metrics (i.e., interaction strength, normalized degree and specialization).

81 RESULTS

Plant strategies. The phylogenetically informed principal component analysis (pPCA) captured by the first two and three axes 51.8% and 70.97% of trait variation, respectively (Fig. 1 and Supplementary Fig. S5) and had a phylogenetic correlation (λ) of 0.76. The first principal component (PC1) represented 26.72% of the trait variation and indicated 85 a trade-off between flower number and flower size. We refer to this axis as the 'flower number - flower size trade-off', as already described in previous studies^{43,44}. Hence, 87 one end of the spectrum comprised species with high investment in flower number and 88 plant height but small flower size, short style length and low ovule number. The other 89 end of this spectrum comprised species that were short in height and invested in large flowers, long styles, many ovules, but few flowers. The main contributing traits to PC1 were plant height, flower number, ovule number and flower size (loadings > 10.51; Supplementary Table S3) but style length also contributed moderately on PC1 (loading = -0.33). The second principal component (PC2) represented 25.05% of the trait variation

and indicated a trade-off between low and high pollinator dependence. We refer to this axis as the 'pollinator dependence trade-off'. The main driver of trait variation on 96 PC2 was autonomous selfing (loading = 0.85) but the other traits (except ovule number) 97 also made moderate contributions (loadings from 0.27 to 0.4; Supplementary Table S3). 98 We found that high pollinator dependence was associated with larger and a higher number of flowers, greater plant height and longer styles. In contrast, species with high 100 levels of autonomous selfing tended to have fewer and smaller flowers, had shorter 101 styles and were shorter in height. Further, PC3 explained a considerable amount of trait 102 variability (19.17%) and the main contributors to this axis were style length (loading 103 = -0.66) and the degree of autonomous selfing (loading = -0.51). The remaining traits, 104 apart from ovule number, were moderately correlated to changes on PC3 (loadings 105 from -0.23 to -0.46; Supplementary Table S3). Thus, because style length was correlated with all traits on PC3 and was the main driver of trait variation, we refer to this axis 107 as the 'style length trade-off'. Further, the pPCA with the subset of species that had 108 nectar and pollen quantity data showed that nectar quantity (microlitres of nectar per 109 flower) was positively associated with flower size, style length and ovule number (PC1, 110 23.40%); and pollen quantity (pollen grains per flower) was positively correlated with 111 flower number and plant height and negatively associated with autonomous selfing (PC2, 21.67%; Supplementary Fig. S6). This pPCA explained similar variance with the 113 first two principal components (45.07%) and similar associations of traits despite some variability in the loadings (Supplementary Table S4).

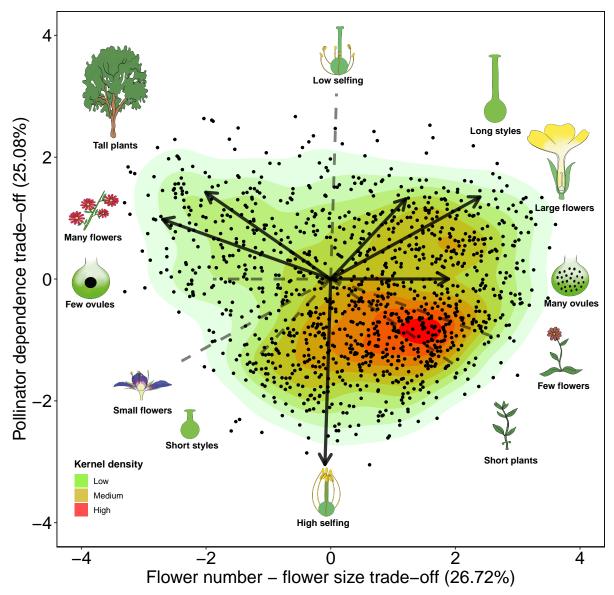
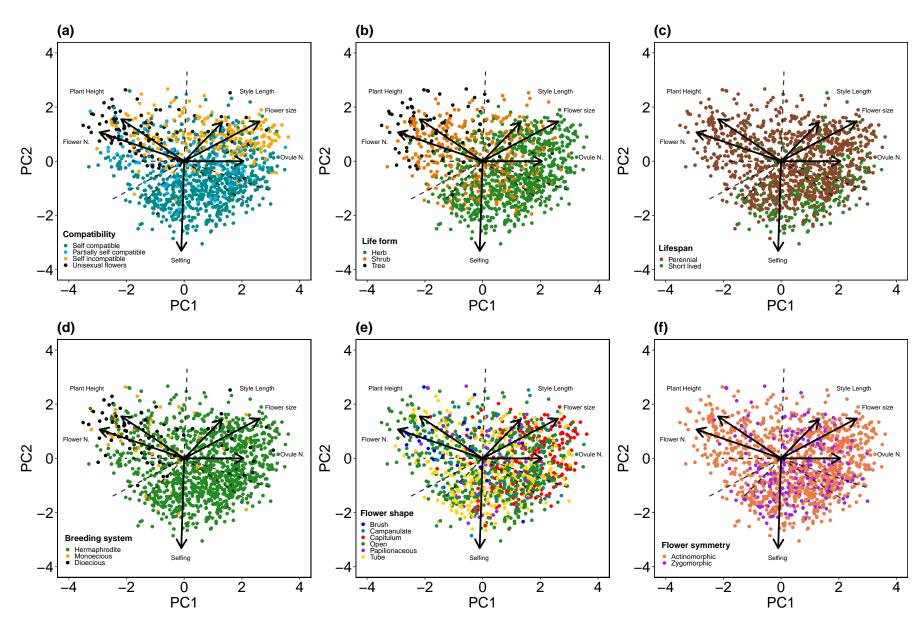


Fig. 1 | **Plant life-history strategies.** Phylogenetically informed principal component analysis (pPCA) of 1,236 plant species from 28 plant-pollinator network studies. The solid arrows indicate the direction of the different quantitative traits (flower number, plant height, style length, flower size, ovule number and level of autonomous selfing) across the two main axes of trait variation. The length of the arrows indicate the weight of the variables on each principal component and the dashed lines show the opposed direction of trait variation. The icons at both ends of arrows and dashed lines illustrate the extreme form of the trait continuum.

We found that most categorical traits were statistically associated with the first two axes of trait variation (Fig. 2 and Supplementary Table S2). Flower symmetry, which was only associated with PC2 (Sum of squares = 8.51, F-value = 14.72, P < 0.01), and nectar provision, which was independent of PC1 and PC2 (PC1: Sum of squares = 0.37, F-value

= 0.29, P = 0.59; PC2: Sum of squares = 0.83, F-value = 1.43, P = 0.23) showed lack of statistical association. In addition, we found (with a Tukey test) statistical differences 121 between the different levels of categorical traits in the trait space (Supplementary Fig. 122 S7). Regarding self compatibility, we found larger differences on PC2 (i.e., species 123 with unisexual flowers that were self incompatible were statistically differentiated from 124 species with partial or full self compatibility; Supplementary Fig. S7a and Fig. S7b). Life 125 forms differed statistically across both axes of trait variation and followed a gradient 126 of larger life forms (trees and shrubs) with higher pollinator dependence to smaller 127 ones (herbs) with lower pollinator dependence (Supplementary Fig. S7c and Fig. S7d). 128 Consequently, lifespan also followed this gradient but perennial and short lived species only differed statistically on PC2 (Supplementary Fig. S7e and Fig. S7f). Species with 130 unisexual flowers (monoecious and dioecious) were clustered on both extremes of the first two principal components and had the highest pollinator dependence and 132 highest number of flowers (Supplementary Fig. S7g and Fig. S7h). Moreover, we found that the campanulate and capitulum flower shapes were differentiated from tube, 134 papilionaceous, open and brush shapes in the trait space. The former morphologies 135 had larger flowers and greater pollinator dependence, while the latter had higher 136 flower number and greater autonomous selfing (Supplementary Fig. S7i and Fig. S7j). Regarding flower symmetry, zygomorphic flowers were associated with lower levels of 138 pollinator dependence, whereas actinomorphic flowers had higher levels of pollinator dependence (Supplementary Fig. S7k and Fig. S7l).



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Fig. 2 | Location of the different qualitative traits on the trait space. The panel is composed by the traits that showed statistical association with the first two axes of trait variation: compatibility system (a), life form (b), lifespan (c), breeding system (d), flower shape (e) and flower symmetry (f).

Phylogenetic signal of traits. We found a strong phylogenetic signal (P < 0.01) in all quantitative traits (Supplementary Table S5). The traits that showed the highest phylogenetic signal were ovule number ($\lambda = 1$), pollen grains per flower ($\lambda = 1$) and plant height ($\lambda = 0.96$), followed by flower length ($\lambda = 0.75$), flower width ($\lambda = 0.73$), number of flowers per plant ($\lambda = 0.69$) and nectar concentration ($\lambda = 0.65$). The traits that showed a moderate phylogenetic signal were inflorescence width ($\lambda = 0.57$), style length ($\lambda = 0.49$) and autonomous selfing ($\lambda = 0.34$). Finally, microliters of nectar per flower showed the lowest phylogenetic signal of all traits ($\lambda = 0.14$).

Visitation patterns. The main axes of trait variation explained partly presence-absence interactions between plant and floral visitors (conditional $R^2 = 0.26$; marginal $R^2 =$ 150 0.20) but little of the overall visitation rates (conditional $R^2 = 0.31$; marginal $R^2 = 0.06$). However, we found relevant trends across the different floral visitor guilds on both 152 presence-absence and visitation interactions (Fig. 3). On the pollinator dependence 153 trade-off, all floral visitor guilds interacted more frequently with plant species with 154 higher pollinator dependence (PC2; Fig. 3b and Fig. 3e). For presence-absence interactions we found that all Diptera, Coleoptera and non-bee-Hymenoptera guilds 156 interacted more frequently with plants with high flower number and small flowers 157 (flower number - flower size trade-off, PC1; Fig. 3a) but bees and Lepidoptera interacted 158 slightly more frequently with plant species with low flower number but large flowers. 159 For presence-absence interactions on PC3 (style length trade-off; Fig. 3c), we found 160 that bees interacted clearly more with plant species with long styles and high selfing 161 and the rest of the guilds interacted slightly more with plant species with short styles 162 and low selfing. In addition, all guilds other than Syrphids and Lepidoptera (i.e., all 163 Hymenoptera, non-syrphid-Diptera and Coleoptera) showed greater visitation rates on 164 species with small numerous flowers (PC1; Fig. 3d). On the style length trade-off, bees, 165 Lepidoptera and non-bee-Hymenoptera showed greater visitation rates on plant species 166 with larger styles and higher levels of selfing; while syrphids, non-syrphid-Diptera 167 and Coleoptera showed higher visitation rates on species with shorter styles and lower selfing (Fig. 3f).

The additional model for both presence-absence of interactions (marginal $R^2 = 0.29$; conditional $R^2 = 0.19$) and visitation rate (marginal $R^2 = 0.30$; conditional $R^2 = 0.03$) for the most represented families of bees showed that the family Apidae was the main driver of the observed patterns and that the contrasting differences between presence-absence and visitation rate for bees on PC1 (Fig. 3a and Fig. 3d) were driven by the family Andrenidae which interacted more frequently on presence-absence interactions with plant species with low number of flowers but large (Supplementary Fig. S8).



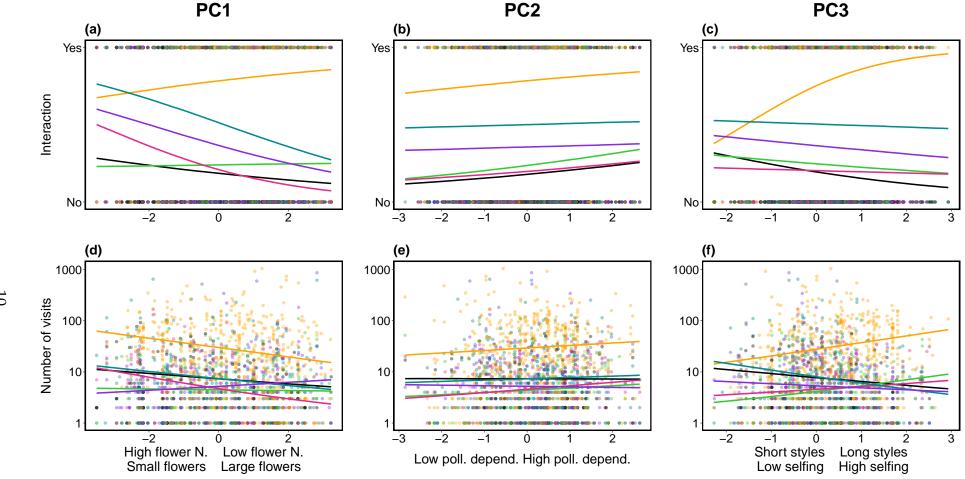


Fig. 3 | Interaction (yes/no) and visitation rates across the three main axes of trait variation per floral visitor guild. Fitted posterior estimates of the presence/absence of interaction (a, b and c) and number of visits (d, e and f) made by the different floral visitors guilds in relation to PC1, PC2 and PC3. PC1 represents the flower number - flower size trade-off, PC2 represents the pollinator dependence trade-off and PC3, the style length trade-off. For visualization purposes, due to large differences between the visitation rates of bees and the rest of guilds, the number of visits was log-transformed (Y-axis of lower panel).

Plant species functional roles. The variance of the different plant species-level network metrics was poorly explained by the three main axes of trait variation (Supplementary 178 Fig. S9; interaction frequency ~ PCs, conditional $R^2 = 0.11$, marginal $R^2 = 0.02$; normal-179 ized degree ~ PCs, conditional $R^2 = 0.24$, marginal $R^2 = 0.02$; and, specialization ~ PCs, 180 conditional $R^2 = 0.37$, marginal $R^2 = 0.03$). Overall, the most notable trends were found 181 on PC1 and PC3 for interaction frequency and specialization. On the flower number 182 - flower size trade-off (PC1), interaction frequency was higher for plant species with 183 more flowers but was lower for plant species with larger flowers (Supplementary Fig. 184 S9a). On PC1, specialization showed the opposite trend (Supplementary Fig. S9g). On 185 the style length trade-off (PC3), interaction frequency was lower for plants with shorter 186 styles and lower autonomous selfing and higher for species with longer styles and 187 higher autonomous selfing (Supplementary Fig. S9c). Again, specialization showed the opposite trend to interaction frequency (Supplementary Fig. S9i). 189

When we further investigate which combination of traits drive plant network roles, 190 we show that the regression tree for visitation frequency was best explained by plant height, nectar concentration and style length (Fig. 4a). Specifically, species taller than 192 3.9m had the highest interaction frequency, while species that were shorter than 3.9m 193 and had a nectar concentration lower than 16% had the lowest interaction frequency. 194 Normalized degree was best explained by nectar concentration, pollen grains per 195 flower, plant height, flower width and autonomous selfing (Fig. 4b). Species with a 196 nectar concentration over 49% had the highest levels of normalized degree, whereas 197 species with nectar concentration lower than 49%, more than 21,000 pollen grains 198 per flower and height less than 0.78m had the lowest normalized degree. Finally, 199 specialization was best explained by plant height, ovule number, pollen grains per 200 flower and autonomous selfing (Fig. 4c). Overall, plant species with the highest 201 specialization were shorter than 1.3m, had more than 14,000 pollen grains per flower 202 and autonomously self-pollinated less than 11% of their fruits. In contrast, species 203 taller or equal than 5.1m and with lower than 14 ovules per flower had the lowest 204 specialization values.

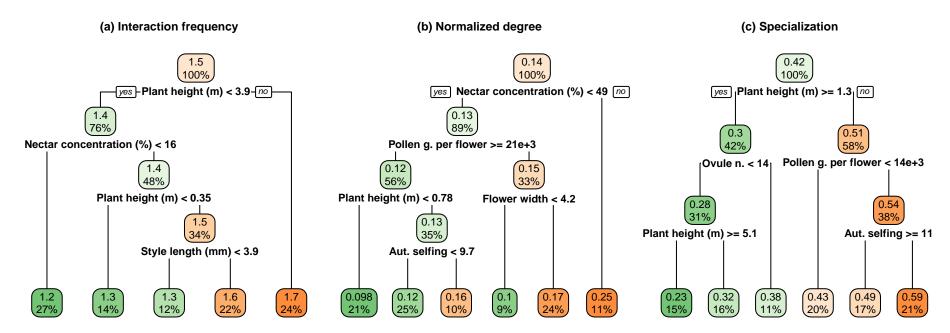


Fig. 4 I **Contribution of traits in plant's network roles.** Regression tree analysis of interaction frequency (log-transformed), normalized degree and specialization for the subset of species with quantitative data for pollen and nectar traits. The superior value inside the node indicates the mean value of the different species-level metric and the lower value, the percentage of species that are considered in each node. Thus, the top node has the mean value of the named trait for the 100% of species. Each node has a yes/no question and when the condition is fulfilled, the branch turns to the 'yes' direction and when not, to the 'no' direction. This rationale is followed in all the regression trees as indicated in the first branch division of the topmost node of each tree.

DISCUSSION

Here, we show that plant species exhibit clear trade-offs among their vegetative and 207 reproductive traits and that these trade-offs determine interactions with floral visitors. 208 These trade-offs are differentiated along three axes of trait variation: (i) flower number 209 - flower size, (ii) pollinator dependence and (iii) style length. These reproductive 210 trade-offs helped explain partly the presence of floral visitor interactions, but not their 211 visitation rates. However, floral visitor guilds formed distinct relationships with the 212 main axes of trait variation. Moreover, we found that the plant species functional roles 213 within pollination networks were best explained by plant size and floral reward related 214 traits. 215

Over half of all plant trait variation was captured by the flower number - flower size and 216 pollinator dependence trade-offs. Trait variation on these two axes was associated with 217 the 'fast-slow continuum' in plant¹² and animal⁴⁵ life-history strategies, as indicated 218 by the different floral and reproductive biology traits associated with plant height, life form and lifespan. The 'slow' part of this continuum (i.e., tall trees and shrubs) 220 included plant species with many flowers, few ovules, higher pollinator dependence, 221 frequent occurrence of self-incompatibility and more complex breeding systems (e.g., 222 monoecious and dioecious species). In contrast, plant species that employed the 'fast' strategy (i.e., short herbs), had fewer flowers, more ovules, frequent occurrence of self-224 compatibility and lower pollinator dependence. Further, on the first two axes of trait 225 variation, we found additional support for the previously described positive association 226 between higher outcrossing rate and larger floral display³². The positive correlation between larger floral display and higher pollinator dependence in our dataset further 228 confirmed this trend (see Supplementary Fig. S10).

Despite the low predictive power of the main trait variation axes for broad-level interaction patterns (presence-absence of interactions and visitation rate), we found changes in the interaction patterns among and within floral visitor guilds across these

axes that suggest plant life-history strategies influence plant-pollinator interactions. For example, all floral visitor guilds visited plant species with higher pollinator dependence 234 more frequently, and high pollinator dependence was associated with large floral 235 displays and greater pollen quantities (Fig. 1 and Supplementary Fig. S6). This trend 236 is consistent with previous studies that show plant species with higher reproductive 237 investment tend to be visited by pollinators more frequently 38,46,47. In regard to the 238 flower number - flower size and style length trade-offs, different pollinator guilds 239 showed contrasting visitation rates across the continuum of trait variation, which could 240 be associated with different pollination syndromes at a macroecological scale. For 241 instance, bees and syrphid flies were clearly associated with opposing life-strategies 242 on PC1 and PC3 (Fig. 3) suggesting possible niche partitioning 48,49 between these two 243 guilds. However, despite floral rewards were not included in the main analysis because there was insufficient data available, floral reward related traits were among the best at 245 characterising species functional roles (Fig. 4), yet the association between reproductive trade-offs and floral visitors did not account for floral rewards because there was 247 insufficient data available. More detailed exploration of reproductive trade-offs in conjunction with floral rewards is needed to help elucidate plant-pollinator associations. 249 In any case, it is worth noting that other local factors such as species relative abundances, surely explain part of the observed variability ^{17,50,51} that reproductive trade-offs do not. 251 To conclude, we provide the first description of plant reproductive trade-offs using a 252 large global dataset of plant traits. We identified the major reproductive strategies of 253 flowering plants and how these strategies influence interactions with different floral 254 visitor guilds. Although the explained variation that we found in the first two axes 255 is lower than previous studies of vegetative traits^{24,26} it is consistent with the largest 256 and most recent study that has characterised plant life strategies with vegetative and 257 reproductive traits¹². Future work needs to integrate the reproductive compromises 258 that we have identified with vegetative and physiological trade-offs to create a more 259 comprehensive spectrum of plant trait variation. Further, the varying level of phyloge-260 netic signal among traits deserves further attention to understand evolutionary changes

on mating and flower morphology in response to pollinators^{52,53}. Finally, including plant-pollinator networks from unrepresented areas of the world and a more complete description of plant reproductive trade-offs is essential for a better understanding of the global patterns in plant-pollinator interactions.

6 MATERIALS AND METHODS

Plant-pollinator network studies. We selected 28 studies from 18 different countries 267 that constituted a total of 64 plant-pollinator networks. These studies recorded plant-268 pollinator interactions in natural systems and were selected so that we had broad 269 geographical representation. Although these studies differ in sampling effort and 270 methodology, all studies provided information about plant-pollinator interactions (weighted and non-weighted), which we used to build a database of plant species that 272 are likely to be animal pollinated. Many of these networks are freely available either 273 as published studies^{54–56} or available in online archives (e.g., The Web of Life⁵⁵ and 274 Mangal⁵⁷). In total, our network dataset (see Supplementary Table S1) constituted 60 weighted (interaction frequency) and 4 unweighted (presence/absence of the interac-276 tion) networks, each sampled at a unique location and year, as well as eight meta-webs where interactions were pooled across several locations and multiple years. 278

Taxonomy of plants and pollinators. All species names, genera, families and orders
were retrieved and standardized from the taxonomy data sources NCBI (https://
www.ncbi.nlm.nih.gov/taxonomy) for plants and ITIS (https://www.itis.gov/)
for pollinators, using the R package *taxize*⁵⁸ version 0.9.99. We filled the 'not found'
searches manually using http://www.theplantlist.org/ and http://www.mobot.org/
for plants and http://www.catalogueoflife.org/ for floral visitors.

Functional traits. We selected 20 different functional traits based on their relevance to plant reproduction and data availability (Table 1). These included twelve quantitative and eight categorical traits belonging to three broader trait groupings (13 floral, 4 reproductive biology and 3 vegetative, Supplementary Information). For each plant

species, we undertook an extensive literature and online search across a wide range of resources (plant databases, online floras, books, journals and images). From a total of 30,120 cells (20 columns \times 1,506 species) we were able to fill 24,341 cells (80.8% of the dataset, see Supplementary Fig. S1 for missing values information for each trait).

Phylogenetic Distance. We calculated the phylogenetic distance between different plant species using the function *get_tree* from the package *rtrees* (https://github.c om/daijiang/rtrees), which downloads phylogenetic distances from the extended R implementation of the Open Tree of Life^{59,60}.

Data Imputation. Trait missing values were imputed with the function *missForest*⁶¹ 297 which allows imputation of data sets with continuous and categorical variables. We 298 accounted for the phylogenetic distance among species on the imputation process 299 by including the eigenvectors of a principal component analysis of the phylogenetic 300 distance (PCoA) which has been shown to improve the performance of *missForest*⁶². 301 To extract the eigenvectors, we used the function PVRdecomp from the package PVR^{63} 302 based on a previous conceptual framework that considers phylogenetic eigenvectors⁶⁴. 303 Although the variable of autonomous selfing had a high percentage of missing values 304 (68%), we were able to solve this by back transforming the qualitative column of 305 autonomous selfing to numerical. The categories of 'none', 'low', 'medium' and 'high' 306 were converted to representative percentages of each category 0%, 13%, 50.5% and 88% 307 respectively. This reduced the percentage of missing values for this column from 68% to 308 35% and allowed the imputation of this variable. However, we were unable to include nectar and pollen traits on the imputation process because of the high percentage of 310 missing values (Supplementary Fig. S1). Hence, the imputed dataset had 1,506 species, 311 seven categorical and eight numerical variables and 5.79% of missing values. Further, 312 we conducted an additional imputation process on the subset of species with data for pollen per flower and microliters of nectar. This subset comprised 755 species, 8.01% 314 missing values and all traits but milligrams of nectar (~50% of missing values) were included in the imputation process.

Table 1 | Quantitative and categorical traits used in this study.

Quantitative traits		Categorical traits		
Type	Traits	Type	Traits	Categories
Vegetative	Plant height (m)	Vegetative	Lifepan	Short-lived Perennial
Floral	Flower width (mm)	Vegetative	Life form	Herb Shrub Tree
Floral	Flower length (mm)	Floral	Flower shape	Brush Campanulate Capitulum Open Papilionaceous Tube
Floral	Inflorescence width (mm)	Floral	Flower symmetry	Actinomorphic Zygomorphic
Floral	Style length (mm)	Floral	Nectar	Presence Absence
Floral	Ovules per flower	Reproductive biology	Autonomous selfing	None Low Medium High
Floral	Flowers per plant	Reproductive biology	Compatibility system	Self-incomp. Part. self-comp. Self-comp.
Floral	Nectar (µl)	Reproductive biology	Breeding system	Hermaphrodite Monoecious Dioecious
Floral	Nectar (mg)			
Floral	Nectar concentration (%)			
Floral	Pollen grains per flower			
Reproductive biology	Autonomous selfing (fruit set)			

Plant strategies. We explored the trade-offs between different quantitative plant functional traits with a phylogenetically informed Principal Component Analysis (pPCA). 318 We did not include the quantitative variables of flower length and inflorescence width 319 because they were highly and moderately correlated to flower width respectively (Pear-320 son's correlation = 0.72, P < 0.01 and Pearson's correlation = 0.36, P < 0.01), and thus 321 we avoided overemphasizing flower size on the spectrum of trait variation. Although 322 qualitative traits were not included in the dimensionality reduction analysis, we also 323 investigated the association of the different qualitative traits with the main axes of trait 324 variation. Prior to the analyses, we excluded outliers and standardized the data. Due to 325 the high sensitivity of dimensionality reduction to outliers, we excluded values within 326 the 2.5th–97.5th percentile range⁶⁵, and thus our final dataset had 1,236 species. Then, 327 we log transformed the variables to reduce the influence of outliers and z-transformed 328 (X= 0, SD=1) so that all variables were within the same numerical range. We performed 329 the pPCA using the function *phyl.pca* from the package *phytools*⁶⁶ (version 0.7-70) with 330 the method lambda (λ) that calculates the phylogenetic correlation between 0 (phylo-331 genetic independence) and 1 (shared evolutionary history) and we implemented the 332 mode covariance because values for each variables were on the same scale following 333 transformation⁶⁷. Moreover, to corroborate that our imputation of missing values did not affect our results, we conducted a pPCA on the full dataset without missing values 335 (see Supplementary Fig. S2). We found little difference between the explained variance 336 with the imputed dataset (51.08%) and the dataset without missing values (52.87%). 337 In addition, the loadings on each principal component had a similar contribution and correlation patterns, with the exception of plant height which showed slight variations 339 between the imputed and non-imputed dataset. Finally, we conducted an additional phylogenetic informed principal component analysis for the subset of species with 341 pollen and nectar quantity. For this, we included all quantitative traits considered in 342 the main pPCA plus pollen grains and microlitres of nectar per flower. 343

Phylogenetic signal of traits. We calculated the phylogenetic signal of the different quantitative traits on the imputed dataset with the full set of species (N = 1,506) with

the package *phytools*⁶⁶ version 0.7-70 and we used Pagel's λ as a measurement of the phylogenetic signal. However, for pollen and nectar traits, phylogenetic signal was calculated only on the subset of species that had quantitative information for these traits (N = 755).

Network analyses. Analyses were conducted on the subset of 60 weighted networks 350 sampled in a unique flowering season and site, which included 556 plant and 1,126 351 pollinator species. These networks were analysed in their qualitative (presence-absence) 352 and quantitative (interaction frequency) form. First, we analysed the binary version of 353 these weighted networks with presence-absence information that assumes equal weight 354 across interactions. Second, we analysed the untransformed weighted networks with 355 interaction frequency that accounts for the intensity of the interaction. Although floral visitors are not always pollinators and interaction frequency does not consider each 357 pollinator species efficiency⁶⁸, interaction frequency can provide valuable information 358 of the contribution of floral visitors to pollination^{69,70}. In total, our network dataset 359 (excluding meta-webs and non-weighted networks) included 2,256 interactions of bees with plants, 1,768 non-syrphid-Diptera interactions, 845 syrphids interactions, 437 361 Lepidoptera interactions, 432 Coleoptera interactions and 362 non-bee-Hymenoptera 362 interactions. Sampling methods varied across networks but this was accounted for 363 in analyses by considering them in the random effects of the modelling process. All 364 analyses were conducted in R version 4.0.3. 365

Visitation patterns. We used Bayesian modelling (see below for details) to explore 366 the effect of floral visitor groups and the main axes of trait variation (pPCA with im-367 puted dataset) on both qualitative (presence/absence) and quantitative (visitation rate) 368 floral interactions per plant species. For this, we divided floral visitors into six main 369 guilds that differ in life form, behaviour and are likely to play a similar ecological 370 role: (i) bees (Hymenoptera-Anthophila), (ii) non-bee-Hymenoptera (Hymenoptera-371 non-Anthophila), (iii) syrphids (Diptera-Syrphidae), (iv) non-syrphid-Diptera (Diptera-372 non-Syrphidae), (v) Lepidoptera and (vi) Coleoptera. Moreover, because the guild of 373 bees was the most represented group with 2,256 records and had the highest frequency

of visits of all groups, we also explored the presence-absence of interaction and visitation rate of the main bee families (Andrenidae, Apidae, Colletidae, Halictidae and 376 Megachilidae) on the trait space. In addition, we found that *Apis mellifera* was the floral 377 visitor with the largest proportion of records counted (7.55% of the total). This finding 378 is consistent with previous research showing that A. mellifera was the most frequent 379 floral visitor in a similar dataset of 80 plant-pollinator networks in natural ecosystems⁷¹. 380 Hence, to control for the effect of A. mellifera on the observed visitation patterns of 381 bees, we conducted an analogous analysis with presence-absence of interaction and 382 visitation rate excluding A. mellifera. We found that A. mellifera, was partly driving 383 some of the observed trends on PC1 (Supplementary Fig. S3). However, we did not 384 detect major differences on PC2 and PC3. 385

We implemented Bayesian generalized linear mixed models using the R package brms⁷² 386 (version 2.14.6). We modelled the frequency of visits as a function of the main axes of 387 plant trait variation and their interactions with floral visitor functional groups (Visits ~ 388 PC1 x FGs + PC2 x FGs + PC3 x FGs). Because we were interested in possible differences in the visitation patterns among floral visitors groups to plants with different strategies, 390 we included interactions between the main axes of trait variation (PC1, PC2 and PC3) 391 and the floral visitor guilds. In this model, we added a nested random effect of networks 392 nested within the study system to capture the variation in networks among studies 393 and within networks. Moreover, we included the phylogenetic covariance matrix as a 394 random factor due to the possible shared evolutionary histories of species and therefore 395 lack of independence across them. We specified this model with a zero inflated negative 396 binomial distribution and weakly informative priors from the brms function. We run 397 this model for 3,000 iterations and with previous 1,000 warm up iterations. We set delta 398 (Δ) to 0.99 to avoid divergent transitions and visualized the posterior predictive checks 399 with the function pp_check using the bayesplot package⁷³ (version 1.7.2). 400

Plant species functional roles. We investigated whether different quantitative traits
determined plant species functional roles using Bayesian modelling and regression
trees. For this, we selected simple and complementary species-level network metrics

commonly applied in bipartite network studies⁷⁴ with a straightforward ecological 404 interpretation relevant to our research goals. The different plant species-level metrics 405 were: (i) sum of visits per plant species; (ii) normalized degree, calculated as the number 406 of links per plant species divided by the total possible number of partners; and (iii) 407 specialization $(d')^{75}$, which measures the deviation of an expected random choice of the 408 available interaction partners and ranges between 0 (maximum generalization) and 1 409 (maximum specialization). Normalized degree and specialization were calculated with 410 the *specieslevel* function from the R package *bipartite*⁷⁴ (version 2.15). 411

First, we modelled the distinct plant species metrics (sum of visits, normalized degree and plant specialization) as a function of the three main axes of trait variation (plant species level metric ~ PC1 + PC2 + PC3). For each response variable (i.e., each plant species level metric), we used different distribution families (zero inflated negative binomial for the sum of visits, weibull for normalized degree and zero one inflated beta for specialization). Finally, we used the same random factors, model settings and conducted the same posterior predictive checks for each model as detailed above in the 'visitation patterns section'.

Second, to better understand these complex trait relationships, we used regression 420 trees. Regression trees are recursive algorithms which can detect complex relationships 421 among predictors and allow identification of the relevance of specific trait combinations 422 on species functional roles. We focused exclusively on quantitative traits because almost 423 all categorical traits were statistically associated with the first two axes of trait variation 424 (Supplementary Table S2). We conducted this analysis using the *rpart* package⁷⁶ version 425 4.1-15 with method 'anova' with a minimum of 50 observations per terminal node and 426 we used the rpart.plot package⁷⁷ version 3.0.9 to plot the regression trees. We considered 427 the species level indices as response variables (interaction frequency, normalized degree 428 and specialization) and we performed one regression tree per metric using the different 429 quantitative traits as predictors. We calculated two regression trees per plant specieslevel metric, one for the full set of species and another for the subset of species for 431 which we had pollen and nectar traits. We focused on regression trees that included

floral rewards because they consistently showed pollen and nectar traits as being the best for explaining the different species-level metrics (see Supplementary Fig. S4).

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590 Acknowledgements

This is study was supported by project SAFEGUARD (101003476 H2020-SFS-2019-2).
We thank all researchers that made their data available for our analysis. We thank
Bryony Wilcox, Greg Bible, Mercedes Sanchez-Lanuza and David Ragel for their help
with data collection. We also thank Jason Tylianakis for his comments on the manuscript
before submission. JBL thanks the University of New England for the funding provided
to carry out this work.