

1 **Sensitivity of bipartite network analyses to incomplete sampling and taxonomic
2 uncertainty**

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18 **Open Research statement:** we provide permanent and open access links to data sources and
19 replication code in Appendix S1.

20 **Abstract**

21 Bipartite network analysis is a powerful tool to study the processes structuring interactions in
22 antagonistic ecological communities. In applying the method, we assume that the sampled
23 interactions provide an accurate representation of the actual community. However, acquiring
24 a representative sample may be difficult as not all species are equally abundant or easily
25 identifiable. Two potential sampling issues can compromise the conclusions of bipartite
26 network analyses: failure to capture the full range of interactions of species (sampling
27 completeness) and failure to identify species correctly (taxonomic resolution). These
28 sampling issues are likely to co-occur in community ecology studies. We asked how
29 commonly used descriptors (modularity, nestedness, connectance and specialisation (H_2')) of
30 bipartite communities are affected by reduced host sampling completeness, parasite
31 taxonomic resolution and their crossed effect. We used a quantitative niche model to generate
32 replicates of simulated weighted bipartite networks that resembled natural host-parasite
33 communities. The combination of both sampling issues had an additive effect on modularity
34 and nestedness. The descriptors were more sensitive to uncertainty in parasite taxonomic
35 resolution than to host sampling completeness. All descriptors in communities capturing less
36 than 70% of correct taxonomic resolution strongly differed from correctly identified
37 communities. When only 10% of parasite taxonomic resolution was retained, modularity and
38 specialisation decreased ~ 0.3 and ~ 0.1 -fold respectively, and nestedness and connectance
39 changed ~ 0.7 and ~ 3.2 -fold respectively. The loss of taxonomic resolution made the
40 confidence intervals of estimates wider. Reduced taxonomic resolution led to smaller size of
41 the communities, which emphasised the larger relative effect of taxonomic resolution on
42 smaller communities. With regards to host sampling completeness, connectance and
43 specialisation were robust, nestedness was reasonably robust (~ 0.2 -fold overestimation), and
44 modularity was sensitive (~ 0.5 -fold underestimation). Nonetheless, most of the communities

45 with low resolution for both sampling issues were structurally equivalent to correctly sampled
46 communities (i.e., more modular and less nested than random assemblages). Therefore,
47 modularity and nestedness were useful as categorical rather than quantitative descriptors of
48 communities affected by sampling issues. We recommend evaluating both sampling
49 completeness and taxonomic certainty when conducting bipartite network analyses. We also
50 advise to apply the most robust descriptors in circumstances of unavoidable sampling issues.

51 **Keywords**

52 Host-parasite interactions; bipartite networks; sampling issues; sampling completeness;
53 taxonomic resolution; additive effect

54 **Introduction**

55 Ecological and evolutionary processes occur in networks of interacting species. Species
56 interactions are diverse, numerous and often asymmetric due to the unequal dependence
57 between the interacting species (Dormann et al. 2017). These attributes make ecological
58 networks of interactions complex, hampering our ability to disentangle ecological and
59 evolutionary dynamics and to understand responses to changing environments. Despite the
60 complexity of ecological communities, bipartite network analysis has allowed researchers to
61 tackle fundamental research questions and give advice on biodiversity management (Delmas
62 et al. 2019).

63 Bipartite network analysis is based on the assessment of the distribution of
64 interactions between nodes of different guilds (Blüthgen 2010). For example, in host-parasite
65 bipartite networks, host and parasite species are nodes. Bipartite network analysis does not
66 consider interactions among nodes of the same type. For example, parasite-parasite or
67 host-host interactions are not analysed. Therefore, to make ecological communities tractable,
68 bipartite network analysis assumes that inter-guild interactions are more relevant for
69 ecological communities than intra-guild interactions (Poulin 2010). Bipartite interactions can
70 be weighted (as opposed to simple presence-absence of interactions) to capture a quantitative
71 description of the processes in the natural environment. For example, host-parasite
72 interactions can be weighted by the abundance of each parasite species in each host (Cardoso
73 et al. 2021).

74 The study of ecological networks not only relies on recording the species composition
75 but also on obtaining large enough samples to build a fair representation of the interactions in
76 communities (Henriksen et al. 2019). Representative samples of ecological communities can
77 be difficult to obtain due to community diversity (Chacoff et al. 2012), temporal and spatial
78 variation in community structure (Poisot et al. 2015), different level of population and

79 community fragmentation (Frankham et al. 2017) or differences in interaction patterns among
80 individuals of a given species (Guimarães Jr. 2020). Insufficient sampling of both species and
81 their interactions makes it difficult to tease apart biological processes from methodological
82 artifacts. Sampling issues may therefore influence the observed network properties and the
83 conclusions extracted from them (Vizentin-Bugoni et al. 2016).

84 It is assumed that a sample is a good representative of the actual community when
85 species richness, interaction richness or even network descriptors reach an asymptote
86 (Henriksen et al. 2019). However, acquiring an asymptotic sample of the interactions in a
87 community requires a higher sampling effort than estimating species richness because there
88 are more combinations of pairwise interactions than species (Henriksen et al. 2019). In
89 addition, common interactions of abundant species are detected with low effort, but high
90 sampling effort is required to record rare interactions of less abundant species (Chacoff et al.
91 2012, Henriksen et al. 2019).

92 Another confounding factor for bipartite network analysis is the reliability of species
93 identification (Thompson and Townsend 2000). Although, taxonomic accuracy and
94 community size usually represent a trade-off (Renaud et al. 2020), small networks may be
95 more affected by inappropriate identification of a species since it would represent a higher
96 proportion of taxa than in a large network. Taxonomic resolution can be variable both within
97 and between communities, which complicates comparative studies. Often, some nodes are
98 identified as species, whereas other nodes aggregate coarser taxonomic categories or entities
99 within a community (e.g., detritus) or include hidden diversity (e.g., cryptic species)
100 (Thompson and Townsend 2000). Furthermore, loss of taxonomic resolution was found to
101 have a higher impact on the predicted structure of antagonistic insect-plant networks than on
102 their mutualistic counterparts due to the closer dependence of the consumers on their
103 resources in the former type (Rodrigues and Boscolo 2020). Opposite to low taxonomic

104 resolution is species over-splitting, that is identifying individuals of the same species as
105 different species due to phenotypic or other differences (Isaac et al. 2004).

106 Finally, these sampling issues occur independently and may coincide in the same
107 dataset. For instance, an ecological dataset may present poor sampling completeness
108 regardless of the taxonomic resolution of the few sampled taxa. Then, researchers must strive
109 to control all potential sampling issues at the same time to ensure a correct representation of
110 an ecosystem. Even though sampling issues are known to affect bipartite network descriptors
111 (Rivera-Hutinel et al. 2012, Rodrigues and Boscolo 2020) and may simultaneously affect the
112 same survey, we do not yet know how the combined effect of sampling issues can mislead
113 the interpretation of the structure of ecological communities. We will address this issue by
114 focussing on host-parasite bipartite networks. However, since sampling issues can occur in
115 any community study, our approach is not restricted to host-parasite interactions and can be
116 applied to any bipartite symbiotic interactions.

117 Parasitic life-history strategies are spread across the whole tree of life. Parasites are
118 present in all ecosystems and dominate diversity in terms of richness and abundance of
119 species, and biomass (Carlson et al. 2020). This astonishing diversity makes host-parasite
120 associations one of the most common types of interactions in ecological communities
121 (Lafferty et al. 2006). Bipartite network analysis has been a key method for research in
122 evolutionary ecology of host-parasite interactions over the last decades (Runghen et al. 2021),
123 including epidemiological and public health issues (Bellekom et al. 2021).

124 Host individuals are typically the sampling units in ecological and evolutionary
125 parasitology. Commonly, data from host individuals of the same species are pooled together
126 to obtain the parasite community of each host species (Morand and Krasnov 2008). As more
127 host individuals are sampled in a community, the probability of finding an unrecorded
128 parasite species or a new host-parasite interaction reduces, and parasite species richness or

129 number of species interactions approaches an asymptote (Henriksen et al. 2019). At the same
130 time, studies listing parasite species are often characterised by poor taxonomic resolution at
131 least for certain taxa. Such inaccurate assessments of parasite diversity seriously hamper our
132 ability to understand host-parasite dynamics (Poulin and Leung 2010) since it decreases the
133 variability in the interaction pattern of different species (Delmas et al. 2019).

134 Our goal was to understand how decreasing gradients of host sampling completeness,
135 parasite taxonomic resolution and their crossed effect affect four commonly-used descriptors
136 of host-parasite communities: modularity, nestedness, connectance and specialisation (H_2')
137 (Table 1). We generated replicates of a simulated host-parasite community, which are not
138 usual in empirical datasets. We resampled the replicate simulated communities controlling for
139 both sampling issues. First, we gradually removed host-parasite interactions to infer the effect
140 of decreasing host sampling completeness on the four descriptors. Second, we evaluated how
141 the four descriptors were influenced by decreasing resolution of parasite taxonomy. To do so,
142 we gradually reduced the number of parasite species in the communities by hierarchically
143 lumping their interactions according to their overlap in host use, which resembles closely
144 related cryptic species that have ecologically similar requirements. Finally, we evaluated the
145 crossed effect of both sampling issues as they are likely to occur simultaneously.

146 We hypothesised that the descriptors would be more robust to host sampling
147 completeness than to parasite taxonomic resolution, at least in communities that are not
148 severely affected by sampling issues (Hypothesis 1). Host individuals of the same species
149 commonly sustain similar parasite communities and, in this sense, represent biological
150 replicates of the same system (Llopis-Belenguer et al. 2020). Therefore, when decreasing
151 host sampling completeness, the overall infection pattern of the community is maintained
152 until the sample size reaches a threshold below which no inference is supported. On the
153 contrary, we expected the reduction in parasite taxonomic resolution to have a greater impact

154 on the community descriptors. Commonly, parasite species are not redundant in their host
155 ranges. Specialisation in their host limits the ability of parasite species to infect many host
156 species (i.e., environmental filtering) (Llopis-Belenguer et al. 2020). Therefore, the detection
157 of the infection patterns would be more sensitive to taxonomic resolution following the loss
158 of inter-species variability. In addition, we expected the combined effect of both sampling
159 issues to cause a greater bias in the descriptors than either of the simulated sampling biases in
160 isolation (Hypothesis 2). Finally, we also hypothesised that the four network descriptors
161 would differ in sensitivity (Hypothesis 3). Based on the results of previous studies on
162 ecological systems outside the host-parasite realm (Blüthgen et al. 2006, Vizentin-Bugoni et
163 al. 2016), redundant interactions would make the descriptors considerably robust against
164 reduced sampling completeness. With regard to taxonomic resolution (Thompson and
165 Townsend 2000, Rodrigues and Boscolo 2020), modularity, nestedness and specialisation
166 would be reasonably robust to loss of taxonomic resolution. However, communities in the
167 gradient of parasite taxonomic resolution varied in size. Connectance expresses the
168 proportion of realised interactions out of all possible interactions (Table 1). A realised
169 interaction represents a higher proportion in a small network than in a larger network. For the
170 same number of interactions, communities with low parasite taxonomic resolution (small
171 networks) would present higher connectance than communities with correct taxonomic
172 resolution (large networks). Then, we expected connectance to be sensitive to parasite
173 taxonomic resolution.

174

175 **Material and Methods**

176 *Building simulated communities*

177 Our main dataset consists of 10 replicate simulated networks (hereafter, “full communities”)
178 that were constructed using host-parasite community parameters extracted from published

179 host-parasite community data ($n = 6$, “natural communities”) (Fig. 1a, Appendix S1). To
180 build the full communities, we used a quantitative niche model (see below) that was initiated
181 with the mean number of host and parasite species ($n_{host} = 13$; $n_{para} = 42$) of the six natural
182 communities. The mean number of interactions per parasite species in the full communities
183 ($maxobs.rf = 2,067$) was the mean overall number of interactions in the six natural
184 communities ($n_i = 86,794$) divided by n_{para} . In other words, these 10 replicate full
185 communities represent a generalisation of different natural host-parasite communities with
186 respect to their number of species and their number of interactions (Fig. 1a). We performed
187 all the analyses in R (R Core Team 2021). If not specified otherwise, the functions mentioned
188 below are available in bipartite package (Dormann 2011). Replication code and data are
189 provided in Llopis-Belenguer et al. (to be published in Zenodo after acceptance).

190 We used the quantitative niche model described in Fründ et al. (2016) to create the
191 full communities (Fig. 1b). The model generates weighted bipartite networks reflecting a
192 chosen specialisation parameter (Fründ et al. 2016). First, the model creates a matrix of
193 interaction probabilities based on quantitative trait values of each host and parasite species
194 (Fig. 1b: 1. Matrix of interaction probabilities). Equal trait values of a host and a parasite
195 represent a realised interaction. Non-equal trait values receive an interaction probability
196 depending on the specialisation parameter (Fründ et al. 2016), which defines the shape
197 (width) of the gaussian niche function. In our case, we assigned trait values to host and
198 parasite species from an exponential power distribution, since the expected distribution of
199 key traits (e.g., body mass) for interaction establishment is usually skewed (Poulin and
200 Morand 1997, Kozłowski and Gawelczyk 2002). We used the highest specialisation
201 parameter used in Fründ et al. (2016) ($specpar = 55$) (Appendix S2) because specialisation is
202 the general trend in metazoan host-parasite interactions (Poulin 2007). We implemented this
203 procedure with the function *makeweb* (Fründ et al. 2016). Second, we multiplied the

204 interaction probability matrices by species abundance-distribution vectors with the function
205 *make_trueweb* (Fründ et al. 2016) (Fig. 1b: 2. Abundance-distribution adjusted matrix of
206 interaction probabilities). This step adjusts the interaction probability matrix according to the
207 relative abundance of each species (Fründ et al. 2016), i.e. it considers that it is more likely to
208 record interactions between two abundant species than between two rare ones. We assumed
209 an even abundance distribution of the host species. This corresponds to sampling procedures
210 where an effort is made to capture the same number of individuals of each host species
211 (Poulin 1998). We distributed the abundance of parasite species from a log-normal
212 distribution with mean 5.89 and SD 1.45 both in the log-scale, which are similar to the mean
213 and SD of parasite species in the natural host-parasite communities, with the function
214 *get_skewedabuns* (Fründ et al. 2016). Therefore, only the abundance distribution of parasite
215 species affected the interaction probability in our simulation. As the last step, we weighted
216 the full communities with parasite abundances according to the given interaction probability
217 matrix with the function *sampleweb* (Fründ et al. 2016) (Fig. 1b: 3. Full communities). We
218 assumed a mean number of interactions per parasite species equal to maxobs.rf.

219

220 *Simulating sampling completeness and taxonomic resolution biases*

221 We resampled the full communities with a reduced effort to simulate communities along
222 decreasing gradients of host sampling completeness, parasite taxonomic resolution and their
223 crossed effect (hereafter, “resampled communities”) (Fig. 1c). Each full community was
224 resampled in 10% steps from 90% to 10% of host sampling completeness and parasite
225 taxonomic resolution, thus simulating a situation where researchers do not have a-priori
226 knowledge of the true size and taxonomic structure of the communities they are sampling.

227 To simulate the decreasing gradient of host sampling completeness, we used data on
228 parasite abundance in 3,258 fish host individuals from 51 locations and of 41 species ($63.9 \pm$

229 71.4 fish individuals per species) (Appendix S1). Only one of these datasets belongs to the
230 six natural communities we used to derive the full communities (Valtonen et al. 2001). Fish
231 individuals of each fish species and location formed an independent dataset. We resampled
232 host individuals of each independent dataset by reducing the sample size in 10% steps
233 starting from 90% and ending with 10% of the original host individuals. Then, we quantified
234 the mean percentage of interactions per parasite species remaining in all datasets (

235 Table 2a). We applied these resampled percentages to the mean number of
236 interactions per parasite species (`maxobs.rf` = 2,067) to fill the existing matrix of interaction
237 probabilities in each of the 10-replicate full communities. Thus, we simulated the effect of a
238 decreasing number of sampled host individuals by reducing the mean number of interactions
239 per parasite species in the full communities (

240 Table 2a). We derived 90 resampled communities to examine the effect of host
241 sampling completeness.

242 To simulate the effect of incomplete parasite taxonomic resolution, we calculated
243 pairwise Jaccard similarities between all parasite species based on their host-range overlap
244 (Martinez 1991). These pairwise distance estimates were used to distribute the species to a
245 number of groups according to the decreasing gradient of parasite taxonomic resolution (

246 Table 2b). Similar parasite species in the Jaccard calculation were assigned to the
247 same group. We implemented the “around medoids” clustering, which is a more robust
248 version of “k-means” clustering, to distribute parasites into groups. This was performed with
249 the function *clara* in cluster package (Maechler et al. 2021). For example, in the simulation of
250 “50%” of parasite taxonomic resolution, we asked the function to assign parasite species to
251 21 groups, which represents 50% of the original number of parasite species in the full
252 communities (npara). Consequently, we clustered parasite species based on the similarity of
253 their host range, which resembles the taxonomic resolution issues common in the
254 parasitological data given that closely related species may share hosts.

255 Table 2b shows the number of groups for each decreasing resolution class. Note that
256 the overall number of interactions (ni) was kept unchanged by this regrouping of parasite
257 species to fewer groups. For each replicate full community, we ran a new clustering
258 algorithm using the same target number of groups (

259 Table 2b). We obtained 90 resampled communities to examine the effect of parasite
260 taxonomic resolution.

261 Finally, we simulated the crossed effect of host sampling completeness and parasite
262 taxonomic resolution. A gradient of parasite taxonomic resolution (as described above) was
263 created for each resampled community used to examine host sampling completeness. This
264 produced 810 additional resampled communities, which were biased for both sampling issues
265 to varying degrees.

266

267 *Community and species level descriptors*

268 We assessed four weighted community level descriptors for each of the 1,000 full and
269 resampled communities: modularity, nestedness, connectance and specialisation (H_2) (Table
270 1). Specifically, we used the Becket algorithm (Beckett 2016) to calculate modularity in our
271 communities with the function *computeModules*. The function *networklevel* was used to
272 measure the weighted versions of the algorithms: NODF (Nestedness metric based on
273 Overlap and Decreasing Fill, Almeida-Neto & Ulrich, 2011), connectance (Tylianakis et al.
274 2007) and H_2 (Blüthgen et al. 2006). We standardised modularity and nestedness of each web
275 since raw values of these descriptors are not directly comparable. To do this, we created
276 1,000 null communities for each of the 1,000 full and resampled communities with the
277 function *vaznull* (Vázquez et al. 2007). This algorithm creates null host-parasite communities
278 by randomising the total number of host-parasite interactions observed in the full
279 communities. Thus it constrains connectance but not the marginal totals (Vázquez et al.
280 2007). We then calculated the mean value and the standard deviation of modularity and
281 nestedness of each set of 1,000 null communities. Finally, we standardised modularity and
282 nestedness of each full and resampled community following the equation of the Standardised
283 Effect Size (SES) (Gotelli and Rohde 2002) (Equation 1):

$$SES = \frac{\text{value of a full or replicate community} - \text{mean of its 1,000 null communities}}{\text{SD of its 1,000 null communities}}$$

284 Finally, to assess the effect of each sampling issue and their crossed effect on the community
285 descriptors, four two-way ANOVAs were used with host sampling completeness and parasite
286 taxonomic resolution as fixed factors. If the two fixed factors are significant, a significant
287 interaction term indicates a synergistic effect of both sampling issues, otherwise additive
288 (Ferguson and Stiling 1996).

289 We used t-tests to establish whether network descriptors of the simulated full
290 communities differed significantly from those of natural communities. Additionally, we
291 aimed to know whether the full communities reproduced the pattern of interactions of the
292 natural communities at the species level. For each full and natural community, we computed
293 Rao alpha diversity of the parasite communities of each host species, and two species-level
294 network descriptors of centrality for both host and parasite species: weighted betweenness
295 and weighted closeness (Table 1). Rao alpha diversity, which accounts for the richness and
296 abundance of species (Pavoine et al. 2004), was calculated with the function *dpcoa* in *ade4*
297 package (Thioulouse et al. 2018). To make alpha diversity comparable across host species,
298 we transformed alpha diversity results into their equivalent numbers (E_{alpha}) following
299 Equation 2 (Ricotta and Szeidl 2009):

$$E_{\text{alpha}} = \frac{1}{1 - \text{Rao alpha diversity}}$$

300 We used a linear regression of E_{alpha} on the communities followed by ANOVA to test
301 differences in E_{alpha} between the full and natural communities. Finally, the function
302 *specieslevel* was used to compute the two descriptors of centrality, betweenness and
303 closeness (Table 1). Both are based on the Dijkstra's algorithm to find the shortest path in
304 networks of interactions (Newman 2001). We ran the analyses of betweenness and closeness
305 for host and parasite species independently. We excluded those species that were not linked

306 to any other species in the community since no centrality measure could be calculated. To
307 compare these descriptors across communities independently of their sizes, we first regressed
308 each descriptor on their community size. We used the residuals of these regressions as the
309 dependent variables in linear models as a function of the type of study (natural vs simulated)
310 followed by ANOVA to test the differences between full and natural communities (Morris et
311 al. 2014).

312

313 **Results**

314 Community and species level descriptors of the full communities did not significantly differ
315 from descriptors of the natural communities, except for closeness (Table 3).

316 Standardised modularity and nestedness showed opposite patterns with respect to host
317 sampling completeness (Fig. 2a and Fig. 2b, darkest purple points and lines). While
318 modularity decreased with decreasing host sampling completeness (~0.5-fold), nestedness
319 increased (~0.2-fold). Estimates of modularity in simulations capturing 70% or less of host
320 sampling completeness strongly differed from those values of the full communities (Fig. 2a,
321 error bars do not overlap). Estimates of nestedness in simulations from 40% of host sampling
322 completeness and below strongly differed from estimates of the full communities (Fig. 2b,
323 error bars do not overlap). In contrast, weighted connectance and H_2' were robust to host
324 sampling completeness since resampled communities showed little evidence of difference
325 from estimates for full communities (Fig. 1c-d, Table 4).

326 The four indices were affected by parasite taxonomic resolution (Table 4, Fig. 2,
327 100% of host sampling completeness). Standardised modularity increased up to 50% of
328 parasite taxonomic resolution in resampled communities, followed by a decline in lower
329 percentages of parasite taxonomic resolution. Estimates of modularity given 70% of parasite
330 taxonomic resolution and below differed from modularity calculated for the full communities

331 (~0.3 underestimation, Fig. 2a, error bars do not overlap). Both nestedness and connectance
332 increased ~0.7 and ~3.2-fold, respectively, as parasite taxonomic resolution decreased.
333 Nestedness estimates at 60% of parasite taxonomic resolution and below differed from
334 nestedness of the full communities (Fig. 2b, error bars do not overlap). We found moderate to
335 strong differences between connectance of the full communities and connectance of the
336 resampled communities at 80% of parasite taxonomic resolution or less (Fig 2c, error bars do
337 not overlap). H_2 decreased with parasite taxonomic resolution. We found moderate (~0.1-
338 fold underestimation) differences between H_2 of full communities and resampled
339 communities with 50% or less of parasite taxonomic resolution (Fig. 2d, error bars do not
340 overlap).

341 The crossed effect of host sampling completeness and parasite taxonomic resolution
342 was additive for both sampling issues for modularity and nestedness, as both effects were
343 significant and no evidence of an interaction was found (Fig. 2, Table 4). Additionally,
344 parasite taxonomic resolution had higher influence on network metrics than host sampling
345 completeness. The standard error of the mean tended to increase with sampling bias, showing
346 proportionally higher variation for connectance than for the other three indices (Fig. 2, Table
347 4).

348 Finally, all full and resampled communities were significantly modular. Only in a few
349 severely resampled communities (10% parasite taxonomic resolution capturing less than 50%
350 host sampling completeness) nestedness did not differ from nestedness of 1,000 random
351 assemblages (results not shown). These cases represented Type II errors.

352

353 **Discussion**

354 Sampling completeness (representative sample of a community) and taxonomic resolution
355 (accuracy of species assignment) are common sources of uncertainty and bias in community

356 ecology and influence the interpretation of bipartite interactions (Chacoff et al. 2012,
357 Rodrigues and Boscolo 2020). In accordance with our Hypothesis 1, we found that
358 community descriptors are more sensitive to parasite taxonomic resolution than to host
359 sampling completeness. The combination of both sampling issues also resulted in an additive
360 effect for modularity and nestedness (Hypothesis 2, Table 4). Additionally, the descriptors
361 differed in their sensitivity to both sampling issues. This partially concurs with our
362 Hypothesis 3 since modularity was not as robust as in previous studies. Acknowledging that
363 these sampling issues are inevitable to some extent, studies should: (i) avoid applying
364 bipartite network analyses to communities with a low resolution of species identification or
365 low sampling effort; (ii) use the most robust measures to evaluate community structure in
366 communities severely affected by sampling issues (only connectance and H_2' were robust to
367 severely under-sampled communities); (iii) pay attention to the conclusions relying on more
368 sensitive metrics (all descriptors were sensitive to taxonomic resolution); and (iv) compare
369 interaction patterns over time and space in communities with comparable and adequate
370 sampling efforts. This is especially true for taxonomic resolution since all descriptors were
371 sensitive to it.

372 Antagonistic communities are often highly modular (Runghen et al. 2021), most
373 likely due to parasite specialisation on its host resource (Krasnov et al. 2012). We found that
374 modularity was sensitive to both reduction in host sampling completeness and parasite
375 taxonomic resolution. Lower sampling effort left less frequent interactions undetected and
376 eventually decreased resolution in module uniqueness. These results are contrary to those
377 reported in mutualistic communities, in which modularity was found to be a robust descriptor
378 (Rivera-Hutinel et al. 2012, Vizentin-Bugoni et al. 2016). Moreover, an increase in
379 modularity was observed in mutualistic communities with the lowest sampling effort due to
380 increased module identity through removal of between-module interactions (Rivera-Hutinel

381 et al. 2012, Vizentin-Bugoni et al. 2016). A decrease in modularity due to low taxonomic
382 resolution has been found in other plant-insect mutualistic and antagonistic systems
383 (Rodrigues and Boscolo 2020, Renaud et al. 2020). In our study, we found that modularity
384 tended to increase up to a point after which it rapidly decreased in the case of parasite
385 taxonomic resolution, also evident for the crossed effect.

386 Dallas and Cornelius (2015) found a similar result in their host-parasite co-extinction
387 analyses using in-silico experiments in which they sequentially removed host species first
388 based on species extinction risks and then randomly. These communities with decreasing
389 gradient of host species varied in size and number of interactions, as did our resampled
390 communities which were affected by the crossed effect of both sampling issues. They found
391 that modularity increased up to a critical point and then decreased with both extinction-risk
392 and random removal of host species. However, connectance was robust to random removals
393 but increased with extinction-risk removals in their experiment. Because of the differences
394 between modularity and connectance, they suggested that the behaviour of modularity could
395 be due to either a statistical artifact or that it is a property of complex networks (Dallas &
396 Cornelius, 2015). Here, we suggest that the pattern of initial increase in modularity followed
397 by a decrease may be explained by the way species resolution is lost. Resampled
398 communities from 90% to 60% of parasite taxonomic resolution grouped parasite species
399 with a high overlap in host use. As a result, within-module interactions were strengthened,
400 and modularity increased in these communities. On the other hand, in resampled communities
401 with 20-10% of parasite taxonomic resolution, even parasite species with a low overlap in
402 host use were grouped together. That made host species that actually differ in their parasite
403 communities members of the same module. However, these host species were additionally
404 connected to other modules where the rest of their parasite species were placed. Hence, the
405 loss of parasite taxonomic resolution decreased modularity and made between-module

406 interactions more frequent.

407 In accordance with our results, nestedness has been shown to be reasonably robust to
408 low sampling completeness in both mutualistic (Nielsen and Bascompte 2007, Vizentin-
409 Bugoni et al. 2016, Fründ et al. 2016) and antagonistic communities (Henriksen et al. 2019).
410 However, as with modularity, previous studies have shown opposite patterns. In earlier
411 studies, nestedness was high in communities with high sampling completeness, and decreased
412 when sampling completeness was lost (Nielsen and Bascompte 2007, Vizentin-Bugoni et al.
413 2016, Fründ et al. 2016, Henriksen et al. 2019). Interactions in many ecological communities
414 are truly nested (Staniczenko et al. 2013). When such a nested community is under-sampled,
415 one can expect a weaker signature of the nested pattern, or decreasing nestedness with
416 decreasing sampling completeness (Nielsen and Bascompte 2007, Vizentin-Bugoni et al.
417 2016). However, host-parasite communities are different from other ecological communities
418 and typically show low values of nestedness (Runghen et al. 2021), possibly resulting from
419 coevolution leading to trade-offs in parasite transmission (McQuaid and Britton 2013). The
420 full communities had low values of nestedness (Fig. 2b, negative values or less nested than
421 random assemblages). Hence, low sampling actually opposed the true low nested pattern of
422 antagonistic communities and resulted in increasing nestedness. Moreover, nestedness was
423 not robust since it quickly increased as parasite taxonomic resolution was lost. Along the
424 gradient of taxonomic resolution, parasite species with some shared hosts were grouped.
425 These species appeared as a single generalist parasite species able to infect not only the
426 shared hosts of their foundational parasite species, but also the non-shared hosts. At the same
427 time, specialist parasites remained as separate entities because they were not grouped with
428 any other species. Then, host spectrum of specialist parasites was a subset of the host species
429 used by generalist parasites, or in other words, the network structure became more nested.

430 Connectance and specialisation (H_2') were robust to decreasing host sampling

431 completeness, but not to parasite taxonomic resolution. These descriptors showed opposite
432 patterns, as expected by definition (Table 1). Our results were consistent with previous
433 studies reporting robustness of these metrics to the loss of interactions (Nielsen and
434 Bascompte 2007, Vizentin-Bugoni et al. 2016, Fründ et al. 2016, Henriksen et al. 2019), but
435 not to the loss of species, or the loss of both species and interactions (Dallas and Cornelius
436 2015, Fründ et al. 2016, Henriksen et al. 2019, Rodrigues and Boscolo 2020, Renaud et al.
437 2020). The strong dependence of connectance on network size hinders the interpretation of
438 many biological processes (Blüthgen et al. 2006). This pattern was evident along our crossed-
439 effect gradient, where decreasing parasite taxonomic resolution increased the relative
440 contribution of the interactions. H_2' was developed as an alternative index of specialisation to
441 overcome the scale dependence issue of connectance (Blüthgen et al. 2006). We found that
442 H_2' was sensitive to the loss of parasite taxonomic resolution. However, H_2' was only
443 overestimated ~0.2-fold in the resampled communities with the lowest efforts (10% host
444 sampling completeness \times 10% parasite taxonomic resolution), against ~3-fold in the case of
445 connectance.

446 We observed that the loss of parasite taxonomic resolution made the descriptor
447 confidence intervals wider. Communities in the gradient of parasite taxonomic resolution
448 vary in size. Large and small communities are known to be biased to different degrees
449 (Shvydka et al. 2018, Henriksen et al. 2019). The full communities represented the largest
450 communities, whereas resampled communities in the lower end of the gradient of parasite
451 taxonomic resolution represented the smallest communities (

452 Table 2b). The later aggregated most of the parasite species with similar infection
453 patterns, losing redundant interactions. Typically, large communities show higher overlap in
454 interaction patterns compared to small communities, where redundancy is low (Henriksen et
455 al. 2019). Therefore, sampling issues are expected to have a limited impact on the network
456 structure of large communities because, if a species is not recorded, the actual infection
457 patterns are nevertheless recorded in redundant interactions. However, inclusion or exclusion
458 of species or interactions produces a greater change among the interaction patterns of small
459 communities. Therefore, the redundancy-size relationship could explain the increasing
460 variance observed in the resampled communities along the parasite taxonomic resolution
461 gradient (Fig. 2, error bars). Nonetheless, severely biased resampled communities were
462 structurally equivalent to full communities (Type II error results) and still useful to
463 categorically describe the structure of ecological communities (e.g., if a community is
464 modular or not), but not the quantitative values of the descriptors (Vanbergen et al. 2017).

465 The combination of both sampling issues produced an additive effect to modularity
466 and nestedness. Therefore, when both sampling issues coincide in a sampled dataset, this is
467 similarly affected by both sampling issues simultaneously than by the sum of the effects of
468 both sampling issues in isolation. This entails that both sampling issues can be controlled
469 independently. For example, the use of predictive models potentially overcomes the
470 limitation of incomplete interaction richness. These models identify where interactions are
471 most likely to have been missed in a sampled community and eventually include them in the
472 dataset to improve the study of ecological networks (Terry and Lewis 2020). Despite
473 producing greater biases in community descriptors, solutions to taxonomic limitations may
474 not be straightforward. For example, it may require collaborations between ecologists and
475 taxonomists (Poulin and Presswell 2022).

476 The full communities resembled community and species level descriptors of the

477 natural communities, except for closeness. Earlier studies have evaluated species centrality
478 descriptors, such as closeness, of both parasites (Poulin et al. 2013) and hosts (Dallas et al.,
479 2019). Taxonomic identification at family level was one of the main factors explaining
480 centrality of parasite and host species, suggesting that phylogeny could help in predicting
481 centrality of each species according to their taxonomic affiliation (Poulin et al. 2013). We did
482 not account for the phylogenetic structure of the guilds in the full communities. Instead, each
483 interaction acquired a probability according to the specialisation we represented in the model,
484 but independently of the phylogenetic distance among the members of each guild. The
485 consideration of the phylogenetic structure of parasites and hosts in our model could improve
486 our representation of host-parasite communities and predictions. For example, if parasites
487 infected a range of phylogenetically close hosts, modularity would even be higher because of
488 homogenisation of module composition. Nonetheless, we consider our approach
489 representative of natural communities as most of the community and species level descriptors
490 were effectively captured in the full communities.

491 Our research shows that studies of communities with low sampling effort and
492 taxonomic resolution may result in wrong conclusions. The implementation of the latest
493 methodological advances in open access software facilitates the use of network analysis in
494 parasitology (Runghen et al. 2021). The increasing availability of host-parasite interaction
495 datasets also favours the comparison or aggregation of communities to address
496 macroecological questions (Doherty et al. 2021). Furthermore, data for some host-parasite
497 communities is already 100 years old. These represent unique case studies to evaluate long-
498 term dynamics and trends at ecosystem level (Carlson et al. 2020) owing to the role of
499 parasites as connectors of all the species they infect throughout their life cycles (Lafferty et
500 al. 2006). However, if communities in such comparative studies notably differ in, or do not
501 include sufficient completeness and species resolution, the conclusions extracted from the

502 network analyses of such data will be of limited use, if not defective.

503

504 **Author Contributions**

505 CLB and JJ conceived the ideas; JAB, IBC and VS collected some of the natural
506 communities; AK complied one of the datasets; CLB designed methodology, arranged and
507 analysed data; CLB led the writing of the manuscript. All authors contributed to the drafts
508 and gave final approval for publication.

509

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659

660 **Tables**

661 Table 1. Effect of sampling issues on community and species level descriptors.

Weighted descriptors	Definition	Host sampling completeness	Parasite taxonomic resolution	Crossed effect
Standardised Modularity	Network level descriptor. Pattern in which host-parasite communities are organised in subsets of species that interact more frequently among themselves than with other members of the community (Beckett 2016). Higher values indicate higher modularity.	Decreases as host sampling completeness decreases.	Increases up to 50% of parasite taxonomic resolution. Then, it drastically decreases as parasite taxonomic resolution decreases.	Overall decreasing tendency. Additive effect of both sampling biases.
Standardised Nestedness	Network level descriptor. Pattern in which less rich parasite assemblages are subsets of richer parasite assemblages (Almeida-Neto and Ulrich 2011). Higher values indicate higher nestedness.	Increases as host sampling completeness decreases.	Increases as parasite taxonomic resolution decreases.	Overall increasing tendency. Additive effect of both sampling biases.
Connectance [0,1]	Network level descriptor. Relationship between linkage density and number of species (Tylianakis et al. 2007). Values closer to 1 indicate higher connectance.	Robust along the decreasing gradient of host sampling completeness.	Increases as parasite taxonomic resolution decreases.	No evidence of a crossed effect.
H_2 [0,1]	Network level descriptor of specialisation (Blüthgen et al.	Reasonably robust along the	Decreasing tendency along	No evidence of a crossed effect.

	2006). Higher values of H_2 indicate higher specialisation.	decreasing gradient of host sampling completeness.	the decreasing gradient of parasite taxonomic resolution.	
Betweenness	Species level descriptor. Extent to which a species funnels the interactions among all other species in the community. Values >0 represent a species connecting groups of species that would be sparsely or not connected at all, otherwise (Newman 2001, Martín González et al. 2010)			
Closeness	Species level descriptor. Average distance of a species to all other species in the community. Higher values indicate species closer to all the other species (Newman 2001, Poulin et al. 2013).			
Rao alpha diversity	Host species level descriptor. Diversity of the parasite community of each host species in terms of richness and abundance of parasite species (Pavoine et al. 2004)			

663 Table 2. Decreasing gradients of (a) host sampling completeness and (b) parasite taxonomic
664 resolution.

	Full communities	Resampled communities									
(a) Host sampling completeness											
% of remaining host individuals	100	90	80	70	60	50	40	30	20	10	
% of remaining interactions	100	85.1	78.5	69.3	57.2	50.5	36.8	27.7	17.9	8.2	
Mean number interactions per parasite species	2067	1759	1622	1433	1182	1043	761	574	371	170	
(b) Parasite taxonomic resolution											
% of parasite species	100	90	80	70	60	50	40	30	20	10	
Remaining number of parasite species	42	37	33	29	25	21	16	12	8	4	

665

666 Table 3. Comparisons of the weighted descriptors between the full and natural communities.

667 M: standardised modularity. N: standardised nestedness. C: connectance. H₂': specialisation.

668 B: betweenness. Cl: closeness. p: parasites. h: hosts.

		Community level				Species level				
		M	N	C	H ₂ '	Bp	Bh	Clp	Clh	Rao alpha diversity
Full communities (n=10)	Minimum	54.32	-14.03	0.05	0.67	0	0	0.001	0.02	1.08
	Maximum	77.80	-10.59	0.07	0.84	0.46	0.46	0.13	0.22	7.9
	Mean	66.25	-11.90	0.05	0.76	0.02	0.08	0.02	0.09	3.22
	Standardised error	2.30	0.30	0.00	0.01	0.003	0.01	0.001	0.004	0.12
Natural communities (n=6)	Minimum	36.93	-13.39	0.04	0.44	0	0	10 ⁻⁵	0	1
	Maximum	150.21	-8.67	0.07	0.88	0.77	0.72	0.08	0.7	9.54
	Mean	74.76	-11.09	0.05	0.66	0.02	0.08	0.005	0.06	2.73
	Standardised error	17.47	0.71	0.00	0.06	0.005	0.02	6×10 ⁻⁴	0.01	0.19
t-test (community level) ANOVA (species level)										
	p-value	0.65	0.33	0.92	0.16	0.33	0.88	0.00	0.00	0.24

669

670 Table 4. Two-way ANOVA of host sampling completeness and parasite taxonomic resolution
671 for (a) standardised modularity, (b) standardised nestedness, (c) connectance and (d)
672 specialisation (H_2).

(a) Standardised modularity	df	SS	MS	F	p-value
Sampling Completeness	9	91709	10189.9	62.28	0.00
Taxonomic Resolution	9	64658	7184.3	43.91	0.00
Interaction	81	9020	111.4	0.68	1
Residuals	900	147257	163.6		
(b) Standardised nestedness	df	SS	MS	F	p-value
Sampling Completeness	9	353.9	39.32	37.75	0.00
Taxonomic Resolution	9	5610.3	623.36	598.41	0.00
Interaction	81	108.6	1.34	1.29	0.05
Residuals	900	937.5	1.04		
(c) Connectance	df	SS	MS	F	p-value
Sampling Completeness	9	0.00	0.00	0.57	0.82
Taxonomic Resolution	9	2.6	0.3	1942.05	0.00
Interaction	81	0.00	0.00	0.32	1
Residuals	900	0.13	0.00		
(d) H_2	df	SS	MS	F	p-value
Sampling Completeness	9	0.01	0.00	0.28	0.98
Taxonomic Resolution	9	1.85	0.21	66.47	0.00
Interaction	81	0.05	0.00	0.2	1
Residuals	900	2.78	0.00		

673

674 **Figures**

675 Figure 1. Analysis steps. a) Obtain mean parameters of the natural communities to fit the
676 model. b) Create host-parasite simulated communities (full communities). (1) Build a matrix
677 of interaction probabilities by trait matching and according to a specialisation parameter. (2)
678 Adjust the matrix of interactions probabilities by species abundance distributions. (3)
679 Distribute interactions through the abundance adjusted matrix of interaction probabilities
680 (Fründ et al. 2016). c) Simulate nine levels of sampling biases for host sampling
681 completeness and parasite taxonomic resolution, and their crossed effect. d) Assess and
682 compare network descriptors between (1) natural and full communities and (2) full and
683 resampled communities.

684 Figure 2. Effect of the decreasing gradient of host sampling completeness, parasite taxonomic
685 resolution and their crossed effect on host-parasite community descriptors.

686

687 **Supporting information.** Llopis-Belenguer, C., J. A. Balbuena, I. Blasco-Costa, A.
688 Karvonen, V. Sarabeev, J. Jokela. Sensitivity of bipartite network analyses to incomplete
689 sampling and taxonomic uncertainty.

690 **Appendix S1: Data sources**

691 • Full communities:

692 Replication code and data for these analyses is available in:

693 Llopis-Belenguer, C., J. A. Balbuena, I. Blasco-Costa, A. Karvonen, V. Sarabeev, J.
694 Jokela. Replication code and data for: Sensitivity of bipartite network analyses to incomplete
695 sampling and taxonomic uncertainty. *Zenodo*, DOI### (to be published in Zenodo after
696 acceptance)

697 • Natural communities (retrieved from <http://www.ecologia.ib.usp.br/iwdb/>):

698 Arai, H. P., and D. R. Mudry. 1983. Protozoan and Metazoan Parasites of Fishes from the
699 Headwaters of the Parsnip and McGregor Rivers, British Columbia: A Study of Possible
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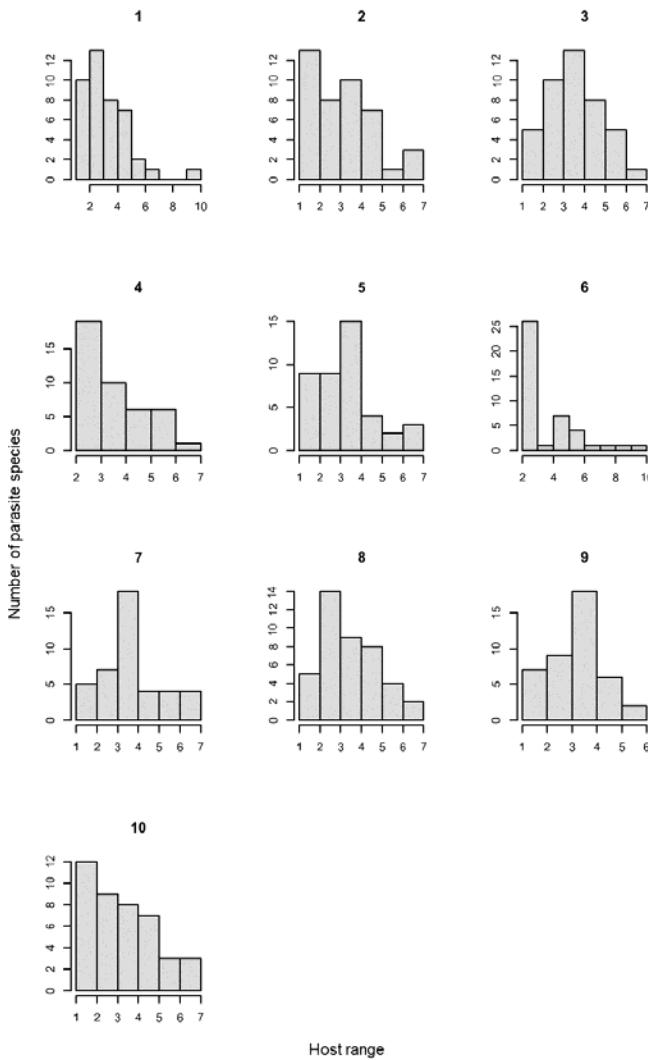
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709 • Natural communities and Host sampling completeness (data in Valtonen et al.
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711 Llopis-Belenguer, C. et al. Parasite communities of fishes from Northeastern Baltic Sea (data
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718 *Dataverse*, <https://doi.org/10.7910/DVN/RX3R2X>
719 Llopis-Belenguer, C. et al. Parasite communities of *Coregonus* spp. from Swiss and
720 Norwegian Lakes. *Zenodo*, DOI### (to be published in Zenodo after acceptance)

721 **Supporting information.** Llopis-Belenguer, C., J. A. Balbuena, I. Blasco-Costa, A.
722 Karvonen, V. Sarabeev, J. Jokela. Sensitivity of bipartite network analyses to incomplete
723 sampling and taxonomic uncertainty.

724 **Appendix S2: Fig. S1**



725

726 Fig. S1. Host range distribution of the parasite species in the 10-replicate full
727 communities. Bar plots show the number of parasite species that infect a given number of
728 host species. Almost all parasite species infect less than half of the host species (nhost=13)
729 due to the high specialisation parameter (specpar=55). The mean intensity of each parasite
730 species in a given host species was not considered in these plots, but presence-absence data.

a) Natural communities (n=6)

Mean parameters

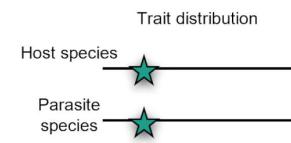
- N host species (nhost) = 13
- N parasite species (npara) = 42
- N interactions (ni) = 86794
- Mean n of interactions per parasite species (maxobs.rf) = 2067
- Parasite species abundance log-normal distribution: mean 5.89 and SD 1.45

b) Full (simulated) communities (n=10)

Parameters = Mean parameters of natural communities

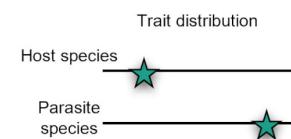
Distribution of interactions (Model in Fründ et al., 2016)

- Assign trait values to hosts and parasites from an exponential power distribution.



Trait values (★): Equal → interaction

Trait values (★): Non-EQUAL → interaction probability depends on the specialisation parameter, specpar = 55

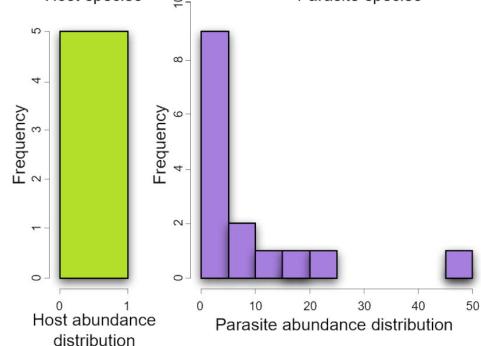


1

Matrix of interaction probabilities

- Represent equal abundance distribution of host species (i.e., all host species are sampled under the same effort).
- Represent parasite species abundance log-normal distribution.

Host species

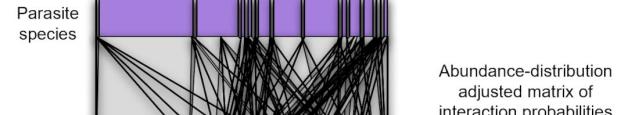


2

Matrix of interaction probabilities
×
Vectors of species abundance distribution
=

Abundance-distribution adjusted matrix of interaction probabilities

Parasite species



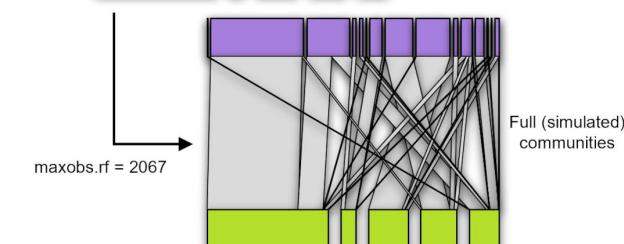
Abundance-distribution adjusted matrix of interaction probabilities

3

Distribute interactions through the abundance-distribution adjusted matrix of interaction probabilities
=

full communities

Host species



Full (simulated) communities

d) Descriptors

- Assess community level (modularity, nestedness, connectance and H_2) and species level (alpha diversity, betweenness and closeness) descriptors
- Compare natural and full communities
- Compare full and resampled communities

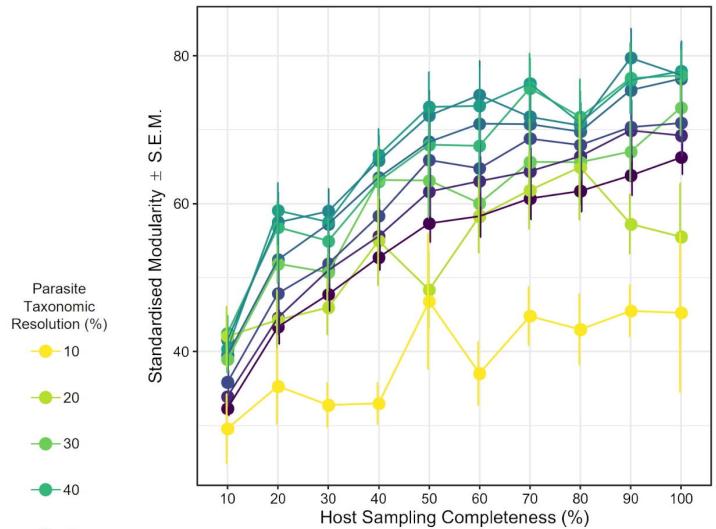
c) Resampled communities with reduced effort

Host sampling completeness (n=90)

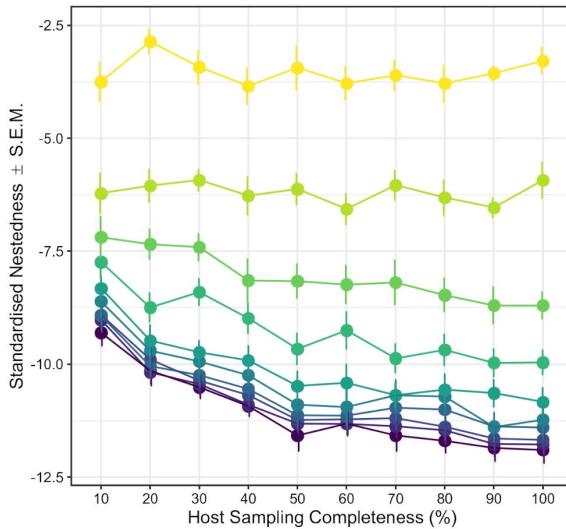
Parasite taxonomic resolution (n=90)

Crossed-effect (n=810)

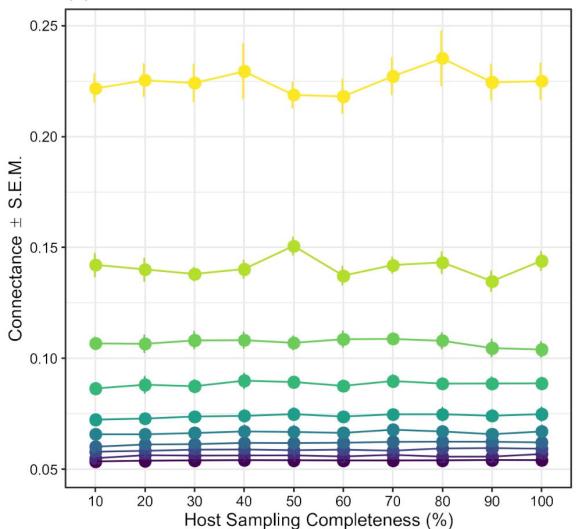
(a) Standardised Modularity



(b) Standardised Nestedness



(c) Connectance



(d) H_2^i

