

1 **Title:**

2 The affinity between flowers and their pollinators

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4 **Author:**

5 Zaal Kikvidze

6 ORCID 0000-0002-5007-4484

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8 **Affiliation:**

9 Institute of Botany, Ilia State University, Tbilisi, Georgia

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11 **Corresponding author:**

12 Zaal Kikvidze, email: zaal.kikvidze@iliauni.edu.ge

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14

15 **Abstract**

16 It is a common knowledge that the probability of the fertilisation of a flower by its pollinator
17 is a function of species abundances. However, this relation was rarely formalised for
18 analysing pollination networks. In this opinion paper, a simple model borrowed from physical
19 chemistry is introduced to formalise this functional dependence. This led to a well-known
20 biochemical concept of affinity, which refers to the strength of the binding interaction of a
21 protein to its ligand. This affinity is explained as the “attraction” or “fit” between the two
22 molecules, and is attributed to complementarity or the precise matching of the protein's active
23 site and the ligand's shape, charge, and hydrophobic or hydrophilic properties. Analogously,
24 we can think of a complementarity between the pollinator and flower morphologies, the
25 ability of a pollinator to locate the desirable flower, which might involve sophisticated
26 behaviours and the use of memory. The protein-ligand affinity is considered to be crucial
27 since it determines how effectively the metabolism functions. We can think in similar terms
28 when analysing pollinator-flower interactions: affinity can define the effectiveness of a
29 pollinating networks and give us new insights about its functional mechanisms.

30

31 **Keywords:** Abundance, Affinity, Interaction, Pollination network

32

33 **Introduction**

34 Studies on pollination networks have seen rapid progress, particularly evident in the
35 development of an array of quantitative tools of analysis based on graph and network theory
36 (Dale 2017). These tools enabled to reveal several characteristics, the most salient of which
37 are the low levels of connectance and the nested distribution of interactions, consistently
38 repeating across various habitats and communities (Bascompte and Scheffer 2023; Lanuza et al. 2025). However, there are concerns that the achieved advances are not well connected
39 with the key concepts of community ecology (Blüthgen and Staab 2024; Peralta et al. 2024).
40 For example, the major structural characteristics of pollination networks, such as low
41 connectance, nestedness, modularity and asymmetry, are being derived from the binary
42 matrices which ignore the variability in the strength of interactions and abundances of both
43 flower and pollinator species (Staniczenko et al. 2013). This is surprising since ignoring these
44 variability can seriously deprive us from seeing clearly the place of ecological interactions in
45 community processes (Blüthgen and Staab, 2024; Peralta et al. 2024). In fact, abundance
46 distribution can have profound effects on species interaction networks, for example, it was
47 shown that the resilience of a pollination network depends on the presence of abundant and
48

49 highly linked species (Winfree et al. 2014). Since the probability that a pollinator visits a
50 flower is a function of their abundances (Vázquez et al. 2009), one can assume that the
51 reciprocal is true too: logically, frequent encounters require numerous individuals, and *vice*
52 *versa*. Yet this is not always the case and the models that attempt to extrapolate species
53 abundances from the frequency of their interactions appeared to be inaccurate and little
54 reliable (Vizentin-Bugoni et al. 2014, Gardner et al. 2020). The importance of having
55 abundance distribution data has been recently recognised in the guidelines of the European
56 Database of Plant-Pollinator Networks (EuPPollNet, Lanuza et al. 2025), which requires the
57 contributors to provide flower counts. Regretfully, this approach is too “phytcentric” as it
58 does not request abundance distribution data for pollinators.

59

60 The frequency of flower visits by pollinators depends not only on species abundances but
61 also on other factors such as morphology (trait matching) and phenology (Peralta et al. 2024).
62 Yet, while species abundance distribution types are remarkably consistent across ecosystems
63 and communities (Ulrich et al. 2010), the other factors clearly depend on geographical,
64 historical and phylogenetic contexts. Here I argue that we might expect important benefits
65 from the inclusion of species abundance of both flowers and pollinators in the analyses of
66 pollination networks. For this purpose, below I introduce a simple model of the dependence
67 of interaction frequency on species abundance. The model is explained with the help of an
68 illustrative example. Then the model is used to analyse a data set which does include species
69 abundances of both pollinators and flowers collected independently from the data on the
70 frequencies of their interactions (Vizentin-Bugoni et al. 2016).

71

72 **The data and their reanalyses**

73 Before the reanalysis proper, I introduce the model that links species abundances with
74 interaction frequencies using an illustrative matrix. It is smaller than the real one yet retains
75 its essential properties (next section). After introducing the key ideas, I proceed with the
76 reanalysis of the above real matrix.

77

78 The data set I reanalyse here is contributed by Vizentin-Bugoni et al. (2016), downloadable
79 from the website of IWB (Interaction Web Data Base, see also Supplementary Material). The
80 authors conducted an intensive sampling in the Atlantic Rainforest from in SE Brazil (23°S,
81 45°W) over 4–10 days per month for two years. Network or rather a subnetwork is
82 represented by over 300 individuals of 9 hummingbird species and 83931 counted flowers of

83 55 plant species. Importantly, the distributions of both flowers and hummingbirds are known
 84 from independent sampling. 2793 interactions among 123 hummingbird-flower pairs were
 85 recorded. The data were organised in a network matrix (Table S11 of Supplementary
 86 Information). The abundances in this matrix are standardised as densities (number of
 87 individuals per unit area). The new metrics (affinities) derived from the model were
 88 standardised by dividing by its maximum values and then presented graphically.

89

90 **An illustrative example**

91 The illustrative example includes only five pollinator and five flower species, and shows the
 92 same general characteristics and real network matrices (Table 1A).

93

94 **Table 1.** Illustrative matrices of pollination network including pollinator and floral
 95 abundances (red font). A: raw data from the field; B: raw data in binary form; C: matrix of
 96 the same network with affinity values (k_{ij}).

A

Species	Pollinators	Poll_1	Poll_2	Poll_3	Poll_4	Poll_5
Flowers	Abundances	160	80	40	20	10
Flor_1	1600		64	32		32
Flor_2	800	128			16	
Flor_3	400	300		64		
Flor_4	200		10			
Flor_5	100	128				

B

Species	Pollinators	Poll_1	Poll_2	Poll_3	Poll_4	Poll_5
Flowers	Abundances	160	80	40	20	10
Flor_1	1600	0	1	1	0	1
Flor_2	800	1	0	0	1	0
Flor_3	400	1	0	1	0	0
Flor_4	200	0	1	0	0	0
Flor_5	100	1	0	0	0	0

C

Species	Pollinators	Poll_1	Poll_2	Poll_3	Poll_4	Poll_5
Flowers	Abundances	160	80	40	20	10
Flor_1	1600	0	0.0005	0.0005	0	0.002
Flor_2	800	0.0010	0	0	0.001	0
Flor_3	400	0.0047	0	0.004	0	0
Flor_4	200	0	0.0006	0	0	0
Flor_5	100	0.0080	0	0	0	0

97

98 The matrix is “complete” in the sense that it is furnished with the abundance data both of
99 pollinators and flowers (red font). The columns and rows represent the pollinators and the
100 flower species, respectively. The frequency of interactions between pollinator-flower pairs
101 are given in the cells. The empty cells show the absence of interactions. In the binary version
102 of this matrix (Table 1B) empty cells are represented with 0-s and the links with 1, regardless
103 of the frequency of interactions recorded). The metric usually calculated from the binary
104 matrices is connectance. The modern software calculate connectance in a rather sophisticated
105 way, but perhaps the simple original equation shows the idea of connectance equally well:

106

$$107 \quad C = L / (M * N),$$

108

109 where C is connectance, L is the number of links (sum of cells with 1 in the matrix), M and N
110 are the number of flower and pollinator species, respectively: C is simply the proportion of
111 possible links between species that are realised. For our illustrative example, $L = 9$, $M = 5$
112 and $N = 5$, consequently $C = 9 / (5 * 5) = 0.36$.

113

114 The binary matrix (Table 1B), however, does not show the differences in the frequencies of
115 interactions, whilst from the previous matrix (Table 1A) we can see that the interaction was
116 recorded 300 times for the pair of Poll_1 – Flor_3, the minimum detected interactions
117 frequency being equal to 10 for the pair of Poll_2 – Flor_4: the difference is 30-fold! In
118 binary form we loss this information, as all non-zero frequencies are equated to 1.

119

120 The great majority of real network matrices in open access data bases, unlike our illustrative
121 example, lack species abundance data for pollinators and often for plants as well. We can
122 only see what species are present in the network. But from the illustrative example we see
123 that the difference between the most and least abundant species is 16, which is considerable.
124 Thus, the matrices lacking abundance data deprive us opportunities to incorporate this
125 variation in the analysis.

126

127 In the real network matrix, the differences in interaction frequencies and species abundances
128 are comparable or even more impressive (Table S11): the most frequent interaction was
129 recorded 198 times, the least equalled to 1, which means 198-fold difference. Likewise, the
130 most abundant flower exceeded the least abundant one 5191 times! The difference is less but
131 still dramatic in hummingbirds: the most abundant species exceeded the least abundant one

132 113 times. This is the extent of information lost when presenting the network without
133 abundance data. This information, if the abundances are given in a matrix can be used in
134 various ways, one such approach is described in the next section.

135

136 **Linking species abundances to the connectance in pollination networks**

137 The model is introduced below with the help of the same illustrative example matrix used in
138 the previous section (Table 1C). The model is based on the common knowledge that the
139 interaction frequency is a function of the abundances of participant species (Blüthgen and
140 Staab, 2024; Vázquez et al. 2009). In the simplest form, this function can be presented as
141

$$142 \quad z = k * x * y,$$

143

144 where x and y are flower and pollinator species abundances, respectively; z is the interaction
145 frequency (“link strength”), and k is the constant of proportionality. This constant can be
146 understood as the “affinity” between the species of a given interacting flower-pollinator pair.

147 The term “affinity” is borrowed from biochemistry where it refers to the strength of the
148 binding interaction of an enzyme to its substrate. In our model, the high values of k_{ij} mean
149 high likelihood of interactions between a flower and its pollinator, and *vice versa*. The
150 frequency of interactions thus will be high at high abundances of the interacting species and
151 high values of their k_{ij} . The model allows for calculating the affinity for each pair of
152 interacting species since all other variables are presented the matrix (Table 1A). Therefore:

153

$$154 \quad k_{ij} = z_{ij} / (x_i * y_j),$$

155

156 which allows us to create a new matrix of affinities (Table 1C). We see that the k_{ij} values are
157 generally small but vary considerably.

158

159 How to distinguish “high” and “low” affinities? A reference value of k_{ij} could be introduced:

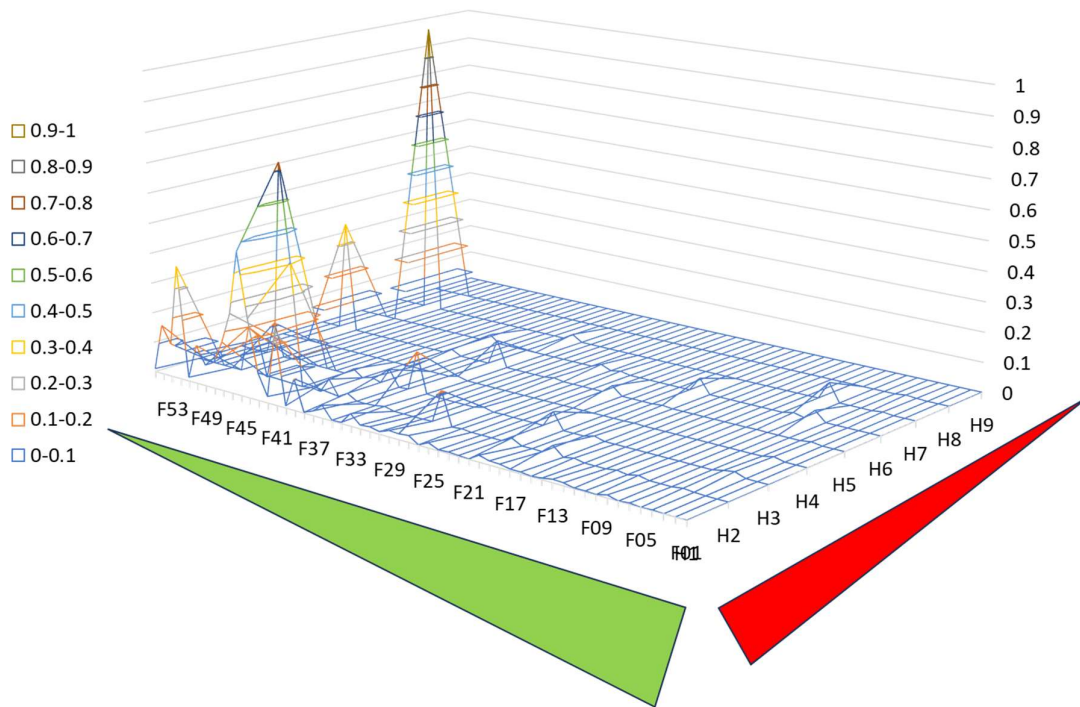
160

$$161 \quad k_{\text{ref}} = \underline{Z}_{\text{tot}} / (X_{\text{tot}} * Y_{\text{tot}}),$$

162

163 where $\underline{Z}_{\text{tot}}$, X_{tot} and Y_{tot} are the totals of interaction occurrence, floral and pollinator
164 abundances respectively. This value corresponds to a network where all flowers and all

165 pollinators are represented by a single species each. For our illustrative example $k_{ref} = 0.0011$.
 166 Naturally, some values of k_{ij} are more and others are less than the obtained k_{ref} (those more
 167 than k_{ref} are in bold font, Table 1C).
 168
 169 The reference constant k_{ref} can be used as a metric of a network related to the connectance.
 170 Imagine a network and let us vary its connectance but keep k_{ref} on the same level. This is
 171 translated into the redistribution of interactions while their total frequency of occurrence
 172 remains the same; if the connectance level lowers, this would mean less species interacting
 173 but with increased frequency and *vice versa*. In a word, there is a sort of reciprocal
 174 complementarity between C and k_{ref} , and if we use both of these indices, we will know not
 175 only the species which interact, but also how strong (frequent) these interactions are as
 176 expressed by the affinity values.



177
 178 **Figure 1.** Affinities of pollinator-flower species pairs; The vertical axis shows standardised values of
 179 k_{ij} . The abundances are ranked in descending order, as indicated by the narrowing end of red
 180 (hummingbirds) and green (flowers) triangle arrows. The affinities are higher in the pairs made of less
 181 abundant “subordinate” species.

182
 183

184 **The real network**

185 The reanalysed matrix of the real network is furnished with species abundance data (Table
186 SI1) and thus allows for performing all the above procedures to construct an affinity matrix
187 with k_{ij} values for each flower-pollinator pair of species. Naturally, if no interaction is
188 detected for a species pair, the affinity becomes equal to 0. Altogether, non-zero affinities
189 were calculated for 123 species pairs. Then we calculated the value of k_{ref} for this matrix,
190 which appeared to be equal to 0.0001. Nineteen out of 123 pairs showed affinity values
191 below this reference level, while the maximum affinity was as high as 0.1050, which is over
192 1000 times higher than the values of k_{ref} . The affinity matrix can be shown as a corresponding
193 3D chart (Figure 1, the previous page), which reveals a trend that the highest affinities occur
194 mostly at low species abundances. In other words, at high abundance of flower and pollinator
195 species the affinity tends to be small, while at low affinities it tends to be large.

196

197 The observed trend is in line with findings of Simmons et al. (2019) that hummingbird
198 pollinators are generalised because they are abundant, but there was little evidence that
199 hummingbirds are abundant because they are generalised. However, this study used a null
200 model that assumed interaction neutrality (interaction probabilities defined by species relative
201 abundances). Adding affinity to this model would be an interesting development.

202

203 The concept of affinity introduced above can also complement to the studies on the
204 asymmetry of interactions in pollination networks. For example, Vázquez et al. (2007)
205 constructed a null model with species interactions occurring at random among individuals;
206 This model was used to test the hypothesis that the observed asymmetry is a result of the
207 unequal abundances of species. They found that asymmetry correlated with abundance, and
208 that rare species contributed more to the asymmetry than the abundant ones. They concluded
209 that abundance provides a sufficient explanation of the asymmetry structure in some
210 networks, but suggests the role of additional factors in others – this “additional factor” can be
211 the affinities between flowers and pollinators developed through coevolution.

212

213 **Discussion**

214 The presented model might be seen as a simplistic one, but I hope I have shown its potential
215 analytical power. Certainly, the model is certainly open for adjustments, improvements and
216 further sophistication. Importantly, the model can be used for individual species, small

217 subnetworks or large networks depending on the design of data collection: as long as the
218 densities or relative abundances of target species or taxonomic groups are reliably known, the
219 affinities can be calculated. In biochemistry and physiology, affinity refers to the strength of
220 the interaction between a protein (enzyme, receptor) and its binding ligand (substrate, ion,
221 transmitter, hormone, biologically active compound). In textbooks it is often explained as the
222 “attraction” or “fit” between the two molecules, and is attributed to complementarity or the
223 precise matching of the protein's active site and the ligand's shape, charge, and hydrophobic
224 or hydrophilic properties. Analogously, we can think of a complementarity between the
225 pollinator and flower morphologies, the ability of a pollinator to locate the desirable flower,
226 which might involve sophisticated behaviours and the use of memory (Kandori and Ohsaki
227 1996). The introduction of these details can enhance our understanding of pollinations
228 networks. In metabolism, the protein-ligand affinity is considered to be crucial since it
229 determines how effectively the metabolic reaction is catalysed or a regulatory act performed.
230 We can think in similar terms when analysing pollinator-flower interactions: affinity can
231 define the effectiveness of a pollinating interactions.

232

233 A high affinity both between molecules and organisms must be a result of long evolutionary
234 processes, and therefore the model presented above can facilitate an introduction of
235 phylogenetic history in pollination networks. By the same token, high affinity can be
236 indicative of specialised interactions among a few species and by this define the breadth of
237 ecological niche (Junker et al. 2013). The niche concept has been thought to be underutilised
238 in the analyses of pollination networks (Phillips et al. 2020). A new metrics based on affinity
239 might facilitate the integration of the concept in the theory of pollination networks.

240 Altogether, linking species abundance with interaction frequency has a potential to change
241 the angle we see the network properties. The suggested reference constant can be used jointly
242 with the connectance, and see it not as a binary distribution of “permitted” and “forbidden”
243 links in a network. Rather, we can talk about the continuum of the probabilities of concrete
244 interactions to occur in a three-dimensional continuum of species abundance, their interaction
245 frequencies and affinities of interacting species.

246

247 Knowing the affinity between concrete flower and pollinator species can be insightful in
248 important instants. For example, a high affinity can be indicative of a long coevolution
249 history of given species or groups, and thus help to introduce evolutionary history and

250 contribute to “phylogenetically informed network ecology *sensu* Peralta (2016). The
251 presented model can also help examine whether the affinity of a specialist species is high
252 towards its target, or whether a generalist species shows a moderate to low affinity to a wide
253 range of interacting species, or whether common pollinators become generalists because of
254 their abundance (*sensu* Simmons et al. 2016).

255

256 **Conclusions**

257 An introduction of species abundance data in pollination network analyses is possible with
258 simple models, provided all necessary data are given. The model introduced here, despite its
259 simplicity, can effectively connect species abundance distribution with the frequency of
260 interactions. At the same time, it helps calculate an affinity of a given flower to its pollinator.

261

262 Sampling separately and independently for plants, pollinators and their interactions certainly
263 necessitates a coordinated cooperation among botanists and zoologists. The increased efforts
264 to achieve this will pay off with the opening of new avenues for data analyses and ultimately
265 the better understanding of pollination network structure and functions.

266

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