



EDITOR'S CHOICE: REVIEW: Trait matching of flower visitors and crops predicts fruit set better than trait diversity

Article

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Title: Trait matching of flower visitors and crops predicts fruit set better than
2 trait diversity

4 **Running title:** *Trait matching and crop pollination*

6 Lucas A. Garibaldi^{1,*}, Ignasi Bartomeus², Riccardo Bommarco³, Alexandra M. Klein⁴, Saul A.
Cunningham⁵, Marcelo A. Aizen⁶, Virginie Boreux⁴, Michael P. D. Garratt⁷, Luísa G.
8 Carvalheiro^{8,9}, Claire Kremen¹⁰, Carolina L. Morales⁶, Christof Schüepp^{11,12}, Natacha P. Chacoff¹³,
Breno M. Freitas¹⁴, Vesna Gagic³, Andrea Holzschuh^{15,16}, Björn K. Klatt^{16,17}, Kristin M.
10 Krewenka^{16,18}, Smitha Krishnan¹⁹, Margaret M. Mayfield²⁰, Iris Motzke^{4,16}, Mark Otieno²¹, Jessica
Petersen²², Simon G. Potts⁷, Taylor H. Ricketts²³, Maj Rundlöf²⁴, Amber Sciligo¹⁰, Palatty Allesh
12 Sinu²⁵, Ingolf Steffan-Dewenter¹⁵, Hisatomo Taki²⁶, Teja Tscharntke¹⁶, Carlos H. Vergara²⁷,
Blandina F. Viana²⁸, Michal Woyciechowski²⁹.

14

¹Grupo de Investigación en Agroecología (AGRECO), Sede Andina, Universidad Nacional de Río
16 Negro (UNRN) and Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), San
Carlos de Bariloche, Río Negro, Argentina. lgaribaldi@unrn.edu.ar

18 ²Estación Biológica de Doñana (EBD-CSIC), Dpto. Ecología Integrativa, Sevilla, Spain.
nacho.bartomeus@gmail.com

20 ³Department of Ecology, Swedish University of Agricultural Sciences, Uppsala, Sweden.
Riccardo.Bommarco@slu.se , vesna.gagic@slu.se

22 ⁴Chair of Nature Conservation and Landscape Ecology, Faculty of Environment and Natural
Resources, University of Freiburg, Freiburg, Germany. alexandra.klein@nature.uni-freiburg.de ,
24 virginie.boreux@nature.uni-freiburg.de iris.motzke@agr.uni-goettingen.de

⁵CSIRO Land and Water, Canberra, ACT, Australia. saul.cunningham@csiro.au

26 ⁶Laboratorio Ecotono, INIBIOMA, Universidad Nacional del Comahue–CONICET, Bariloche, Río
Negro, Argentina. marcelo.aizen@gmail.com , moralesc@comahue-conicet.gob.ar

28 ⁷Centre for Agri-Environmental Research, School of Agriculture, Policy and Development, Reading
University, Reading, UK. m.p.garratt@reading.ac.uk , s.g.potts@reading.ac.uk

30 ⁸School of Biology, University of Leeds, Leeds, UK. lgcarvalheiro@gmail.com

⁹Naturalis Biodiversity Center, Leiden, Netherlands.

32 ¹⁰Environmental Sciences Policy and Management, University of California – Berkeley, Berkeley,
CA, USA. ckremen@berkeley.edu , amber.sciligo@gmail.com

34 ¹¹Institute of Ecology and Evolution, University of Bern, Bern, Switzerland.
christof.schuepp@gmail.com

36 ¹²Institute for Environmental Sciences, University of Koblenz-Landau, Landau, Germany.

¹³Instituto de Ecología Regional, Facultad de Ciencias Naturales e IML, Universidad Nacional de
38 Tucumán, Yerba Buena, Tucumán, Argentina. nchacoff@gmail.com

¹⁴Departamento de Zootecnia–CCA, Universidade Federal do Ceará, Campus Universitário do Pici,

40 Fortaleza–CE, Brazil. freitas@ufc.br
15Department of Animal Ecology and Tropical Biology, Biocenter, University of Würzburg,
42 Würzburg, Germany. ingolf.steffan-dewenter@uni-wuerzburg.de , andrea.holzschuh@uni-wuerzburg.de
44 16Agroecology, Department of Crop Sciences, Georg-August-University, Goettingen, Germany.
ttschar@gwdg.de
46 17Centre for Environmental and Climate Research, Lund University, Lund, Sweden.
klattbk@googlemail.com
48 18Ecology and Evolution of Plants, Biocentre Klein-Flottbek and Botanical Garden Biodiversity,
University of Hamburg, Hamburg, Germany. kristin.marie.krewenka@uni-hamburg.de
50 19Department of Environmental Systems Science, ETH Zürich, Zürich, Switzerland.
smitha.krishnan@env.ethz.ch
52 20School of Biological Sciences and the Ecology Centre, The University of Queensland, Brisbane,
QLD, Australia. m.mayfield@uq.edu.au
54 21Department of Agricultural Resource Management, Embu University College, Embu, Kenya.
mmarkotieno@gmail.com
56 22Department of Entomology, Cornell University, New York State Agricultural Experiment Station,
Geneva, NY, USA. jessdpetersen@gmail.com
58 23Gund Institute for Ecological Economics, University of Vermont, Burlington, USA.
taylor.ricketts@uvm.edu
60 24Department of Biology, Lund University, Lund, Sweden. maj.rundlof@biol.lu.se
25Department of Animal Science, Central University of Kerala, Kerala, India. sinu@cukerala.edu.in
62 26Department of Forest Entomology, Forestry and Forest Products Research Institute 1
Matsunosato, Tsukuba, Ibaraki, Japan. htaki@affrc.go.jp
64 27Departamento de Ciencias Químico-Biológicas, Universidad de las Américas Puebla, Cholula,
Puebla, Mexico. carlosh.vergara@udlap.mx
66 28Instituto de Biologia, Departamento de Zoologia, Universidade Federal da Bahia, Salvador–BA,
Brazil. blande.viana@gmail.com
68 29Institute of Environmental Sciences, Jagiellonian University, Krakow, Poland.
michal.woyciechowski@uj.edu.pl

70 * **Corresponding author:** Lucas A. Garibaldi, Grupo de Investigación en Agroecología
72 (AGRECO), Sede Andina, Universidad Nacional de Río Negro (UNRN) and Consejo Nacional de
Investigaciones Científicas y Técnicas (CONICET), Mitre 630, CP 8400, San Carlos de Bariloche,
74 Río Negro, Argentina. Email: lgaribaldi@unrn.edu.ar

76 **Keywords:** agroecosystems, body size, ecosystem functioning, ecosystem services, mouthpart
78 length, nectar accessibility, pollination, trait evenness, trait richness.

80 **Summary**

1. Understanding the relationships among trait diversity, species diversity, and ecosystem

82 functioning is essential for sustainable management. For functions comprising two trophic levels,
trait matching between interacting partners should also drive functioning. However, the predictive
84 ability of trait diversity and matching is unclear for most functions, particularly for crop pollination,
where interacting partners did not necessarily co-evolve.

86 **2.** Worldwide, we collected data on traits of flower visitors and crops, visitation rates to crop
flowers per insect species, and fruit set in 469 fields of 33 crop systems. Through hierarchical
88 mixed-effects models we tested whether flower-visitor trait diversity and/or trait matching between
flower visitors and crops improve the prediction of crop fruit set (functioning) beyond flower-
90 visitor species diversity and abundance.

3. Flower-visitor trait diversity was positively related to fruit set, but surprisingly did not explain
92 more variation than flower-visitor species diversity.

4. The best prediction of fruit set was obtained by matching traits of flower visitors (body size and
94 mouthpart length) and crops (nectar accessibility of flowers) in addition to flower-visitor
abundance, species richness, and species evenness. Fruit set increased with species richness, and
96 more so in assemblages with high evenness, indicating that additional species of flower visitors
contribute more to crop pollination when species abundances are similar.

98 **5. *Synthesis and applications.*** Despite contrasting floral traits for crops worldwide, only the
abundance of a few pollinator species is commonly managed for greater yield. Our results suggest
100 that the identification and enhancement of pollinator species with traits matching those of the focal
crop, as well as the enhancement of pollinator richness and evenness, will increase crop yield
102 beyond current practices. Furthermore, we show that field practitioners can predict and manage
agroecosystems for pollination services based on knowledge of just a few traits that are known for a
104 wide range of flower-visitor species.

106 **Introduction**

Sustainable management of agroecosystems is a global challenge, with more than 35% of Earth's
108 land area covered by farmland (FAO 2013). It has been suggested that species diversity is critical
for sustainability because it increases the level and stability of agroecosystem functioning,
110 represented by measures of ecosystem services and agricultural production (Cardinale *et al.* 2012;
Bommarco, Kleijn & Potts 2013). There is a growing consensus that such influences of species
112 diversity on functioning are mediated by changes in trait diversity (Díaz & Cabido 2001; Cadotte,
Carscadden & Mirotnick 2011; Cardinale *et al.* 2012; Fründ *et al.* 2013). However, empirical
114 evidence for the role of trait diversity on agroecosystem functioning is scarce (Martins, Gonzalez &
Lechowicz 2015).

116 Trait diversity reflects the among-species variation in morphological, physiological, and
behavioural traits relevant to a specific function. Hence, newly developed indices of trait diversity
118 are expected to better predict functioning than traditional indices of species diversity (Díaz &
Cabido 2001; Cadotte, Carscadden & Mirotnick 2011; Schleuning, Fründ & García 2015). To
120 become a parsimonious and practical tool for predicting functioning, i.e. high goodness of fit and
low complexity, trait diversity should be based on fewer traits than species. This occurs when some
122 species share similar traits, known as partial functional redundancy (Cadotte, Carscadden &
Mirotnick 2011). Alternatively, if increased functioning is caused by numerous traits with low
124 redundancy among species, trait and species diversity will perform similarly in explaining
functioning. In such cases, species diversity will be a good proxy of trait diversity. To date, the few
126 studies on the relationship between trait and species diversity have revealed mixed results (reviewed
by Cadotte, Carscadden & Mirotnick 2011; Schleuning, Fründ & García 2015). Furthermore,
128 most of the evidence on the role of trait diversity is based on studies using primary production in
plant communities as the targeted function (Díaz & Cabido 2001; Díaz *et al.* 2007), whereas this
130 relationship remains unresolved for most functions driven by plant–animal interactions (Cadotte,
Carscadden & Mirotnick 2011; Gagic *et al.* 2015; Schleuning, Fründ & García 2015).

132 The relative abundance of a certain trait state in the community, hereafter trait identity, may
predict functioning independently of trait or species diversity. Trait identity should be an important
134 predictor when there is a trait state that performs best for a given function (Díaz *et al.* 2007;
Mokany, Ash & Roxburgh 2008) and when functioning increases with the abundance of species
136 carrying that trait state (mass ratio hypothesis) (Grime 1998). If so, abundant species should have
greater influence on trait identity and consequently on functioning than their less common
138 counterparts (Grime 1998; Díaz *et al.* 2007; Mokany, Ash & Roxburgh 2008).

For functions comprising two trophic levels, trait identity effects may depend on the
140 matching of trait states between interacting partners, hereafter trait matching (Schleuning, Fründ &
García 2015). For example, the effect of the abundance of herbivores on primary production
142 depends on the match between grazing habit and plant life forms (Asner *et al.* 2004). Trait matching
between individual species of plants and animals resulting from co-evolution has been examined in
144 the scientific literature (e.g. Stang, Klinkhamer & van der Meijden 2006; Vázquez *et al.* 2009;
Junker *et al.* 2013), but its effects on functioning at the community level have not (but see Fontaine
146 *et al.* 2006), especially for crop pollination, where in many regions crops are exotic but pollinators
are native, without a co-evolutionary history.

148 Our objective was to assess whether trait diversity and/or matching contributed to crop fruit
set (functioning), above and beyond the predictive ability of flower-visitor species abundance and
150 diversity. Fruit set, the proportion of a plant's flowers that develop into mature fruits or seeds,
reflects pollination success when other resources (e.g. nutrients) are not limiting (Wesselingh 2007).
152 Fruit set is a key component of agricultural yield, and has been shown to increase with the
abundance and richness of wild insects visiting crop flowers (Garibaldi *et al.* 2013). Such
154 dependency may be explained by pollinator trait diversity and/or matching. For example, social and
solitary bees visited flowers on radishes at different times of day, suggesting temporal
156 complementarity among these pollinator groups (Albrecht *et al.* 2012). Insects with distinctive

mouthpart lengths, hoverflies vs. bumble bees, complemented each other in the pollination of
158 flowers with easily accessible rewards vs. those with rewards hidden at the bottom of a tubular
corolla, respectively (i.e. trait matching) (Fontaine *et al.* 2006; Campbell *et al.* 2012). Small sized
160 bees transported less pollen to pumpkin flowers than bigger bees, but this pollen was distributed
more uniformly on the stigma (Hoehn *et al.* 2008). Here, we collected data on traits of flower
162 visitors and crops, visitation rates to crop flowers per insect species, and fruit set in 469 fields of 33
crop systems all over the world. This synthesis provides a unique opportunity to test the strength of
164 the relationship between trait and species diversity, and of the relative ability of trait vs. species
indices for predicting functioning, across contrasting crop systems. Our results show that trait
166 matching between flower visitors and crops, but not trait diversity, improves our ability beyond
species abundance and diversity, to predict and understand the spatial variation in crop fruit set.
168

Materials and methods

Field sampling

We collected data from crops on all continents (except Antarctica) matching the following selection
172 criteria: (i) data sampled from at least four spatially separated fields; (ii) observations of insect
species visiting crop flowers in the sampled fields; (iii) information on traits of flower visitors; (iv)
174 an estimate of fruit or seed set as the percentage of flowers setting mature fruits or number of seeds
per flower, respectively (hereafter fruit set) and (v) at least partial dependence on flower visitors for
176 maximum fruit set. This led to a total of 33 crop systems distributed among 469 fields (see
Appendix S1 in Supporting Information), with a crop system defined as a single crop species in a
178 particular region in a single study. Eight of the 33 crop systems have not been included in a
previous synthesis (Garibaldi *et al.* 2013), namely apple in the UK, black cardamom in India,
180 cardamom in India, field bean in the UK, oilseed rape in Sweden, strawberry in Germany,
strawberry in the UK, and strawberry in the USA (Appendix S2, Table S1). Furthermore, for all

182 crop systems, data on traits are presented here for the first time. The sampled fields were subjected
to a diversity of agricultural practices, including large monocultures and small and diverse
184 cultivations. A wide array of annual and perennial fruit, seed, nut, and stimulant crops was included.

In each field, we measured flower visitation per unit of time and flower for each insect
186 species, from which we estimated species richness and evenness. Bee taxa observed in many crop
systems (Table S2) included apex-furrowed (or sweat) bees (Halictidae), bumble bees (Apidae:
188 *Bombus* spp.), carpenter bees (Apidae: Xylocopini), plasterer bees (Colletidae), sand bees
(Andrenidae), small carpenter bees (Apidae: Ceratinini), stingless bees (Apidae: Meliponini), the
190 eastern honey bee *Apis cerana*, the giant honey bee *Apis dorsata*, and the western honey bee *Apis*
mellifera. In some crop systems, ants (Hymenoptera: Formicidae), syrphid flies (Diptera:
192 Syrphidae), other flies, and various beetle species (Coleoptera) were common flower visitors. We
also measured fruit set, which is usually correlated with crop yield across fields (e.g. see Figure S1
194 in Garibaldi *et al.* 2013). Given that we measured fruit set in several plants open to insect
pollination per field, our results properly represent field conditions and are not biased by resource
196 translocation among different developing fruits within plants (Wesselingh 2007).

198 ***Trait diversity***

If trait indices are to be employed by field practitioners for predicting and managing agroecosystem
200 functioning, they should be based on relatively few and relevant traits, for which there is accessible
information for a wide range of flower-visitor species. We measured eight traits of the flower
202 visitors that were expected to influence pollinator efficiency and therefore fruit set (Fontaine *et al.*
2006; Hoehn *et al.* 2008; Albrecht *et al.* 2012; Martins, Gonzalez & Lechowicz 2015). Sociality
204 (yes vs. no) was defined as colony building, including all eusocial as well as semi-social species
(Table S2). Oligolectic (yes vs. no) included flower visitors that collect pollen from one or a few
206 closely related plant species, whereas polylectic species collect pollen from a variety of flowers

belonging to different plant families. Seasonal activity (complete vs. partial) (Junker *et al.* 2013)
208 was classified according to whether the pollinator species visit the crop during the whole flowering
period or only during early or late periods. Cleptoparasitic (yes vs. no) was defined as flower
210 visitors that lay eggs in the nests of other insect species (e.g. cuckoo bees). Cleptoparasitic insects
do not actively collect pollen, which may impair their efficiency as crop pollinators. Body size was
212 defined according to the intertegular span (ITD), the distance between the two insertion points
(tegula) of the wings of female workers of each species. Body size classes for bees were as
214 following: tiny (< 1.5 mm ITD, typical foraging distance < 50 m), small (1.5–2.0 mm ITD, typical
foraging distance 50–300 m), medium (2–3.3 mm ITD, typical foraging distance 300–1100 m), and
216 large (> 3.3 mm ITD, typical foraging distance > 1100 m) (Greenleaf *et al.* 2007). We follow the
same classification for syrphids for consistency and butterflies and moths were commonly classified
218 as large. Mouthpart length, i.e. tongue or proboscis, was classified as short (< 3 mm), medium (3–8
mm) or long (> 8 mm; see figure 1 in (Stang, Klinkhamer & van der Meijden 2006). Finally, we
220 classified flower visitors according to whether they are capable of buzz pollination (yes vs. no), and
if they were central place foragers (yes vs. no). As our study represents a major effort of data
222 sampling at a global scale, we could not measure intra-specific differences for all flower-visitor
species in all crop systems and we focus only on inter-specific differences (i.e. mean values per
224 species for all crop systems). However, except for size measurement (body and mouthparts), these
traits (e.g. sociality) are not likely to vary among individuals within a species.

226 Crops were also classified according to four traits expected to be relevant for pollination
success (Table S1) (Fontaine *et al.* 2006). Flower diameter at the widest part of the flower was
228 classified as small (1–10 mm), medium (> 10–35 mm), or large (> 35 mm). Nectar accessibility,
high vs. low, reflected the accessibility of the nectar resources (nectaries) to the flower visitors
230 (Stang, Klinkhamer & van der Meijden 2006; Fontaine *et al.* 2006; Junker *et al.* 2013). Crops with
low nectar accessibility had narrow or tubular flowers, and showed a ratio between flower diameter

232 (mm) and the distance of the nectaries to the anthers (mm) lower than 1.5. Generally, crops with
less accessible nectar are expected to suffer a greater degree of nectar robbery (e.g. see page 178 for
234 oilseed rape in Free 1993). For acerola and annato, crops that do not secrete nectar, the
classification refers to accessibility of oil and pollen, respectively. Pollinator dependence was
236 defined as the percentage of yield reduction in the absence of pollinators (Klein *et al.* 2007). We
also classified crops according to their typical duration of flowering into short (< 10 days per plant),
238 medium (10–25 days), or long (> 25 days).

We chose three complementary, uncorrelated, trait diversity indices (Laliberté & Legendre
240 2010; Mouchet *et al.* 2010) and calculated these indices using the eight traits of flower visitors
described above as predictors of fruit set. Trait richness, defined as the total branch length of a trait
242 dendrogram, measures the extent of trait complementarity among species (Petchey & Gaston 2006).
This index is highly correlated with the trait richness proposed by Villéger, Mason & Mouillot
244 (2008) but allows quantification of assemblages with low species richness. Trait evenness is defined
as the regularity of the abundance distribution in the volume of the trait space occupied by the
246 pollinator assemblage (Villéger, Mason & Mouillot 2008). Trait dispersion is defined as the mean
distance in multidimensional trait space of individual species to the centroid of all species, and is
248 mathematically related to Rao's Q (Laliberté & Legendre 2010).

The community weighted mean (hereafter, CWM) is a single trait index that provides an
250 estimate of the trait states that dominate in a community (i.e. trait identity; Díaz *et al.* 2007). It is
calculated by weighting the measure of a trait by the relative abundance of all species carrying that
252 trait, and summing over all trait states. For example, CWMs for body size range from zero when all
species in a field are tiny to four when all species are large, whereas CWMs for sociality range from
254 zero when all species are solitary to one when all species are social. Package FD (R Development
Core Team 2013) and publicly-available code (<https://github.com/ibartomeus/fundiv>) were used to
256 calculate all indices.

258 *Statistical analyses*

Observations for fruit set and each predicting variable (y) in each field (i) of each crop system (j)
260 were standardized using z-scores ($z_{ij} = \frac{(y_{ij}-\bar{y}_j)}{SD_j}$) to allow comparisons among crop systems, despite
contrasting means (\bar{y}_j) and standard deviations (SD_j), and differences in methodology. Unlike other
262 standardizations, such as logarithms, z-scores do not modify the form (e.g. linear or curvilinear) of
the relationship between response and predicting variables. Furthermore, z-scores allow for direct
264 comparison of the values of the partial regression coefficients, and therefore are useful for
understanding the relative effects of predicting variables.

266 We evaluated how trait richness varied with species richness across fields (and the same for
trait and species evenness). In case of functional redundancy, trait richness would increase with
268 species richness across sites with a regression coefficient < 1 . Alternatively, in the case of little
functional overlap between species, an approximately one to one relationship would be expected
270 (see Introduction). Because both trait and species richness are random variables, model I
regressions (e.g. through ordinary least squares) will underestimate the slope of the linear
272 relationship (see section 10.3.2 of Legendre & Legendre 1998). Instead, we performed model II
regressions, as the emphasis was not on forecasting trait richness but on estimating the correct value
274 of the slope for the relationship between trait and species richness (R software version 3.0.2,
lmodel2 package, lmodel2 function) (R Development Core Team 2013; Legendre 2014). Among
276 the estimation methods for model II regressions, we chose major axes because both variables were
in the same units (z-scores), variance of error was about the same for both variables, and
278 distribution was approximately bivariate normal (Legendre & Legendre 1998).

To forecast fruit set, we estimated the influences of *a priori* selected combinations of
280 predicting variables through general linear mixed-effects models (R software version 3.0.2, nlme
package, lme function, with Gaussian error distribution) (R Development Core Team 2013;

282 Pinheiro *et al.* 2014), which are effective for integrated analysis of data from many sources (Qian *et*
284 *al.* 2010). This approach produces similar results to Bayesian hierarchical models when
286 uninformative priors are employed, especially with large samples, as in our case (Gelman & Hill
2007; Qian *et al.* 2010). By including crop system as a random variable, our models estimated
288 intercepts (α_j) for each system (j) to account for the hierarchical data structure and differences
among systems (random intercept models) (Gelman & Hill 2007; Qian *et al.* 2010). Each partial
290 regression coefficient (β_+) was considered a fixed effect reflecting the influence of a predicting
variable on fruit set over all crop systems. We tested the Gaussian and homoscedasticity
assumptions for the standardized residuals of the models with graphical analyses and Kolmogorov-
Smirnov tests (Type I error rate = 0.05). These assumptions were valid in all cases.

292 To test whether trait diversity better predicts fruit set than species diversity, we compared
Akaike's Information Criterion (hereafter, AIC) values for three *a priori* models (Table S3). All
294 models included visitation rate to control for abundance variation among fields, combined with
either species richness and evenness based on Pielou's J (model A), trait richness and evenness
296 (model B), or trait dispersion (model C) as predicting variables. Model B is conceptually equivalent
to model A but used trait instead of species diversity indices, whereas model C was included to be
298 comprehensive in the trait indices employed (see previous section). In the three models we
estimated all possible interactions among predicting variables. We expected models B and C to
300 show lower AIC than model A (see second paragraph of the Introduction). We also present a fourth
"best" model, which was the one with the lowest AIC, after evaluating the models resulting from all
302 possible combinations of the six predicting variables (visitation rate, species richness, species
evenness, trait richness, trait evenness, and trait dispersion) and their paired interactions (MuMIn
304 package, dredge function) (Bartoń 2014). The four models were compared to a fifth, "null" model
without any fixed predicting variable to understand if they provide any relevant fit. The five models
306 did not present multicollinearity, and all variance inflation factors (VIFs) were lower than 1.4 (see

also Table S4). AIC values were obtained based on maximum likelihood estimates of regression
308 coefficients, because models differed in the fixed structure but shared the same random structure
(random intercepts for different crop systems), whereas parameter estimates for models presented in
310 tables and figures were obtained using the restricted maximum likelihood method (Zuur *et al.*
2009).

312 It is important to note that evenness indices have different approaches for weighting rare and
common species and this can influence the results (Ricotta & Avena 2003; Marini *et al.* 2014).
314 Therefore, we repeated the analyses using nine other evenness indices, including Evar, inverse of
Simpson index, and seven evenness profiles covering the entire spectrum of weights for dominant
316 species (Ricotta & Avena 2003; Marini *et al.* 2014). These analyses did not modify our conclusions
based on Pielou's J (data not shown).

318 Finally, we evaluated how individual traits of flower visitors and crops (trait identity and
matching) might increase our ability to predict fruit set. Specifically, we compared AIC of four *a*
320 *priori*, mixed-effects models of the influences of selected crop traits, CWM of flower visitor traits,
and their interaction on fruit set (Table S5). An interaction between crop traits and flower visitor
322 traits indicates trait matching, whereas no interaction indicates that a given trait is best for all crops
(i.e. only trait identity). In addition, the models always included all the fixed effects of the best
324 model tested in Table S3. Among the eight traits measured for flower visitors, we selected three for
which we had *a priori* expectations (Stang, Klinkhamer & van der Meijden 2006; Fontaine *et al.*
326 2006; Hoehn *et al.* 2008; Albrecht *et al.* 2012; Martins, Gonzalez & Lechowicz 2015) and for
which we found variation within and across studies, namely sociality, mouthpart length, and body
328 size (e.g. little variation was found for cleptoparasitism, as most flower visitors were non-
cleptoparasitic, see Results section). Similarly, we selected four relevant crop traits: nectar
330 accessibility, degree of pollinator dependence, flower diameter, and flowering length. The four
models included the three selected flower-visitor traits but varied in the crop trait considered to

332 evaluate trait matching. We always estimated all possible interactions among predicting variables.
We also compared these four *a priori* models with the previous best model, with the null model,
334 and with the model with the lowest AIC after evaluating the models resulting from all possible
combinations of the predicting variables and their pair interactions (MuMIn package, dredge
336 function) (Bartoń 2014). None of the models presented multicollinearity, and all VIFs were lower
than 2 (see also Table S4).

338

Results

340 Crop flower visitors were typically polylectic, non-cleptoparasitic, central place foragers, and active
during the whole flowering period of the crop (Table S2). However, flower visitors had contrasting
342 mouthpart lengths, body sizes, social behaviour, or buzz pollination behaviour. Community
weighted means for these traits did not differ among crops with high vs. low nectar accessibility
344 (Fig. S1), different flower diameter, pollinator dependence, or flowering length, as linear mixed-
effects models including crop traits as predictors of CWMs showed no improvement (lower AIC) to
346 null models. On average, fields with bigger flower visitors (CWMs for body size) also had greater
dominance of flower visitors with larger mouthparts (CWMs for mouthpart length; Fig. S2, Table
348 S4).

Trait and species richness were strongly and positively associated across fields, indicating
350 low redundancy among species of flower visitors (Fig. 1). Similarly, trait and species evenness were
positively associated across fields. In both cases, the slopes of the model II regressions did not
352 differ from a one to one relationship (Fig. 1), as denoted by the 95 % confidence intervals (CI
richness: 0.90–1.13; CI evenness: 0.85–1.34). We found no clear improvement (lower AIC) when
354 considering curvilinear relationships between trait and species richness (or evenness), and therefore
we present only models with linear form. In addition, there was no benefit of including crop system
356 specific slopes or intercepts (Fig. S3).

Fruit set increased with trait and species diversity of flower visitors across fields worldwide
358 (models A and C in Table S3). However, trait diversity did not improve model fit on fruit set
beyond species diversity, as models including trait diversity indices did not achieve lower AIC
360 (compare models B and C to model A). The model with the lowest AIC included visitation rate,
species richness, species evenness using Pielou's J , and richness \times evenness interaction (model
362 "best"). Fruit set increased linearly with species richness of flower visitors, but richness effects
were greater in fields with high species evenness as denoted by a positive richness \times evenness
364 interaction (Fig. 2). The relationships of fruit set with species richness and evenness were
independent of visitation rate, which was also positively associated to fruit set and showed the
366 highest partial regression coefficient. In our synthesis, richness ranged between 0 (zero visits
recorded in those fields) and 28 species, with a mean value of 7 species per field (the median was 6
368 species per field). For evenness, we found all the possible range of values for Pielou's J (from 0 to
1) showing a mean of 0.67 per field (the median was 0.73 per field). For visitation rate and species
370 richness, we tested models with both linear and curvilinear (i.e. second order polynomial) forms.
We found no clear improvement (lower AIC) when considering curvilinear relationships in mixed-
372 effects models, and therefore we present only models with linear form. In addition, inclusion of
system-specific partial regression coefficients (β_j) for each of the predicting variables (random
374 slopes) in the best model did not decrease AIC, showing that the fixed effects (β_+) considered
explained the heterogeneity of responses among crop systems.

376 In contrast to trait diversity, models including information on trait identity and matching
increased model fit beyond species diversity and visitation rate (see models in Table S5).
378 Specifically, the model with the lowest AIC (model "best") included as predictors of fruit set the
CWM of sociality, body size, and mouthpart length, the nectar accessibility of the flowers, and the
380 interactions (trait matching) of CWM for body size and mouthpart length with the nectar
accessibility, in addition to visitation rate, species richness, species evenness, and richness \times

382 evenness interaction. Fruit set of crops with less accessible nectar decreased at fields with flower
visitors of larger bodies and shorter mouthparts (Fig. 3; Fig. S4), whereas crops with more
384 accessible nectar showed the opposite pattern (Fig. 3; Fig. S5). The values (in z-score scale) of the
partial regression coefficients (β_+) for the interactions (trait matching) of CWM for body size and
386 mouthpart length with the nectar accessibility were the greatest (Table S5). The β_+ values for
visitation rate, species richness, and species evenness were similar to the ones obtained from a
388 previous model (“best” in Table S3) that did not include as predicting variables aspects of trait
identity and matching, reflecting their independent contribution to model fit on fruit set. Similarly,
390 our results were not confounded by differences in crop management system (Table S6). The effects
of CWM for sociality on fruit set were not clear.

392

Discussion

394 If trait diversity indices predict functioning better than species diversity indices, it suggests that
there are a subset of traits shared across species that are overwhelmingly important for functioning.
396 Contrary to this idea, here we demonstrate that although trait diversity indices were positively
related to crop fruit set (functioning), they did not provide greater model fit compared to species
398 diversity indices (including both richness and evenness). Furthermore, we found very low
functional redundancy among flower-visitor species, suggesting that there is not enough sharing of
400 important traits among species to make the trait diversity indices more useful than species diversity.

Worldwide, we found positive and linear (one to one) relationships between trait and species
402 richness across 33 crop systems. It is important to note that trait richness increases, and functional
redundancy decreases, with the number of traits included in richness indices (Cadotte, Carscadden
404 & Mirotnick 2011). In our synthesis, the low functional redundancy across flower-visitor species
was mainly related to different combinations of mouthpart lengths, body sizes, social behaviour,
406 and buzz pollination behaviour. Therefore, our results cannot be explained by an excess of traits,

but by the variation across species in the *a priori* selected morphological and behavioural traits
408 known to affect pollination efficiency (Fontaine *et al.* 2006; Hoehn *et al.* 2008; Campbell *et al.*
2012; Albrecht *et al.* 2012; Martins, Gonzalez & Lechowicz 2015). In contrast, previous evidence
410 indicated that the relationship between trait and species diversity was complex and context
dependent (Cadotte, Carscadden & Mirotnick 2011). This lack of consistency across studies may
412 reflect different criteria for trait selection, a limitation that was overcome in our synthesis.

The failure of trait diversity indices to improve predictions of fruit set is not explained by a
414 lack of information on key traits in our synthesis, because we did find important trait effects, as
specific combinations of individual traits of flower visitors and crops (i.e. interactions) increased
416 model fit to species diversity. Specifically, flower visitors with large bodies and short mouthparts
were more effective on crops with high rather than low nectar accessibility (i.e. trait matching).
418 These results agree with previous studies on wild plants that thoroughly discussed the benefits of
longer pollinator mouthparts for narrow or tubular flowers (Fontaine *et al.* 2006; Campbell *et al.*
420 2012). However, here we could test the effects of body size and mouthpart length on functioning
after accounting statistically for the co-variation between both, and our findings on body size are in
422 contrast to previous studies that could not separate these effects (Fontaine *et al.* 2006; Campbell *et al.*
et al. 2012). Larger bodies may deposit more pollen (e.g. Hoehn *et al.* 2008) and can increase the
424 probability that pollinators contact the reproductive parts of crops with open flowers and accessible
nectar. Examples in our data include the larger bodies but similar mouthparts of *Xylocopa frontalis*
426 and *X. grisescens* vs. *Apis mellifera* making the former more effective pollinators of passion fruit
(Fig. S5, Table S2). Such benefit of increased body size for improved pollination may not be shared
428 in crops with more compact flower structures and less accessible nectar. Reasons for this may be
related to nectar robbery and flower damage (Morris, Vázquez & Chacoff 2010; Aizen *et al.* 2014),
430 which are more likely by larger insects possessing stronger mandibles. For example, rates of raiding
the relatively inaccessible nectar of field bean flowers can be higher for larger *Bombus terrestris*

432 when compared to the smaller *Apis mellifera*, despite similar mouthpart lengths (Fig. S4, Table S2;
for nectar robbery data see Garratt *et al.* (2014). These potential mechanisms should be tested in
434 experimental studies.

Our results agree with studies on wild plants that emphasize the role of trait matching in
436 structuring plant–pollinator networks (Stang, Klinkhamer & van der Meijden 2006; Vázquez *et al.*
2009; Junker *et al.* 2013). Here, we further demonstrate that trait matching increases functioning at
438 the agroecosystem level across crops worldwide, independently of the positive contribution of
species abundance, richness, or evenness. Moreover, in relative terms, the effects (partial regression
440 coefficient values) of trait matching on functioning were even greater than the effects of species
abundance, richness, or evenness.

442 The positive effect of species richness on fruit set was stronger in fields with high species
evenness, suggesting that additional species contribute more to agricultural functioning when their
444 abundances are more similar. Effects of species richness and evenness were independent from those
of visitation rate (abundance), which agrees with other results suggesting that increasing pollinator
446 diversity enhances pollination (e.g. Schleuning, Fründ & García 2015)). These effects are expected
because of different non-exclusive mechanisms (Tschardt *et al.* 2005), including pollination niche
448 complementarity (Hoehn *et al.* 2008; Fründ *et al.* 2013), interspecific interactions such as synergism
(Greenleaf & Kremen 2006; Carneiro *et al.* 2011; Brittain *et al.* 2013), or sampling effects
450 (Cardinale *et al.* 2006; Schleuning, Fründ & García 2015). However, our study contrasts with
previous evidence (Garibaldi *et al.* 2013) in finding an effect of richness that is statistically
452 independent from visitation rate (abundance), which could be a consequence of the different set of
studies included in our synthesis (see Materials and methods). Furthermore, here we show for the
454 first time an ubiquitous and strong positive interaction between the effects of richness and evenness.
Pollinator evenness may enhance fruit set via pollination complementarity among flower visitors, or
456 diminish it if a dominant species is the most effective pollinator (Hillebrand, Bennett & Cadotte

2008). Our results clearly point to the former, positive effect of species evenness on functioning.
458 Moreover, a positive interaction between richness and evenness may further suggests synergistic
interactions among species of flower visitors, such as has been found between honey bees and wild
460 insects in the few studies on this topic (Greenleaf & Kremen 2006; Carvalheiro *et al.* 2011; Brittain
et al. 2013). Previous studies have shown that agricultural expansion and intensification reduces
462 both species richness of pollinator assemblages and wild insect visitation (e.g. Garibaldi *et al.*
2011). In contrast, the effects of agricultural expansion and intensification on species evenness have
464 been rarely accounted for (Marini *et al.* 2014), but may also drive ecosystem functioning
(Bommarco *et al.* 2012).

466 Sustainable intensification of agroecosystems represents one of the greatest challenges for
humanity (Bommarco, Kleijn & Potts 2013). To succeed in this challenge it is critical to quantify
468 the relationships among trait diversity, species diversity, and agroecosystem functioning
(Schleuning, Fründ & García 2015). Here we show that crop fruit set, an important component of
470 agricultural yield, can be increased through both higher species richness (showing a linear increase,
ranging from 0 to 28 species in our synthesis) and evenness (ranging from 0 to 1 in our synthesis) of
472 flower visitors. Fruit set might be further enhanced by agricultural practices targeted to promote
specific flower visitors with traits that match those of the focal crop. Indeed, trait matching showed
474 the greatest influence on fruit set. Current management practices for greater pollination, however,
focus mostly on enhancing flower-visitor abundance, often of a single species, namely *Apis*
476 *mellifera*. Although greater abundance is an important contributor to pollination function, our
results show that it cannot replace the additional benefits of species richness, species evenness, and
478 trait matching between flower visitors and crops.

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494

Data accessibility

496 The data sets supporting this article have been uploaded as online Supporting Information.

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634

636 **Figure legends**

Fig. 1. Globally, trait and species richness (or evenness) of insect visitors to crop flowers are
638 strongly linked. Left panel: trait richness of flower visitors increases with species richness at an
indistinguishable rate (solid line) from a 1:1 relationship (broken line) indicating low functional
640 redundancy among species. Right panel: trait evenness also increases with species evenness at an
indistinguishable rate (solid line) from a 1:1 relationship (broken line). The solid line is the overall
642 regression where each point is a field in a crop system. Data from individual crop systems were
standardized by z-scores prior to analysis, permitting comparison of fields across crop systems.

644

Fig. 2. Fruit set increases with species richness of flower visitors at a higher rate in assemblages
646 with high (blue: fields with evenness higher than the 3rd quartile) than low evenness (orange: fields
with evenness lower than the 1st quartile). The solid line is the overall regression where each point
648 is a field in a crop system. Data from individual crop systems were standardized by z-scores prior to
analysis, permitting comparison of fields across crop systems.

650

Fig. 3. Flower visitors with large bodies and short mouthparts are more effective on crops with high
652 (open flowers) rather than low (narrow, tubular flowers) nectar accessibility. Data show fruit set of
crops with high (orange) and low (blue) nectar accessibility as a function of community weighted
654 means (CWM) of flower visitors for body size (upper panel) and mouthpart length (lower panel).
The solid line is the overall (fixed-effect) prediction from the best model (Table S5), where each
656 point is a field in a crop system. Data from individual crop systems were standardized by z-scores
prior to analysis, permitting comparison of fields across crop systems. Flowers of almond (left) and
658 red clover (right) are shown as examples of crops with high or low nectar accessibility, respectively
(colours indicate nectar location within the flowers).

660

662 **Supporting Information**

Additional Supporting Information may be found in the online version of this article:

664 **Appendix S1.** Data supporting our results.

Appendix S2. Methods for unpublished studies.

666 **Table S1.** Plant traits and other characteristics of the 33 crop systems analyzed.

Table S2. Examples of abundant flower visitors and trait classification.

668 **Table S3.** Akaike's Information Criterion (AIC) and partial regression coefficients for mixed-
effects models of the influences on fruit set, including for flower visitors: visitation rate, species
670 richness, species evenness, trait richness, trait evenness, and trait dispersion.

Table S4. Correlation coefficients between the quantitative variables measured in our study.

672 **Table S5.** Akaike's Information Criterion (AIC) and partial regression coefficients for mixed-
effects models of the influences on fruit set, including for flower visitors: visitation rate, species
674 richness, species evenness, community weighted mean (CWM) of sociality, CWM of body size, and

CWM of mouthpart length.

- 676 **Table S6.** The inclusion of crop management practices, such as policulture *vs.* monoculture, do not influence our results.
- 678 **Fig. S1.** Sociality, body size, and mouthpart length of flower visitors do not differ between crops with high *vs.* low nectar accessibility.
- 680 **Fig. S2.** Community weighted means (CWMs) of body size and mouthpart length are positively related across crop fields globally.
- 682 **Fig. S3.** For contrasting crops worldwide, trait richness of flower visitors increases with species richness at a 1:1 relationship indicating low functional redundancy among species.
- 684 **Fig. S4.** Fruit set of crops with less accessible nectar generally decrease at fields with bigger flower visitors.
- 686 **Fig. S5.** In contrast to crops with low nectar accessibility, fruit set of crops with high nectar accessibility generally increase at fields with bigger flower visitors.