1	Linking Species Functional Roles To Their Network Roles
2	Camille COUX ¹ , Romina RADER ² , Ignasi BARTOMEUS ³ , Jason M. TYLIANAKIS ^{1,4}
3	
4	¹ Centre for Integrative Ecology, School of Biological Sciences, University of Canterbury, Private Bag
5	4800, Christchurch 8140, New Zealand
6	² Ecosystem Management, School of Environment and Rural Sciences, University of New England,
7	Armidale, NSW, Australia
8	³ Estación Biológica de Doñana (EBD-CSIC), Dpto. Ecología Integrativa, Avda. Américo Vespucio s/n
9	Isla de la Cartuja 41092, Sevilla, Spain
10	⁴ Department of Life Sciences, Imperial College London, Silwood Park Campus, Buckhurst Road,
11	Ascot, Berkshire SL5 7PY, UK
12	
13	SHORT RUNNING TITLE (45 characters incl. spaces): Linking species functional and network roles
14	KEY WORDS: Biodiversity, ecosystem functioning, mutualistic network, interaction, web, stability,
15	resilience
16	TYPE OF ARTICLE: Letters
17	WORD COUNT: Abstract: 150; Main text: 5243; number of references: 50
18	5 figures, 1 Table, 1 Supporting Information.
19	STATEMENT OF AUTHORSHIP
20	CC wrote the manuscript and conducted analyses with inputs from JT and IB. RR designed and
21	conducted the field study with assistance from JT. RR and IB compiled the trait data. All authors
22	conceptualised the study and commented on the manuscript. JT secured funding.
23	
24	CORRESPONDING AUTHOR:
25	Camille Coux

- 26 Centre for Integrative Ecology, School of Biological Sciences, University of Canterbury, Private Bag
- 27 4800, Christchurch 8140, New Zealand

- 29 Email: camille.coux@orange.fr
- 30 Cell phone +64-22-186-5969
- 31 Fax +64-3-364-2590

32

- 33
- 34
- 35

36 ABSTRACT

37 Species roles in ecological networks combine to generate their architecture, which contributes to 38 their stability. Species trait diversity also affects ecosystem functioning and resilience, yet it remains 39 unknown whether species' contributions to functional diversity relate to their network roles. Here 40 we use 21 empirical pollen transport networks to characterise this relationship. We found that, apart from a few abundant species, pollinators with original traits either had few interaction partners or 41 42 interacted most frequently with a subset of these partners. This suggests that narrowing of 43 interactions to a subset of the plant community accompanies pollinator niche specialisation, congruent with our hypothesised trade-off between having unique traits vs. being able to interact 44 45 with many mutualist partners. Conversely, these effects were not detected in plants, potentially 46 because key aspects of their flowering traits are conserved at a family level. Relating functional and 47 network roles can provide further insight into mechanisms underlying ecosystem functioning. 48

49

51 INTRODUCTION

52

53 The role biodiversity plays in ecosystem functioning has received much attention (Hooper et al. 54 2005), motivated by increasing species extinction rates (Pimm et al. 2014) and potential loss of 55 ecosystem services (Thompson & Starzomski 2007). Early findings that the positive biodiversity-56 ecosystem functioning relationship (e.g. Tilman et al. 1996) was not universal (Thompson & 57 Starzomski 2007) drew attention to the redundancy of functional traits across species (Walker 1991). 58 The diversity of traits (i.e. 'functional diversity'; Lavorel & Garnier 2002) has become a focus of 59 considerable research, as it can predict the rates of ecosystem processes more accurately than does 60 species richness (Reiss et al. 2009; Gagic et al. 2015), and differences in the redundancy of traits 61 within a community can yield various biodiversity-ecosystem functioning relationships (e.g. 62 saturating or sigmoidal).

63

64 Species' traits define their functional role by accounting for the morphological, physiological and 65 phenotypic features that affect ecosystem processes or respond to the environment (Lavorel & 66 Garnier 2002). The originality and uniqueness of a species' traits relative to others in the community 67 define its functional role and contribution to the community functional diversity, i.e. the total 68 diversity of traits displayed by all species (and which reflects a community's functional "capacity" 69 (Laliberté & Legendre 2010). The loss of species following land-use change has been shown to 70 reduce this functional diversity (Laliberté et al. 2010; Rader et al. 2014) and alter ecosystem 71 functioning and services (Larsen et al. 2005). Moreover, these losses may non-randomly select 72 certain species based on their 'response' traits (Larsen et al. 2005), and the interplay of response 73 and effect traits can produce non-random functional changes following environmental change 74 (Lavorel & Garnier 2002). We do not attempt here to infer response and effect trait correlations a 75 priori, but rather seek to understand how known response and effect traits will also affect the 76 propensity of species to interact, and thereby generate changes to interaction networks.

78	Indeed, species traits are also known to influence ecological interactions to the point where whole
79	interaction-network topology can be predicted (Eklöf et al. 2013), and this topology can have
80	important impacts on resilience (Gao et al. 2016). For example, Montoya et al. (2015) assigned
81	species to functional groups based on their trophic function (e.g. pollination or decomposition) and
82	found that network modularity favoured higher functional group diversity. Furthermore, a species'
83	function within a community has also been defined relative to the traits of the species with which it
84	interacts (Dehling et al. 2016), based on the idea that interactions mediate morphological trait-
85	matching. Thus, the global structure of ecological networks, as well as the relative arrangement of
86	each species' interactions that define their network roles, may capture important elements not only
87	of species diversity, but also functional diversity (Poisot et al. 2013).
88	
89	However, these functional and network roles may place different constraints on species traits, as the
90	benefits that emerge from functional originality could oppose those arising from acquiring
91	mutualistic interactions. In fact, the benefits of reduced competition that emerge through niche
92	partitioning and drive the functional diversification of species (Grime 2001) may reinforce individual
93	mutualisms through co-specialisations mediated by the cost-benefit balance for the involved
94	partners. Yet, this process may oppose the preservation of many mutualistic interactions in which
95	species are involved, and which constrain their traits to match those of a range of partners, thereby
96	potentially favouring interaction generalism (Fontaine <i>et al.</i> 2009). We therefore hypothesise a
97	trade-off between species traits being sufficiently unique to exploit different resources, while
98	remaining similar enough to maintain interactions with a higher number of mutualistic partners. In
99	addition, species relative abundances in a community may further complicate this trade-off, e.g. by
100	affecting species functional diversification through intra- and inter-specific competition (Chesson
101	2000), as well as the partner selection process, which is likely density-dependent (Fort et al. 2015).
102	Despite the fact that a network approach could encapsulate these previous trade-offs and thereby

103	improve our understanding of their relationships, it remains unknown whether functional roles of
104	species are related to their network roles (Reiss <i>et al.</i> 2009; Thompson <i>et al.</i> 2012).

106	Here we use empirical data from 21 pollen transport networks to characterise the network roles of
107	plant and pollinator species, and investigate whether these are linked to their functional roles.
108	Specifically, we test whether the position of a species in the network relates to its contribution to
109	community functional diversity (i.e. the uniqueness of its traits). We hypothesise that a species'
110	functional originality will be positively related to its degree of resource specialisation, because
111	specialists should have evolved original traits to better access a single resource, whereas generalists
112	should have average, widespread trait values that do not limit their ability to interact with other
113	species, even if generalist species could also be rare.
114	
115	
116	METHODS.
117	
118	Site description and experimental design
119	
120	Six replicates of each of four land-use types (in decreasing order of intensity): rotational cropping,
121	dairy farms, blackcurrant orchards and native gardens were sampled in the Canterbury plains region,
122	a highly modified agricultural landscape in the South Island of New Zealand (see Rader et al. 2014 for
123	site details). We chose this dataset because the gradient of land-use intensity has been shown to
124	generate a decline in community functional diversity (Rader et al. 2014), thereby ensuring that we
125	had a broad range in this predictor variable to test whether it was related to the pollen transport
126	network structure.
127	
128	Sampling methods

130	At each of the 24 sites, insect pollinators were trapped for five days per month from November 2008
131	to 2009 using flight-intercept and pan traps. The two trapping methods were used to maximize the
132	diversity and sample size of insects captured. At the end of each day, insects were removed and
133	trapping materials replenished (see Rader et al. 2014 for further details of trapping methods).
134	Insects were sorted to species (Table S1) using existing collections, identification keys (Donovan
135	2007; Landcare Research, 2013) and assistance from expert taxonomists. The pollen found on the
136	underside of pollinator species was sampled by pressing insects onto a cube of gelatine-fuchsin (c. 3
137	mm \times 3 mm \times 3 mm) and slide mounted. Pollen grains were then counted manually under a
138	microscope using a pollen library of plant specimens collected at each site at the time of sampling
139	(as in Rader et al. 2011, see Appendix 1 in S.I. for more details on pollen identification and
140	quantification, and Table S2 for a list of plant species). Data were pooled across trap types (pan and
141	flight-intercept traps) and time (i.e. monthly trap collections for 1 year) to achieve the best
142	resolution possible when identifying interactions among species. Of the initial 24 sites, 3
143	communities were excluded due to their small sample sizes. Voucher specimens are housed at the
144	New Zealand Institute for Plant and Food Research in Lincoln, New Zealand.
145	
146	Trait measurement
147	
148	Pollinator and plant traits, as well as some species-level behavioural responses to changing
149	environments comprising many traits, were compiled using existing published and unpublished
150	datasets from the Canterbury region (Tables S3, S4, S.I.). In some cases, the traits are fixed attributes
151	of a species, whereas others are continuous and vary among individuals within species. In the latter
152	case, we used mean values from ten representative specimens (Table S3) (Rader et al. 2014),
153	because our aim was to relate species traits with their roles in the interaction network, the nodes of
154	which represent species, rather than individuals.

156 We recorded two traits pertaining to pollinator body size (length and width), which is known both to 157 constrain the breadth of species' trophic niches and correlate negatively with reproductive rate 158 (Stang et al. 2006) and also to moderate pollination efficiency (e.g., larger insects are hypothesised 159 to have a higher pollen carrying capacity than smaller ones, Larsen et al. 2005; Hoehn et al. 2008). 160 Likewise, the time spent on the inflorescence (in seconds) is a trait that could simultaneously 161 influence pollination efficiency (Hoehn et al. 2008) and be an expression of a response to changes in 162 resource quality (according to optimal foraging theory, Pyke 1978). We also estimated phenology 163 using time of daily abundance peak as well as month of seasonal abundance peak for each insect 164 species during the sampling season (i.e. daily and seasonal activity), as this will determine the 165 amplitude of the match with the plants that flower at a given period, and phenology may respond to 166 environmental changes such as climate (Bartomeus et al. 2011). Foraging behaviour can underpin 167 pollination success, hence we recorded the diet preferences of adults (proportions of their diet 168 made up of nectar versus pollen based on field observations; Rader et al. 2014) and the type of 169 carrying structure used for pollen transport (corbicula, scopa or none). Moreover, diet preferences 170 of larvae (whether their diet included nectar, plant matter, carrion, dung, parasitism of other insects, 171 and/or predation of other insects) and nesting behaviour (social vs. solitary) are traits that have 172 been shown to influence species responses to environmental changes such as land use or habitat 173 fragmentation (Williams et al. 2010). Because we had no a priori reason to weight some traits more 174 than others, we considered each trait to be of equal importance in its ability to influence a species' 175 functional niche. However because body length and width are non-independent features relating to 176 body size, we grouped them together by assigning them a weight of 1/2 throughout the analyses so 177 that the 'body size' trait had an equal weight to all the other measured traits. For the same reason, 178 the use of each kind of larval food resource was given a fractional weighting so that all components 179 of larval diet summed to a single trait. See Table S3 in Appendix 1 of the S.I. for a summary of 180 pollinator traits.

182	For the plant community, we recorded morphological traits that pertained to plant type (grass, herb,
183	shrub or tree), inflorescence morphology (number of flowers per inflorescence, flower symmetry
184	e.g., actinomorphic or zygomorphic; branching organisation type e.g., spike, catkin, umbel,
185	capitulum or other), pollen and nectar access, and physiological characteristics (life span, sex,
186	fragrance, amount of nectar). We also kept a phenological record when flowering of each plant
187	occurred throughout the sampling season (presence/absence of flowers spanning spring, summer,
188	fall and winter), and as for pollinator body size, we gave each season a weight of 0.25 in order to
189	obtain one final 'season' trait (see Table S4, Appendix 1 of the S.I. for a record of plant traits).
190	
191	The selected traits reflect the capacity for plants to adapt to changing environments as well as their
192	availability and attractiveness for pollinators ("pollination syndrome" traits, Fenster et al. 2004).
193	
194	Species functional originality and uniqueness
104	species junctional originality and anqueriess
194	Species junctional originality and aniqueness
	For a given community, functional diversity is defined by the matrix comprising the trait attributes of
195	
195 196	For a given community, functional diversity is defined by the matrix comprising the trait attributes of
195 196 197	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space,
195 196 197 198	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space, where each trait corresponds to an axis (Petchey & Gaston 2006; Laliberté & Legendre 2010). The
195 196 197 198 199	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space, where each trait corresponds to an axis (Petchey & Gaston 2006; Laliberté & Legendre 2010). The functional niche (or phenotypic range) of the community depends both on the number of traits (i.e.
195 196 197 198 199 200	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space, where each trait corresponds to an axis (Petchey & Gaston 2006; Laliberté & Legendre 2010). The functional niche (or phenotypic range) of the community depends both on the number of traits (i.e. axes, which were constant in each of our networks) and on the range of trait values. The boundaries
195 196 197 198 199 200 201	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space, where each trait corresponds to an axis (Petchey & Gaston 2006; Laliberté & Legendre 2010). The functional niche (or phenotypic range) of the community depends both on the number of traits (i.e. axes, which were constant in each of our networks) and on the range of trait values. The boundaries of this functional niche are delimited by species with the most extreme trait values, and the centroid
195 196 197 198 199 200 201 201 202	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space, where each trait corresponds to an axis (Petchey & Gaston 2006; Laliberté & Legendre 2010). The functional niche (or phenotypic range) of the community depends both on the number of traits (i.e. axes, which were constant in each of our networks) and on the range of trait values. The boundaries of this functional niche are delimited by species with the most extreme trait values, and the centroid corresponds to the 'average' trait values of all species of the community. We calculated two
195 196 197 198 199 200 201 202 203	For a given community, functional diversity is defined by the matrix comprising the trait attributes of every species. These are used to calculate the coordinates of the species in a multivariate space, where each trait corresponds to an axis (Petchey & Gaston 2006; Laliberté & Legendre 2010). The functional niche (or phenotypic range) of the community depends both on the number of traits (i.e. axes, which were constant in each of our networks) and on the range of trait values. The boundaries of this functional niche are delimited by species with the most extreme trait values, and the centroid corresponds to the 'average' trait values of all species of the community. We calculated two different metrics: functional originality and uniqueness. Functional originality is the distance of a

207 values are located closer together in trait space, and therefore the distance of a species to its 208 nearest neighbour is a good measure of its functional uniqueness (conceptually, it is the opposite of 209 functional redundancy, Walker 1991; Buisson et al. 2013). These two measures could at first glance 210 seem related, but in fact, two species can simultaneously be functionally original by having a 211 combination of traits differing from that of the community average, and still not be unique if they 212 are similar to each other in their trait combinations. This distinction would be particularly apparent if 213 species formed clusters in trait space, but these clusters were all distant from the centroid. Figure 1 214 is a 2-dimensional representation of this multivariate trait space, where species are represented by 215 points.

216

217 Species' relative abundances can be used to weight the average trait values when calculating the 218 functional trait space, thereby shifting the position of the centroid towards the most abundant 219 species (the red cross in Figure 1 is closer to larger points corresponding to abundant species). In this 220 quantitative measure of functional originality (Laliberté & Legendre 2010), rarer species displaying 221 different trait attributes contribute more to extending community diversity than do abundant 222 species, because that combination of traits itself is rarer in the community than if it had belonged to 223 an abundant species. In contrast, when only qualitative (species presence/absence) data are used, 224 the centroid is the unweighted average of community trait values, which sets each species on an 225 even ground and prevents abundant species with trait values that deviate from those of other 226 species from appearing less 'original' simply because they comprise a large proportion of the 227 individuals in the community. The coordinates of each species however remain identical whether the 228 community average is weighted or not; hence the measure of functional uniqueness is independent 229 of species' relative abundances and only changes with species presences or absences from a 230 community.

231

232 In our study, we used the weighted measure of originality for the pollinator community, for which 233 we had independent measures of abundances based on the number of insects caught in the traps. 234 This corresponds to a trait-centred approach that quantifies the occurrence of traits in a community 235 and fully endorses the underlying aim of functional diversity, which is to focus on traits rather than 236 species to quantify biodiversity and ecological processes (Mouillot et al. 2005; Petchey & Gaston 237 2006). We did not have independent measures of plant abundances (see below), and we therefore 238 used the unweighted measure of plant functional originality, which in comparison, corresponds to a 239 species-centred approach based on the number of species characterised by that trait. As species 240 form the nodes of our networks, they remain an important functional unit of our framework. We 241 provide the unweighted version of the analysis for the pollinator community for comparison in Appendix 2, S.I. 242

243

244 We used the functional originality and uniqueness of each species as measures of their functional 245 role. With the traits measured for pollinator and plant species across the 21 out of the initial 24 246 sites, we calculated sets of coordinates for each species and the centroid for each site using a 247 Principal Coordinates Analysis (PCoA), as used in other studies of functional diversity (e.g. Buisson et 248 al. 2013; Mouillot et al. 2013b; Gagic et al. 2015). Even though species' coordinates were fixed 249 across sites, changes in species composition, as well as in pollinator relative abundances, shifted the 250 position of the centroid in each plant and pollinator community. This yielded different site-specific 251 measures of species originality and uniqueness, thereby defining their functional role within each 252 site. This approach allowed us to provide a measure of relative functional diversity that was scaled 253 and comparable across sites, because we essentially defined a maximal functional diversity (by fixing 254 the multivariate space of all species) against which to compare each local community's functional 255 properties. In this sense, a species can only be 'original' or 'unique' when compared with others in its 256 community, such that originality is not a fixed trait of a species but rather depends on its community 257 context. Therefore, functional originality is only conserved across different communities if a species

has a combination of traits so different from all the other species that it is seldom average, or if the
composition of other species is conserved. The primary aim of this approach was thus to obtain a
measure of a given species' contribution to functional diversity, relative to its community context,
rather than determining which particular traits were most important in driving the functional roles
of species in the networks (but see Appendix 3 of the S.I. for an evaluation of the most important
traits in our communities).

Each trait was standardised (mean = 0, variance = 1) for the estimation of functional originality, and non-numerical traits were standardised according to Gower's (1971) standardisation by range prior to their conversion into dissimilarity matrices for the computation of the PCoA. These calculations were realised using version 1.0-12 of the dbFD function from the FD package (Laliberté & Legendre 2010; Laliberté & Shipley 2011); R version 3.2.2 (2015-08-14); analysis code can be found in Appendix 4, and is accessible online at: https://github.com/CamilleCoux/Ntw_FD_roles).

270

271 Interaction networks

272 Two methods are commonly used to generate plant-pollinator interaction networks; (i) pollinator 273 visitation surveys conducted on focal plants and (ii) pollen transport networks. Visitation surveys 274 generally comprise high proportions of pollinator species linked to a single plant species, thus this 275 approach may overestimate ecological specialization (Bosch et al. 2009). In contrast, pollen 276 transport networks often reveal additional plant-pollinator links (that would otherwise have gone 277 undetected) due to the physical presence of pollen on a pollinator. Yet, this approach may 278 underestimate ecological specialization and be influenced by pollinator grooming behaviour and/or 279 body size (Harder 1990). Here, we used the records we obtained of pollinators and the pollen they 280 carried to construct weighted pollination networks where we quantified the interaction links by 281 recording the number of pollinator individuals of species *i* carrying pollen of a given plant species *j*. 282 From a pollinator's perspective, this measures the frequency with which a plant species is used; from

a plant's perspective, it is related to pollinator visitation frequency, but does not make anyassumptions about the value of carrying more pollen.

285

286 Network structure description

287

288 To evaluate the role occupied by each species in each pollination network, we calculated a set of 289 indices that described i) each species' potential range of interaction partners, and ii) any observed 290 relative preference for certain species within its range of potential partners. i) normalised degree 291 (ND) is the sum of interactions per species (normalised within networks to control for variation in 292 network size), and is a classic descriptor of a node's connectedness, which also correlates with many 293 other aspects of network topology (Gómez & Perfectti 2012). ii) Specificity (HS), as measured by 294 Shannon's entropy divided by the number of partners, measures the specialisation of species i on j, 295 such that the evenness of a species' interactions are quantified within its range of partners. The 296 specificity of species *i* ranges between 1 for a perfect specialist and 0 for a perfect generalist. 297 Normalised degree is a binary metric; specificity was calculated based on quantitative (i.e. weighted) 298 interactions (calculation for ND : 'specieslevel' function, bipartite package 2.04; for HS: 'getspe' 299 function, package ESM 2.0.3-02, Poisot 2011). Combined, these indices describe each species' 300 connectedness and their relative use of each of their interaction partners. Thus, they describe many 301 crucial aspects of a species' role in a network, and also correlate strongly with other species-level 302 network indices, which are mostly variations on the number of interaction partners (resource range, 303 species strength, effective partners, nestedness rank) or generalism/specialism (node specialisation, 304 proportional generality, proportional similarity; Dormann 2011). 305

306 Linking species traits with network roles and relative abundances

308 For the pollinator community, we used linear mixed effects models (LMMs) to test whether the 309 network role of a pollinator species, as defined by its normalised degree (ND) or specificity (HS), was 310 predicted by its functional role, defined as its functional originality (i.e., its distance from the 311 centroid in multidimensional niche space) and uniqueness (its distance to its nearest neighbour). For 312 each model with either ND or HS as response variable, we used weighted originality or uniqueness as 313 fixed effects in separate models (see Appendix 5 of S.I. for correlation structures between predictor 314 variables), which yielded a total of 4 different models. A corresponding set of models was generated 315 for the plant community, except that we used the unweighted measure of originality as plant 316 abundances were not measured. We do not explicitly compare pollinators with plants, so this difference could not confound our results for each level. 317

318

319 In addition to the measures of a species' functional role, we also included pollinator abundance in 320 both pollinator and plant models as fixed covariates to predict network role. Not only is pollinator 321 abundance a measure of sample size, but the abundance of a species is also an important part of its 322 ecology and can determine its functional importance in the community, so it could be one of the 323 mechanisms explaining the correlations between network and functional roles. One of the pollinator 324 species, Lasioglossum sordidum, was found to have an unusually high abundance in the first site. 325 After calculating its leverage, we considered it as a statistical outlier (Crawley 2007). We thus set its 326 abundance to 0 and removed it from the analysis such that other species of that community 327 remained unchanged by this removal (see Appendix 2, S.I. for more details, and results of the 328 analysis comprising the outlier). This did not qualitatively affect the results pertaining to originality 329 or uniqueness.

330

Although ND and HS metrics are both normalised to control for network size, we included the
 product of the number of pollinator species by the number of plant species as a measure of network
 size in our models to control for these potential artefacts. We tested for two-way interactions both

334	between functional role and pollinator abundance (in the pollinator models), and functional role and
335	network size (in all models) to control for any interference of these effects with either species
336	originality or uniqueness. Finally, to control for the non-independence between species from each
337	network, we included site as a random effect in each model. We also tested a final set of models in
338	which unweighted pollinator originality is used (Appendix 2, S.I.).
339	
340	Best-fitting models were obtained after testing every possible subset of these models (with main
341	effects and interactions removed, adhering to the principle of marginality) by minimising Akaike's
342	Information Criterion (AIC). In cases where several competing models had a difference of less than 2
343	in AIC scores, which suggested their fit were not statistically different, we applied model averaging
344	techniques ('model.avg' function MuMIn package 1.15.1, (Barton 2015). The results presented are
345	those of conditional averages.
346	All models were computed using the 'Ime' function (nlme package 3.1-122, Pinheiro et al. 2014).
347	
347 348	
	RESULTS
348	RESULTS
348 349	RESULTS We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links,
348 349 350	
348 349 350 351	We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links,
348 349 350 351 352	We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links, which represents connectance values from 0.22 to 0.87. The mean normalised degree for the
348 349 350 351 352 353	We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links, which represents connectance values from 0.22 to 0.87. The mean normalised degree for the pollinator community across all networks was equal to 0.42; that of plants 0.45. For specificity,
348 349 350 351 352 353 354	We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links, which represents connectance values from 0.22 to 0.87. The mean normalised degree for the pollinator community across all networks was equal to 0.42; that of plants 0.45. For specificity, pollinators showed an average of 0.58 and a higher frequency of highly specific species focussing on
348 349 350 351 352 353 354 355	We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links, which represents connectance values from 0.22 to 0.87. The mean normalised degree for the pollinator community across all networks was equal to 0.42; that of plants 0.45. For specificity, pollinators showed an average of 0.58 and a higher frequency of highly specific species focussing on
 348 349 350 351 352 353 354 355 356 	We obtained pollination networks ranging from 4 to 23 species, comprising 3 to 99 realised links, which represents connectance values from 0.22 to 0.87. The mean normalised degree for the pollinator community across all networks was equal to 0.42; that of plants 0.45. For specificity, pollinators showed an average of 0.58 and a higher frequency of highly specific species focussing on one plant. This effect was enhanced among the plants, which had an average specificity of 0.72.

the community average tended to have fewer interactions (Table 1a, Figure 1). However, a positive
interaction effect between abundance and weighted originality revealed that this effect was
compensated for in the few most abundant pollinator species with original traits (Figure 2, Table 1a).
In addition, we note here that this interaction effect was stronger than the weak, negative main
effect of abundance, such that abundant pollinators generally had more interactions than rare ones,
as would be expected based on sampling effort.

366

367 The relationship between pollinator specificity and weighted originality was also averaged across the 368 2 best-fitting models, and indicated a strong positive relationship. This suggested that pollinators 369 with unique traits that differed from the rest of the community focused preferentially on a limited 370 subset of their partners (Table 1b). As with normalised degree, there was also a significant 371 interaction effect between originality and abundance that moderated this relationship, as the most 372 abundant pollinators showed less specificity than those that had more average traits (Figure 3, Table 373 1b). However, as in the previous model, this interaction effect was stronger than the main effect of 374 abundance, and therefore abundant pollinators were overall less specific than rare pollinators. 375 376 When we examined functional uniqueness as a fixed effect, we found that the average of the 2 best-377 fitting models contained a significant positive relationship with normalised degree, indicating that

species with unique trait combinations had more interaction partners than species that were
functionally similar (Table 1c). Although abundant pollinators had more interaction partners (Table
1c), as would be expected from greater sampling effort, there was no significant interaction between
abundance and uniqueness.

382

Finally, the three averaged best-fitting models considering the effects of pollinator uniqueness,
abundance and network size on pollinator specificity revealed a negative correlation between

uniqueness and specificity, indicating that pollinators with unique trait combinations interacted
more evenly with their plant partners (Table 1d, Figure 4).

387

388	Contrasting with the pollinator community, we did not find any significant relationships between
389	plant normalised degree and species' unweighted originality (P=0.608) or uniqueness (P=0.627). The
390	only significant effects concerned a negative correlation between normalised degree and network
391	size (coef. = -0.004, p=0.010), simply indicating that plants interacted on average with
392	proportionately fewer pollinators in larger networks. Furthermore, we did not find any significant
393	effect of originality (P=0.53) or uniqueness (P=0.472) on plant specificity. This suggests that neither
394	the number of interactions with pollinator partners, nor the evenness in a plant's interactions with
395	its pollinators was influenced by how different the traits of a plant species were compared to the
396	community average or to its most functionally similar plant species counterpart.
397	

398

399 DISCUSSION

400

401 We have found that the role of a pollinator in the interaction network was correlated with its 402 functional role, as defined by its functional originality and functional uniqueness compared with 403 other pollinator species present in the community. Our finding that species with trait profiles that 404 differed from the community average had fewer interaction partners and/or interacted most 405 frequently with only a subset of these (Table 1a, 1b) is congruent with our hypothesised trade-off 406 between having unique traits to avoid competition but needing to retain interaction partners. This 407 suggests that the functional specialisation of pollinators is reflected by the narrowing down of their 408 interactions to a subset of the plant community, possibly as a means to avoid competition between 409 pollinators for shared plant resources (Vamosi et al. 2014).

411 This benefit of reduced competition was most evident when we examined a pollinator's trait 412 difference from its functionally most similar counterpart in a given community (i.e. uniqueness). In 413 this case, the most functionally unique pollinators were those with the most interaction partners. 414 This suggests that competition for access to a shared resource is likely to be more intense between 415 two redundant species than between species that are functionally unique, and further satisfies the 416 idea that the number of interactions of a pollinator depends on its functional status in the 417 community. Thus, species' contributions to community functional diversity were correlated with a 418 combination of network metrics that captured both the range of interaction partners and the 419 quantitative preferential focus on particular partners.

420

421 Although functional roles were associated with certain network roles for pollinator species, this 422 relationship did not hold for plants. This absence suggests that original plant traits (particularly with 423 respect to floral structures and resource allocation to flowering) do not necessarily act as barriers to 424 interaction with pollinators, which may be partly due to the conservation of many categorical traits 425 (such as flower symmetry, inflorescence type) at the family level. Furthermore, this depicts a more 426 homogenous distribution of species in the trait space, where differences in plant originality and 427 uniqueness are less important than in the pollinator community, and are rather levelled out by the 428 use of presence/absence data for plant originality values.

429

In contrast, pollinator's relative abundances were associated with higher normalised degree and lower specificity, which is to be expected given that abundant species have a larger probability to randomly interact than rare species (Fort *et al.* 2015). Interestingly, there was a recurrent interaction effect between abundance and pollinator originality, whereby the relationships between the latter and normalised degree or specificity were reversed for abundant species. Therefore, the trade-off between originality and interaction partner diversity may not apply to species that are successful enough to be abundant, either because or in spite of their unique trait combinations. This was

frequently the case for certain pollinator species, such as *Apis mellifera* or *Lasioglossum sordidum*,
which appeared to have succeeded in being functionally original and retaining many interaction
partners in most of the communities in which they were recorded (Figure 5).

440

441 Most other species, however, were not as consistent in their network or functional roles across sites 442 (Figure 5; see also Figure S4, Appendix 6, S.I.). This context-dependency in the originality of any given 443 species suggests that the correlation between functional and network roles across sites are not 444 driven simply by the identity of a few key species with extreme traits that interact in a certain way. 445 Similarly, important variations in interaction turnover can also occur through time, and specialisation 446 can be highly variable (Brosi & Briggs 2013), which suggests the importance of context-dependency 447 in network roles. In an evolutionary sense, this suggests that it may be difficult for a species to 448 evolve traits that are novel across its entire spatial and temporal range of community contexts. 449 Furthermore, as our communities were sampled over an anthropogenic gradient (Rader et al. 2014), 450 it is likely that the importance of functions fulfilled by specific traits do not occupy the same rank in 451 different sites, which may be reflected here. Moreover, the spatial and temporal scales of differing 452 land uses would likely be sufficient to allow trait-based competitive exclusion of species, but not the 453 evolution of novel traits.

454

455 Our results provide an important step forward in merging the fields of interaction networks with the 456 functional diversity framework (Thompson et al. 2012; Poisot et al. 2013). Recently, Eklöf et al. 457 (2013) found that surprisingly few traits (< 10, similar to the number of traits used here) were 458 needed to predict interactions in different types of ecological networks. This linking of traits with 459 whole-network structure complements work linking network structure to ecosystem functioning 460 (e.g, Peralta et al. 2014) and the importance of functional trait diversity for ecosystem functioning 461 and resilience (Mouillot et al. 2013b). Our finding that there is a context-dependent relation 462 between network roles and trait originality of species opens up possibilities to predict the functional

463	responses of communities to realistic extinction sequences beyond simple trait-matching
464	mechanisms. For example, recent studies have linked the role of species in interaction networks to
465	their extinction risk, concluding that low interaction degree and rarity characterised species and
466	interactions most prone to extinction (Aizen et al. 2012). Mouillot et al. (2013) further found that
467	rare species displayed the least redundant functions. Combined with our findings, these results
468	suggest that the order in which species go extinct from networks may generate a more rapid decline
469	in functional diversity than would be expected if species went extinct at random, as has been
470	observed in highly-modified land uses (Rader et al. 2014). This merging of network and functional
471	diversity approaches highlights the trade-offs associated with niche differentiation within interacting
472	communities, and links species interactions with the response of ecosystem functioning to a
473	changing environment.
474	
475	
476	ACKNOWLEDGEMENTS
476 477	ACKNOWLEDGEMENTS We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the
477	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the
477 478	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous
477 478 479	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen
477 478 479 480	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen Thorpe, Bradley Howlett and Barry Donovan for insect and pollen identification, and the numerous
477 478 479 480 481	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen Thorpe, Bradley Howlett and Barry Donovan for insect and pollen identification, and the numerous land holders who allowed us to conduct this study on their land. This study was funded by a
477 478 479 480 481 482	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen Thorpe, Bradley Howlett and Barry Donovan for insect and pollen identification, and the numerous land holders who allowed us to conduct this study on their land. This study was funded by a Rutherford Discovery Fellowship to JMT. IB was funded by BeeFun project (PCIG14-GA-2013-
477 478 479 480 481 482 483	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen Thorpe, Bradley Howlett and Barry Donovan for insect and pollen identification, and the numerous land holders who allowed us to conduct this study on their land. This study was funded by a Rutherford Discovery Fellowship to JMT. IB was funded by BeeFun project (PCIG14-GA-2013-
477 478 479 480 481 482 483 484	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen Thorpe, Bradley Howlett and Barry Donovan for insect and pollen identification, and the numerous land holders who allowed us to conduct this study on their land. This study was funded by a Rutherford Discovery Fellowship to JMT. IB was funded by BeeFun project (PCIG14-GA-2013-
477 478 479 480 481 482 483 484 485	We thank Etienne Laliberté for advice on the FD framework, Tim Poisot and members of the Tylianakis and Stouffer lab groups for useful comments and discussions, as well as three anonymous reviewers and the handling editor for their constructive comments. We thank Neville Moar, Stephen Thorpe, Bradley Howlett and Barry Donovan for insect and pollen identification, and the numerous land holders who allowed us to conduct this study on their land. This study was funded by a Rutherford Discovery Fellowship to JMT. IB was funded by BeeFun project (PCIG14-GA-2013-

489 1.Aizen, M. a, Sabatino, M. & Tylianakis, J.M. (2012). Specialization and rarity predict nonrandom

490	loss of interactions from mutualist networks. Science, 335, 1486–9.
491 492 493 494	2.Bartomeus, I., Ascher, J.S., Wagner, D., Danforth, B.N., Colla, S., Kornbluth, S., <i>et al.</i> (2011). Climate-associated phenological advances in bee pollinators and bee-pollinated plants. <i>Proc. Natl.</i> <i>Acad. Sci.</i> , 108, 20645–20649.
495 496	3.Barton, K. (2015). MuMIn: Multi-Model Inference. <i>R Packag. version 1.15.1</i> .
497 498 499	4.Bosch, J., Gonzalez, A.M.M., Rodrigo, A. & Navarro, D. (2009). Plant – pollinator networks : adding the pollinator's perspective, 12, 409–419.
500 501 502	5.Brosi, B.J. & Briggs, H.M. (2013). Single pollinator species losses reduce floral fidelity and plant reproductive function. <i>Proc. Natl. Acad. Sci.</i> , 110, 13044–13048.
503 504 505	6.Buisson, L., Grenouillet, G., Villéger, S., Canal, J. & Laffaille, P. (2013). Toward a loss of functional diversity in stream fish assemblages under climate change. <i>Glob. Chang. Biol.</i> , 19, 387–400.
506 507 508	7.Chesson, P. (2000). Mechanisms of maintenance of species diversity. <i>Annu. Rev. Ecol. Syst.</i> , 31, 343–66.
509 510	8.Crawley, M.J. (2007). The R book. John Wiley & Sons Ltd., Chichester, UK.
511 512 513 514	9.Dehling, D.M., Jordano, P., Schaefer, H.M., Boehning-Gaese, K., Schleuning, M. & Hm, S. (2016). Morphology predicts species ' functional roles and their degree of specialization in plant – frugivore interactions. <i>Proc. R. Soc. B Biol. Sci.</i> , 283, 1–7.
515 516 517	10.Donovan, B.J. (2007). Apoidea (Insecta: Hymenoptera). <i>Fauna New Zealand. Landcare Res. Ltd.,</i> Christchurch, New Zeal.
518 519 520	11.Dormann, C.F. (2011). How to be a specialist ? Quantifying specialisation in pollination networks. <i>Netw. Biol.</i> , 1, 1–20.
521 522 523	12.Eklöf, A., Jacob, U., Kopp, J., Bosch, J., Castro-Urgal, R., Chacoff, N.P., <i>et al</i> . (2013). The dimensionality of ecological networks. <i>Ecol. Lett.</i> , 16, 577–83.
524 525 526	13.Fenster, C.B., Armbruster, W.S., Wilson, P., Dudash, M.R. & Thomson, J.D. (2004). Pollination Syndromes and Floral Specialization. <i>Annu. Rev. Ecol. Evol. Syst.</i> , 35, 375–403.
527 528 529	14.Fontaine, C., Thébault, E. & Dajoz, I. (2009). Are insect pollinators more generalist than insect herbivores? <i>Proc. Biol. Sci.</i> , 276, 3027–3033.
530	

531 532	15.Fort, H., Vazquez, D.P. & Lan, B.L. (2015). Abundance and generalization in mutualistic networks : solving the chicken-and-egg dilemma. <i>Ecol. Lett.</i> , 48.
533 534 535 536	16.Gagic, V., Bartomeus, I., Jonsson, T., Taylor, A., Winqvist, C., Fischer, C., <i>et al.</i> (2015). Functional identity and diversity of animals predict ecosystem functioning better than species-based indices. <i>Proc. Biol. Sci.</i> , 282.
537 538 539	17.Gao, J., Barzel, B. & Barabási, AL. (2016). Universal resilience patterns in complex networks. <i>Nature</i> , 530, 307–312.
540 541 542	18.Gómez, J.M. & Perfectti, F. (2012). Fitness consequences of centrality in mutualistic individual- based networks. <i>Proc. Biol. Sci.</i> , 279, 1754–60.
543 544 545	19.Gower, J.C. (1971). A General Coefficient of Similarity and Some of Its Properties. <i>Biometrics</i> , 27, 857.
546 547 548	20.Grime, J.P. (2001). <i>Plant strategies, vegetation processes, and ecosystem properties.</i> ed. 2. New York.
549 550 551	21.Harder, L. (1990). International Association for Ecology Behavioral Responses by Bumble Bees to Variation in Pollen Availability. <i>Oecologia</i> , 85, 41–47.
552 553 554	22.Hoehn, P., Tscharntke, T., Tylianakis, J.M. & Steffan-Dewenter, I. (2008). Functional group diversity of bee pollinators increases crop yield. <i>Proc. Biol. Sci.</i> , 275, 2283–91.
555 556 557	23.Hooper, D, Chapin, F.S.I., Ewel, J, Hector, A., Inchausti, P., Lavorel, S., <i>et al.</i> (2005). Effects of biodiversity on ecosystem functioning: a consensus of current knowledge. <i>Ecol. Monogr.</i>
558 559 560	24.Laliberté, E. & Legendre, P. (2010). A distance-based framework for measuring functional diversity from multiple traits. <i>Ecology</i> , 91, 299–305.
561 562 563	25.Laliberté, E. & Shipley, B. (2011). FD: measuring functional diversity from multiple traits, and other tools for functional ecology. <i>R Packag. version 1.0-11.</i>
564 565 566 567	26.Laliberté, E., Wells, J. a, Declerck, F., Metcalfe, D.J., Catterall, C.P., Queiroz, C., <i>et al.</i> (2010). Land- use intensification reduces functional redundancy and response diversity in plant communities. <i>Ecol.</i> <i>Lett.</i> , 13, 76–86.
568 569 570	27.Larsen, T.H., Williams, N.M. & Kremen, C. (2005). Extinction order and altered community structure rapidly disrupt ecosystem functioning. <i>Ecol. Lett.</i> , 8, 538–547.
571 572	28.Lavorel, S. & Garnier, E. (2002). Predicting changes in community composition and ecosystem

573	functioning from plant traits : revisiting the Holy Grail. <i>Funct. Ecol.</i> , 16, 545–556.
574 575 576	29.Montoya, D., Yallop, M.L. & Memmott, J. (2015). Functional group diversity increases with modularity in complex food webs. <i>Nat. Commun.</i> , 6, 7379.
577 578 579	30.Mouillot, D., Bellwood, D.R., Baraloto, C., Chave, J., Galzin, R., Harmelin-Vivien, M., <i>et al.</i> (2013a). Rare Species Support Vulnerable Functions in High-Diversity Ecosystems. <i>PLoS Biol.</i> , 11.
580 581 582	31.Mouillot, D., Graham, N. a J., Villéger, S., Mason, N.W.H. & Bellwood, D.R. (2013b). A functional approach reveals community responses to disturbances. <i>Trends Ecol. Evol.</i> , 28, 167–77.
583 584 585	32.Mouillot, D., Mason, W.H.N., Dumay, O. & Wilson, J.B. (2005). Functional regularity: a neglected aspect of functional diversity. <i>Oecologia</i> , 142, 353–359.
586 587 588 589	33.Peralta, G., Frost, C.M., Rand, T.A. & Didham, R.K. (2014). Complementarity and redundancy of interactions enhance attack rates and spatial stability in host – parasitoid food webs. <i>Ecology</i> , 95, 1888–1896.
590 591 592	34.Petchey, O.L. & Gaston, K.J. (2006). Functional diversity: back to basics and looking forward. <i>Ecol. Lett.</i> , 9, 741–58.
593 594 595 596	35.Pimm, S.L., Jenkins, C.N., Abell, R., Brooks, T.M., Gittleman, J.L., Joppa, L.N., <i>et al.</i> (2014). The biodiversity of species and their rates of extinction, distribution, and protection. <i>Science</i> , 344, 1246752.
597 598 599	36.Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. & R Core Team (2014). (2014). nlme: Linear and Nonlinear Mixed Effects Models. <i>R Packag. version 3.1-117</i> .
600 601	37.Poisot, T. (2011). ESM: Ecological Specificity Measures. <i>R Packag. version 2.0.3-02/r47.</i>
602 603 604	38.Poisot, T., Canard, E., Mouillot, D., Mouquet, N., Gravel, D. & Jordan, F. (2012). The dissimilarity of species interaction networks. <i>Ecol. Lett.</i> , 15, 1353–61.
605 606 607	39.Poisot, T., Mouquet, N. & Gravel, D. (2013). Trophic complementarity drives the biodiversity- ecosystem functioning relationship in food webs. <i>Ecol. Lett.</i> , 16, 853–61.
608 609 610	40.Pyke, G.H. (1978). Optimal foraging in bumblebees and coevolution with their plants. <i>Oecologia</i> , 36, 281–293.
611 612 613 614	41.Rader, R., Bartomeus, I., Tylianakis, J.M. & Laliberté, E. (2014). The winners and losers of land use intensification: pollinator community disassembly is non-random and alters functional diversity. <i>Divers. Distrib.</i> , 20, 908–917.

615 616 617	42.Rader, R., Edwards, W., Westcott, D. a., Cunningham, S. a. & Howlett, B.G. (2011). Pollen transport differs among bees and flies in a human-modified landscape. <i>Divers. Distrib.</i> , 17, 519–529.
618 619 620	43.Reiss, J., Bridle, J.R., Montoya, J.M. & Woodward, G. (2009). Emerging horizons in biodiversity and ecosystem functioning research. <i>Trends Ecol. Evol.</i> , 24, 505–14.
621 622 623	44.Stang, M., Klinkhamer, P.G.L. & Van Der Meijden, E. (2006). Size constraints and flower abundance determine the number of interactions in a plant-flower visitor web. <i>Oikos</i> , 112, 111–121.
624 625 626	45.Thompson, R. & Starzomski, B.M. (2007). What does biodiversity actually do? A review for managers and policy makers. <i>Biodivers. Conserv.</i> , 16, 1359–1378.
627 628 629	46.Thompson, R.M., Brose, U., Dunne, J. a, Hall, R.O., Hladyz, S., Kitching, R.L., <i>et al</i> . (2012). Food webs: reconciling the structure and function of biodiversity. <i>Trends Ecol. Evol.</i> , 27, 689–97.
630 631 632	47.Tilman, D., Wedin, D. & Knops, J. (1996). Productivity and sustainability influenced by biodiversity in grassland ecosystems. <i>Nature</i> .
633 634 635	48.Vamosi, J.C., Moray, C.M., Garcha, N.K., Chamberlain, S. a. & Mooers, A.Ø. (2014). Pollinators visit related plant species across 29 plant-pollinator networks. <i>Ecol. Evol.</i> , n/a–n/a.
636 637	49.Walker, B.H. (1991). Biodiversity and ecological redundancy. <i>Conserv. Biol.</i> , 6, 18–23.
638 639 640 641	50.Williams, N.M., Crone, E.E., Roulston, T.H., Minckley, R.L., Packer, L. & Potts, S.G. (2010). Ecological and life-history traits predict bee species responses to environmental disturbances. <i>Biol.</i> <i>Conserv.</i> , 143, 2280–2291.
642	
643	
644	

645 TABLE AND FIGURE LEGENDS

646

- 647 **Table 1:** Linear Mixed-effects Model partial coefficient estimates from the averaged best-fitting
- 648 models predicting either pollinator normalised degree (ND) or specificity (HS) and containing either
- 649 weighted pollinator originality (distance to the weighted community centroid) or uniqueness
- 650 (distance to the nearest neighbour). Non-significant results are shown only if they were retained in
- 651 the model; significant results are shown in bold.

a: Weighted pollinator originality predicting ND

Estimate	Std. Error	Adjusted SE	z value	Pr(> z)
0.8149824	0.1000847	0.1018370	8.003	< 2e-16 ***
-0.0009092	0.0004875	0.0004968	1.830	0.06723 .
-0.0038279	0.0026488	0.0027578	1.388	0.16512
-0.4450986	0.1342180	0.1364670	3.262	0.00111 **
0.0029684	0.0009967	0.0010156	2.923	0.00347 **
0.0046083	0.0038590	0.0039334	1.172	0.24136
	0.8149824 -0.0009092 -0.0038279 -0.4450986 0.0029684	0.8149824 0.1000847 -0.0009092 0.0004875 -0.0038279 0.0026488 -0.4450986 0.1342180 0.0029684 0.0009967	0.8149824 0.1000847 0.1018370 -0.0009092 0.0004875 0.0004968 -0.0038279 0.0026488 0.0027578 -0.4450986 0.1342180 0.1364670 0.0029684 0.0009967 0.0010156	0.8149824 0.1000847 0.1018370 8.003 -0.0009092 0.0004875 0.0004968 1.830 -0.0038279 0.0026488 0.0027578 1.388 -0.4450986 0.1342180 0.1364670 3.262 0.0029684 0.0009967 0.0010156 2.923

b: Weighted pollinator originality predicting HS

(conditional average)	Estimate	Std. Error	Adjusted SE	z value	Pr(> z)
(Intercept)	0.3621938	0.1232768	0.1252185	2.892	0.00382 **
pol.abun	0.0004899	0.0008335	0.0008410	0.582	0.56027
w.pol.orig	0.3607632	0.1617809	0.1641896	2.197	0.02800 *
pol.abun : w.pol.orig	-0.0028602	0.0013302	0.0013555	2.110	0.03485 *

c: Pollinator uniqueness predicting ND

(conditional average)	Estimate	Std. Error	Adjusted SE	z value	Pr(> z)
(Intercept)	0.0365432	0.1893075	0.1918268	0.191	0.8489
pol.abun	0.0004353	0.0002028	0.0002064	2.109	0.0349 *
pol.uniq ³	0.493841	0.1953927	0.1983509	2.490	0.0128 *
size	-0.0014741	0.0008303	0.0008866	1.663	0.0964 .

d: Pollinator uniqueness predicting HS

(conditional average)	Estimate	Std. Error	Adjusted SE	z value	Pr(> z)
(Intercept)	1.0677128	0.2209953	0.2246114	4.754	2e-06 ***
pol.abun	-0.0002991	0.0010091	0.0010245	0.292	0.7703
pol.uniq	-0.5274807	0.2458298	0.2500764	2.109	0.0349 *
size	-0.0012802	0.0013282	0.0014184	0.903	0.3668
pol.abun:pol.uniq	-0.0013629	0.0022979	0.0023415	0.582	0.5605

652

1: pollinator abundance; 2: pollinator originality; 3: pollinator uniqueness

653

654

Figure 1: Representation of pollinator species from one site, conserving only the two first axes of
the PCoA used to calculate functional originality and uniqueness. Darker colours represent
pollinators of higher normalised degree. The size of each point corresponds to the square root of
pollinator abundances. When these abundances are accounted for, the location of the centroid
shifts towards the more abundant species (red cross); when only presence-absence of pollinators are
used, the centroid corresponds to the unweighted mean of species' traits, and occupies a central

position (black cross). As shown in Table 1a, the distances to the weighted centroid (i.e. pollinator
weighted originality) are shorter for species with higher normalised degree, and their nearest
neighbours (i.e. pollinator uniqueness) are further away than for species of lower normalised
degree. We show in the S.I. (Appendix 2) that pollinator originality in the unweighted centroid is not
significantly different for pollinators of higher or lower normalised degree.

666

Figure 2: Partial residual plots from the pollinator model representing the effect of pollinator
functional originality on its number of interactions (normalised degree, ND) for fixed values of
pollinator abundances(for presentation, whereas in analyses abundance was treated as a continuous
variate). In each panel, points correspond to partial residuals versus raw values of originality;
pollinator abundance is fixed to the 10th, 50th and 90th quantiles (1, 21 and 202 respectively), while
network size is kept constant at the median (45) to calculate the fitted values (lines). Residuals were
taken from a model that included site as a random effect, to show relationships within sites.

674

Figure 3: Partial residual plots from the pollinator model representing the effect of pollinator
functional originality on specificity (HS) for fixed values of pollinator abundances. In each panel,
points correspond to partial residuals versus raw values of originality; pollinator abundance is fixed
to the same values as in Figure 1 to calculate the fitted values (lines). No other variables were
included in the best-fitting models, except for site, which remained as a random effect.

680

Figure 4: Partial residual plots from the pollinator model representing the effect of pollinator
uniqueness (distance to the nearest neighbour) on its number of interactions (normalised degree,
ND). Points correspond to raw values of pollinator uniqueness versus their partial residuals. The line
represents the fitted values of the model accounting for the random effect of site.

685

- 687 **Figure 5:** Variation in originality (left) and normalised degree (right) across sites according to
- 688 pollinator identity. Raw values are shown to indicate the frequency of each species occurrences
- 689 across sites. Species are ordered according to their increasing mean originality in both figures.