

Scaling from Metawebs to Realised Webs: A Hierarchical Approach to Network Ecology

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Abstract: Ecological networks are increasingly used to understand biodiversity and predict ecosystem responses to environmental change, yet their application is often limited by uncertainty about the assumptions embedded in different network representations. Here, we present a theory-driven framework that views network construction as a hierarchical transition from metawebs, which represent the feasibility of interactions, to realised webs, which represent interactions expressed in specific spatiotemporal contexts. We identify five key processes underlying this transition: evolutionary compatibility and co-occurrence, which define interaction feasibility, and abundance, diet choice, and non-trophic interactions, which determine interaction realisation. We further position these processes along a continuum of network construction methods, from inductive approaches that infer structure from observations to deductive approaches that generate structure from mechanistic principles. By explicitly linking network representations to their underlying assumptions and scale-dependent processes, our framework clarifies the questions that different networks can address, highlights key challenges in moving between potential and realised interactions, and provides a roadmap for developing predictive network ecology. We argue that greater conceptual clarity is essential for advancing biodiversity science and for the effective application of networks in conservation, environmental management, and forecasting ecological change in the Anthropocene.

Keywords: food web, network construction, biodiversity, scale and process, interaction modelling, trophic network

1 Introduction

At the heart of modern biodiversity science are a set of concepts and theories about species richness, stability, and function, which have been discussed since the foundational work of [1], [2], and [3] and more recently [4]. These relate to the abundance, distribution, functions, and services that biodiversity provides. Network representations of interactions among organisms are increasingly argued to be an asset to understanding and predicting the impacts of multiple, simultaneous stress on biodiversity (*e.g.*, foundational studies on food web structure and robustness: [5–8]). Documenting interactions is thus one of the fundamental building blocks of community ecology and provides a powerful abstraction for mathematical and statistical modelling of biodiversity to make predictions, and to mitigate and manage threats [9].

However, there is a growing discourse around limitations to the interpretation and applied use of networks, which have been recognised since early discussions of sampling effort and aggregation in food webs ([5,10,11]; recent discussions: [12,13]). Against this, it is important to evaluate the value and the limitations of the various network conceptualisations and how these relate to biodiversity concepts, such as community structure or ecosystem function [14]. In this perspective we aim to provide an overview of different **food web** representations, particularly how each representation embeds assumptions about the processes that determine interactions (Section 3) about the levels of organisation at which this occurs (*i.e.* the biological, ecological, spatial/temporal scales) and the way in which we construct the resulting networks (Section 4).

Network construction reflects both the data used and the theories governing species interactions. We still lack a clear explanation of the different assumptions and scale dependent processes that underpin network construction alongside extensive discussions about the challenges relating to data collection and observation [6,10,14–20]. Such an understanding should deliver an acceleration in capacity to more effectively predict the impact of multiple stressors on biodiverse communities.

In their recent work, [21] synthesised ecological networks based on node resolution and link type, with a focus on the data and methodologies underlying each representation. Here, we take a complementary theory-driven perspective by framing network construction as a hierarchical transition from feasibility to realisation of interactions. In the following sections, we review how nodes, edges, and interaction processes shape different network representations, highlighting how changes in assumptions alter ecological scale, node and

34 link resolution, modelling approaches, and the relative importance of evolutionary versus
35 ecological processes. We conclude by aligning these representations with key questions in
36 biodiversity science in the Anthropocene.

37 **2 Setting the Scene: The Not So Basics of Nodes and** 38 **Edges**

39 Ecological networks serve multiple uses, representing an ‘object’ from which inferences can
40 be made. While many aspects of community structure can be analysed without networks
41 (*e.g.*, trait distributions or abundance patterns) networks provide a formal framework for
42 capturing the organisation among species. The study of network structure and topology has
43 a long history in ecology, rooted in early theory on energy flow [2,22], and later extended
44 to questions of robustness, stability, and complexity (*e.g.*, [7,20,23–25]). More recent work
45 has built on this foundation to link network structure to ecosystem functioning, persistence,
46 and dynamical behaviour (*e.g.*, [26–28]). Networks are therefore commonly treated as
47 response variables in tests of ecological theory and statistical models of the generative
48 processes that give rise to observed structure and are widely used to compare communities
49 across environmental gradients or through time [*e.g.*, 29,30]. They also provide a platform
50 for evaluating downstream responses to perturbations, including secondary extinctions and
51 robustness to species loss (*e.g.*, [7,31–33]), as well as inference about stability, ecosystem
52 function, invasions, climate change, contaminants, and extinction cascades (*e.g.*, [34–36]).
53 Against this backdrop of multiple research agendas, the definition of ‘edges’ and ‘nodes’,
54 and the levels of organisation at which they are defined, take many forms [17,37], each of
55 which encode a series of assumptions within a network. Here we introduce a perspective
56 on these baseline assumptions.

57 **2.1 How do we define a node?**

58 While nodes are conventionally described as representing species, in practice they may
59 correspond to a range of taxonomic and non-taxonomic units, including sub-species, genera,
60 or families, as well as trophic species (*e.g.*, [38,39]), feeding guilds (*e.g.*, [40]), or life-stage-
61 specific subsets of species (*e.g.*, [41]). These choices reflect differences in the level, type, and
62 consistency of resolution at which networks are constructed, rather than aggregation per se.
63 Representing nodes at coarser or mixed resolutions can limit taxon-specific inference (*e.g.*,
64 whether species *a* consumes species *b*), bias estimates of degree distributions (particularly

65 generality and vulnerability) and complicate downstream analyses such as extinction or
66 invasion dynamics, where species identity and the consequences of loss may be obscured
67 [41,42]. At the same time, there are clear justifications for using aggregated representations
68 when the distribution of interactions among functional or trophic units is more informative
69 than species-level detail, for example when analysing extinction patterns across feeding
70 guilds [43]. More broadly, issues of resolution, scale, and sampling have long been
71 recognised as central to the construction and interpretation of food webs (*e.g.*, [6,44]).

72 **2.2 What is captured by an edge?**

73 Understanding edges requires distinguishing between *potential* and *realised* links - potential
74 links reflect feasibility, whereas realised links reflect fluxes such as energy transfer. Links
75 within food webs are thus a representation of either potential links between species [45] or
76 fluxes within a system *e.g.*, energy transfer or material flow as the result of the feeding
77 links between species [2,46]. Edges can thus correspond to different ‘currencies’ [21].
78 There is also a myriad of ways in which the links themselves can be specified. Links
79 between species can be treated as present or absent (*i.e.*, binary), may be defined as
80 probabilities [47,48] or by continuous functions which further quantify the strength of
81 an interaction [49]. Link definition depends on both the ecological currency and how
82 interactions are represented. For example, feasibility is unlikely to accommodate flux, but
83 does align with binary or probability representations. Taking a food web that consists of
84 links representing feasible interactions among a collection of species will be meaningless if
85 one is interested in understanding the flow of energy through the network as the links are
86 not environmentally/energetically constrained.

87 **2.3 Network representations**

88 Given these definitions of nodes and edges, ecological networks can be divided into two
89 broad types: **metawebs**, which represent all *potential* interactions within a species pool
90 [44], and **realised networks**, which represent the subset of interactions expressed within
91 a particular community at a given place and time. These representations differ in both
92 the scales at which they are constructed and the processes assumed to generate their
93 structure.

94 A metaweb is fundamentally a list of *feasible* interactions between species. Feasibility
95 is determined by trait complementarity, typically related to feeding, and can be further

96 constrained by species co-occurrence, producing a transition from *global* to *regional*
97 metawebs. Metawebs therefore identify evolutionarily and regionally plausible interactions,
98 ecologically impossible (*i.e.*, forbidden) links [50], and the potential diet breadth of species
99 [51].

100 In contrast, realised networks are localised in space and time, with links shaped by co-
101 occurrence, environmental conditions, and diet choice. Even when represented as binary
102 matrices, their links implicitly reflect interaction strength and energy transfer. Realised
103 networks are therefore not simple spatial or temporal subsets of metawebs; they emerge
104 from the processes governing whether feasible interactions are expressed. Consequently,
105 a metaweb and realised network containing the same species may differ substantially in
106 structure because link presence is governed by different constraints. Links absent from a
107 metaweb represent infeasible interactions, whereas links absent from a realised network
108 reflect context-dependent ecological constraints.

109 A key distinction between these representations concerns what constitutes a realised
110 interaction. At its most general, a realised network requires more than the feasibility of
111 species interactions; it must incorporate the ecological context that determines whether
112 feasible interactions are expressed. This context may be represented through observation,
113 abundance-dependent encounter rates, consumer choice, environmental conditions, or
114 other mechanisms that constrain interaction expression. Consequently, realised networks
115 need not be observed directly, but they should reflect processes governing the distribution
116 or strength of interactions within a particular community. In contrast, metawebs represent
117 the space of feasible interactions irrespective of whether those interactions are expressed
118 locally.

119 **3 From Nodes and Edges to Process and Constraints**

120 In the previous section we discussed how the definition of nodes and edges, representing
121 different scales and processes, lead to the concept of a metaweb and a realised web. The
122 fundamental take-homes are that nodes vary in their resolution, edges vary in what kind
123 of process they represent and the intersection of these, defined by meta- vs. realised webs,
124 underpins distinct lines of inquiry and constraints on the type of inference we can make
125 with networks. Here we reveal five core constraints across evolutionary and ecological
126 scales that further delineate the transition from meta- to realised webs, exposing processes
127 that determine the nature of links among nodes: evolutionary compatibility, co-occurrence,

128 abundance, diet choice, and non-trophic interactions Figure 1.

129 [Figure 1 about here.]

130 **3.1 Processes that determine the feasibility of an interaction**

131 Evolutionary compatibility and co-occurrence are the two principal processes that defines
132 the feasibility of an interaction between two species. The scale of inference and set
133 of processes embodied in these two constraints typically combine to define a ‘list’ of
134 interactions that are viable/feasible and defined strictly as present/absent. Reflecting on
135 the previous section, nodes are typically species and rules defining edges are defined by
136 trait complementarity (phylogenetic) and/or co-occurrence. Here we provide more insight
137 into each process.

138 **Evolutionary compatibility**

139 This constraint is defined by shared (co)evolutionary history between consumers and
140 resources [52–55] which is manifested as ‘trait complementarity’ between two species [56].
141 In this body of theory, the consumer has the ‘correct’ set of traits that allow it to acquire
142 and consume the resource. Interactions that are not compatible are defined as forbidden
143 links [50]; *i.e.*, they are not physically possible and will *always* be absent within a network.
144 Networks do not properly arise from models based on this constraint. Instead, interacting
145 species pairs are defined and these are represented as binary (possible vs forbidden) or
146 probabilistic [47]. For example, in the metaweb constructed by [57] probabilities are
147 quantified as the confidence of a specific interaction being *possible* between two species. A
148 network constructed based on evolutionary compatibility is conceptually aligned with a
149 ‘global metaweb’, and gives us information as to the global feasibility of links between
150 species pairs despite the fact that they do not co-occur (see Figure 1).

151 **(Co)occurrence**

152 The co-occurrence of species in both time and space is a fundamental requirement for an
153 interaction between two species to occur (at least in terms of feeding links). Although
154 co-occurrence data alone is insufficient for building an accurate and ecologically meaningful
155 representation of *feeding links* [58], it is still a critical process that determines the possible
156 realisation of a feeding. Knowledge on the co-occurrence of species allows us to spatially
157 constrain a global metaweb to reflect regional metawebs [59]. In the context of Figure 1
158 this would be the metawebs for regions one and two.

159 We reinforce that these two constraints don't deliver a network *per se*, but a list of feasible
160 species pairs. Although it is possible to build a network from the list of interactions
161 generated by these constraints, it is important to be aware that the structure of this
162 network is not constrained by any community context - just because species are able to
163 interact does not mean that they will [60,61].

164 **3.2 Processes that realise networks**

165 In contrast to the above, here we highlight three processes that influence the *realisation* of
166 an interaction between species and thus form the conceptual basis for realised networks.
167 As we show in Figure 1, a 'truly realised' network is the product of properties of the
168 community (**abundance** and **non-trophic interactions**) and the individual (**diet**
169 **choice**). This represents a conceptual shift from considering the feasibility for species
170 pairwise interactions to considering the edge as a representation of energy flow. Such
171 a transition requires information about how the community, the environment and the
172 individual *constrains* network topology as defined by consumer choice ([62], Section 2.3)

173 **Abundance**

174 Abundance as a realising process emerges from a null model for energy acquisition:
175 organisms feeding randomly will consume resources in proportion to their abundance
176 [63]. Here, abundance of different prey species influences the distribution of links in a
177 network [64] by defining a preference linked to individuals among species meeting [47,60].
178 Abundance data (linked to a derived metaweb) delivers a foundation ruleset that can
179 define the distribution and strength of links. Of note, however, is that such abundance
180 constrained interactions are not necessarily contingent on there being any compatibility
181 between species [65–67].

182 **Diet choice**

183 It is well established that consumers make more active decisions than eating items in
184 proportion to their abundance [63]. Ultimately, consumer choice is underpinned by
185 an energetic cost-benefit framework centred around profitability and defined by traits
186 associated with acquisition and consumption of a resource [68,69]. Energetic constraints
187 are invoked to construct networks in a myriad of ways [*e.g.*, 42,70–72].

188 Unlike metaweb approaches, these models generate realised webs as emergent outcomes of
189 consumer behaviour. We also here make a distinction, developed below, with models like

190 the Niche Model [39], where diet choice is implicit in its probabilistic network generating
191 function, but it is working to replicate the *expected* structure of the network, and this
192 structure does not emerge from node-based rules. Note that we select diet choice as a term
193 to capture rules linked to optimal foraging [73] and metabolic theory [74] for capturing
194 the energetic constraints on the distribution and strength of interactions.

195 **Non-trophic interactions**

196 We include non-trophic interactions [see 75] here not as a determinant of links, but a
197 modifier of them - they are the community context above and beyond co-occurrence and
198 abundance. Non-trophic interactions include competition for space, predator interference,
199 refuge provisioning, recruitment facilitation as well as non-trophic effects that increase or
200 decrease mortality. These interactions specifically modify either the realisation or strength
201 of trophic interactions [28,31,76–78] and represent direct (*e.g.*, predator *a* outcompetes
202 predator *b*) and indirect (*e.g.*, mutualistic/facilitative interactions) mechanisms.

203 Some interactions, such as pollination, occupy an intermediate position in this framework,
204 as they combine trophic components (*e.g.*, resource consumption) with non-trophic effects
205 that influence reproduction, recruitment, and population persistence [79–81]. They operate
206 on the realisation of a network by altering the fine-scale distribution and abundance of
207 species and relative contributions of direct and indirect effects to biomass, persistence,
208 stability, and the functioning of the communities [75,82–84].

209 **4 Network construction**

210 The above five processes are central to understanding the assumptions inherent in building
211 different types of networks. Each of the processes, or combinations thereof, deliver a
212 unique set of boundary conditions on what a network represents and can be used for. Here
213 we build on the introduction of these five processes to further categorise the approaches to
214 constructing networks. The utility of a network depends on the processes used to construct
215 it. Different construction approaches encode different assumptions about how interactions
216 arise, and therefore support different ecological questions.

217 **4.1 Why construct networks?**

218 Networks are a representation of biodiversity. In a perfect world, we might know about
219 all interactions. However, the empirical collection of interaction data is both costly and

220 challenging to execute [50,85,86]. In the absence of robust empirical data, we use ‘models’
221 that facilitate interpolation and gap-filling of existing empirical datasets [*e.g.*, 87,88–90],
222 predict the feasibility of interaction among pairs of species, or directly predict network
223 structure [see 91 for a broader discussion].

224 Networks are unique in delivering more than just estimates of species richness. As noted
225 in the introduction, a network embodies the organising structure of biodiversity and allows
226 numerous opportunities for ‘downstream’ analysis, including the comparison of structures,
227 estimation of energy flux or extinction dynamics and ultimately form the structural
228 inputs to dynamical systems models that facilitate ecological and conservation relevant
229 inference about productivity-diversity-stability-function relationships [27] in space and
230 time. But making such inferences requires careful attention to one or more of the processes
231 discussed in Section 3. While these network representations may be simplifications of
232 the truth [92], they remain critically useful tools as they allow us to move beyond simple
233 descriptions of species richness to test hypotheses about community architecture and
234 ecosystem functioning that would be otherwise impossible to assess.

235 **4.2 Construction through induction**

236 Constructing feasible or realised networks can be framed as an ‘inductive reasoning’ process
237 where insight and generalisation arise from a set of observations and relationships around
238 feeding. Inductive reasoning as a foundation for network construction is implemented at
239 node and network levels.

240 **4.2.1 Species specific induction**

241 When applied at the node level, species-specific networks are created based on expected
242 feeding interactions. When applied at the network level, networks are judged by their
243 structural properties. All methods in this inference space rest on a set of three assumptions:
244 there are a set of ‘feeding rules’ that underpin interaction feasibility [93]; these rules are
245 phylogenetically conserved [54,94]; and they can be specified by matching the traits
246 between consumer and resource.

247 Evolutionary compatibility and co-occurrence constraints have been critical to the construc-
248 tion of ‘first draft’ networks for communities for which we have no interaction data [57].
249 They are also central to interpolation in data poor regions and predicting interactions for
250 ‘unobservable’ communities *e.g.*, prehistoric networks [43,95,96] or future, novel community

251 assemblages [97]. Furthermore, they have the capacity to evaluate a role of interactions
252 among species relative to their distribution by accounting for the role of the environment
253 and the role of species interactions [98–101].

254 Feeding rules can be specified in several ways. Expert-based approaches define feasible
255 interactions using trait matching [102,103], while mechanistic approaches often rely on trait-
256 based relationships between consumers and resources [104,105]. Alternatively, statistical
257 and machine-learning methods infer interaction probabilities from observed networks using
258 ecological predictors such as traits and phylogeny [106].

259 Rules are also defined by correlating real world interaction data with suitable ecological
260 proxies for which data is more widely available (*e.g.*, traits) using some sort of binary
261 classifier (see [106] for an overview). These include generalised linear models [*e.g.*, 107],
262 random forest [*e.g.*, 108], trait-based k-NN [*e.g.*, 109], and Bayesian models [*e.g.*, 110,111].

263 Finally, graph embedding uses the structural features of a known network to infer the
264 position of species in an unknown network through the decomposition of the interaction onto
265 the embedding space (see [51]). This decomposition relies on a combination of ecological
266 proxies (*e.g.*, phylogenetic relatedness [57]) in conjunction with known interactions to infer
267 the latent values of species, which can then be mapped onto decomposition of a known
268 network.

269 **4.2.2 Structure-based induction**

270 These models generate ecologically realistic network structures using simple probabilistic
271 rules. They are commonly used as null expectations, for comparative analyses, and as
272 inputs to dynamical models. The determination of links between species is not directly
273 linked to properties of the nodes. This means these networks are usually not species specific.
274 Although they require little empirical information, they encode explicit assumptions about
275 expected network structure.

276 Stochastic network models use a probabilistic ruleset about diet choice and niche breadth
277 to reflect fundamental ideas of foraging biology. These models that are based on the
278 compartmentalisation and acquisition of energy for species at different trophic levels
279 [112,113] and that network structure can be determined by distributing interactions along
280 single dimension (the ‘niche axis’; [114]). Typically, these models parametrise some aspect
281 of the network structure (although see [112] for a parameter-free model). These models
282 include the most used network generator, the Niche model [39], as well as the original

283 Cascade model [5] and the derived Nested hierarchy model [115]. Even though these
284 networks are derived without any real-world data they are still able to recover the structure
285 of empirical networks [116]. These models often form the basis for dynamic models *e.g.*,
286 the allometric trophic network [24,26] and bioenergetic food web models [34].

287 **4.3 Construction through deduction**

288 In contrast to metaweb construction, realised networks require assumptions about the
289 ecological processes that determine whether feasible interactions are expressed. These
290 approaches are deductive because interactions emerge from explicit assumptions about
291 encounters, foraging behaviour, energetic constraints, or interaction modification. These
292 approaches operationalise the abundance, diet-choice, and non-trophic processes introduced
293 in Section 3.1. The resulting networks are widely used to study energy flux, extinction
294 dynamics, and ecosystem functioning. They also provide the structural backbone for
295 dynamical systems modelling to address questions about stability-structure-productivity-
296 function relationships, secondary extinction dynamics, species invasion and climate change.
297 There are two broad groups of models in this deductive category.

298 These models capture the behaviour of the nodes by explicitly considering the properties
299 of the different species in the community. Which means that there is a degree of variance
300 in which links are predicted between species unlike the more ‘static’ predictions made by
301 inductive models. However, these networks are costly to construct in real world settings
302 (requiring data about the entire community, as it is the behaviour of the system that
303 determines the behaviour of the part) and also lack the larger diet niche context afforded
304 by metawebs.

305 **4.3.1 Abundance-based models**

306 Neutral networks are built on the assumption that foraging decisions are tied *only* to the
307 abundance of species within the community [117,118]. Here links are solely determined by
308 the relative abundance of the different species in the community. Although unrealistic as
309 a complete explanation, neutral models can be combined with inductive approaches to
310 generate more localised predictions [67].

311 **4.3.2 Energetics-constrained models**

312 There is a broader group of models that focus on determining interactions in terms of
313 energetic constraints on diet breadth, often using the ratio of consumer-resource body

314 size as a proxy for capturing the energetic constraints of feeding. Models such as those
315 developed by [71] and [68] are similar to the mechanistic approaches discussed in Section 4.2,
316 however instead of determining interactions based on mechanistic feasibility it is rather
317 constrained by the energetic cost of predation. Note that although these models do
318 not place any explicit constraints on the expected structure of the network, the links
319 should still be considered as ‘realised’ owing to the energetic constraint placed on links.
320 A different subset of diet models [*e.g.*, 42,119] use a diet choice approach, however like
321 the stochastic network models they also embed assumptions on network structure. Thus,
322 these models predict both interactions and network structure simultaneously, although
323 they would benefit in being refined by more explicitly accounting for trait-based (*i.e.*,
324 feasibility) parameterisation [35].

325 5 Making Progress with Networks

326 The motivation to leverage network ecology in conservation ecology, environmental risk
327 assessment and natural resource management stems from a shift away from species/popu-
328 lation specific measures of the effects of stress and disturbance to community level metrics
329 of these impacts. These metrics, such as resilience and more generally stability, ecosystem
330 function and biodiversity, are natural properties of networks. This suggests that modern
331 conservation, risk assessment and resource management requires robust network tools to
332 support decision making.

333 This is also true in the disciplines of ecology and environmental science and their focus
334 on abundance, distribution, functions and services that biodiversity provides [4]. Major
335 questions remain, for example, about stability-diversity-productivity relationships, the
336 impacts of extinctions and invasions, and the impacts of multiple stressors operating at
337 multiple ecological scales. A network approach to answering these types of questions
338 specifically allows us to evaluate how environmental gradients and anthropogenic stress
339 map through direct and indirect effects among species in a complex community and reveal
340 fundamental patterns and understanding of processes in the natural world.

341 To effectively use networks to aid us in answering questions about conservation/risk
342 assessment/management and core ecological theory, we need to be mindful that we are
343 mapping the *correct* network representation to the question of interest [21]. Notably, there
344 are certain questions that cannot be answered using specific network representations as
345 the scale of the question of interest is fundamentally misaligned with the process captured

346 by a specific network representation (Section 3.1), the underlying data that is used to
 347 construct it (Section 4), or both.

348 Here we discuss and map the different network representations shown in Figure 1 to
 349 ‘appropriate’ research questions and agendas (see also Table 1). We also highlight some of
 350 the key methodological challenges that currently limit our conceptualisation of a ‘network’
 351 and thus impact their effective practical application in real world settings.

Table 1: Showcasing some of the broader avenues of inquiry, specifically how they map to the different network representations. Additionally, we highlight some studies that address or present opening discussions around each research question. Superscripts at the research question indicate the strength of the current literature in addressing that research question: \checkmark indicates area with strong foundational research, Δ partial/emerging areas of research, and \times areas where research is weak/largely absent

Network		
Representation	Example Research Question	Representative Studies
Global Metaweb	How will novel communities respond to <i>e.g.</i> , extinction, turnover, invasion and rewilding \checkmark	[120]; [7]
	Diet-based conservation focusing not only on the target species but the species it might depend on for food resources Δ	[121]; [122]; [123]
	Rewiring capacity/potential of species by looking at the <i>entire</i> diets of species Δ	[124]; [31]; [125]; [126]
	Eco-Evolutionary dynamics and how they relate to the conservation and origination of feeding strategies \times	[60]; [127]
	Applied use potential of questions highlighted for global metawebs at the management scale <i>e.g.</i> , a protected area Δ	[101]; [128]; [129]

Network		
Representation	Example Research Question	Representative Studies
	Refinement/extension of species distribution models by incorporating co-occurrence and species associations <i>e.g.</i> , predator and prey ✓	[130]; [131]
Realised Webs	The allocation of multiple stressors across networks Δ	[132]; [133]
	Temperature threshold to community collapse Δ	[134]; [135]
	Extinction and persistence after harvesting/invasion/extinction ✓	[136]; [137]
	Stability-diversity-productivity-function ✓	[138]; [121]
	Explicitly tying ecosystem level processes and nutrient flows to networks \times	[139]
	Meta communities and the idea of meta-network-communities Δ	[140]; [141]

352 5.1 Key Eco-Evo-Conservation Questions

353 5.1.1 Global Metawebs

354 Global metawebs are most appropriate for questions centred on interaction feasibility
355 and potential diet breadth. They provide a platform for exploring hypothetical or novel
356 communities under climate change [142], species invasions, reintroductions, and rewilding,
357 and the potential rewiring capacity [126]. Because they focus on feasible rather than
358 realised interactions, global metawebs are also well suited to studying eco-evolutionary
359 dynamics and how evolutionary history, natural selection, and phenotypic plasticity shape
360 interaction niches.

361 **5.1.2 Regional Metawebs**

362 Regional metawebs extend these questions by explicitly incorporating species co-occurrence
363 and therefore provide a more management-relevant perspective. They can be used to
364 refine species distribution models and projections of future community composition [29,40].
365 However, caution is required when comparing regional metaweb structure across space
366 or environmental gradients, as observed differences may reflect species turnover (*e.g.*,
367 β -diversity) rather than changes in interaction processes.

368 **5.1.3 Realised networks**

369 Realised networks are best suited to questions concerning how community and environmen-
370 tal context shape interaction structure and ecosystem functioning [143]. They provide the
371 appropriate framework for studying stability, resilience, biodiversity dynamics, ecosystem
372 functioning, extinction cascades, invasions, climate change impacts, and network rewiring
373 through time. By capturing interactions that are actually occurring, realised networks
374 allow investigation of how perturbations propagate through communities and influence
375 persistence.

376 The increasing availability of long-term interaction datasets is expanding opportunities
377 to address these questions [27,144]. However, empirical datasets often accumulate in-
378 teractions across extended periods, potentially obscuring temporal variation in realised
379 interactions [10]. Developing approaches that better reconcile empirical networks with
380 realised community dynamics therefore remains an important challenge.

381 **5.2 Key methodological challenges**

382 As noted above, the three network types highlight longstanding methodological challenges
383 that limit both the precision and accuracy of ecological inference. Here we briefly review
384 these challenges and emerging opportunities to address them.

385 **Understanding what empirical data represents:** Robust inference requires under-
386 standing what constitutes an observed interaction, whether recorded directly (predation
387 events) or indirectly (*e.g.*, gut contents or stable isotopes). Because empirical networks
388 often accumulate observations across space and time, they may be conceptually closer to
389 metawebs than realised networks.

390 **The validation of network structure:** Considerable progress has been made in
391 assessing how well models recover pairwise interactions [91,145], yet there remains no clear

392 framework for evaluating their ability to recover network structure [114,146]. This raises
393 two related questions: what constitutes an appropriate benchmark, and which aspects of
394 network recovery matter most? For metawebs, accurately identifying both present and
395 forbidden links may be essential, whereas for realised webs it remains unclear whether
396 recovering pairwise interactions, aggregate properties (*e.g.*, connectance), or both should
397 be the primary objective.

398 **Transitioning between metawebs and realised webs:** Most approaches for modelling
399 realised networks do not explicitly incorporate evolutionary constraints (although see
400 [147]; [68]). Progress will likely require either ensemble approaches [148,149] or methods
401 for downscaling metawebs into realised networks [e.g., 150]. However, any such transition
402 must retain clarity about the meaning of links - structurally realistic networks do not
403 necessarily represent realised prey choice or energy flow.

404 Developing frameworks that allow transitioning between metawebs and realised rep-
405 resentations will also facilitate integration with metacommunity, metaecosystem, and
406 ecosystem-level theory [151,152]. Doing so requires clear definitions of what constitutes a
407 network and where its spatial and temporal boundaries lie [153].

408 **Making networks more tractable in applied spaces:** The application of networks
409 to conservation and management remains limited by difficulties in defining network
410 boundaries, aligning them with management units, and interpreting network metrics in
411 policy-relevant ways [154]. Addressing these challenges will require stronger links between
412 network structure and ecosystem function, alongside careful matching of analytical tools
413 and network representations to management objectives [128,155].

414 Taken together, these challenges highlight three overarching messages. (i) Network
415 representations are inseparable from the data and assumptions used to construct them;
416 (ii) validation and benchmarking must be aligned with the intended network type and
417 research question; and (iii) greater conceptual clarity is needed when transitioning between
418 metawebs and realised networks, particularly in applied contexts. Explicitly articulating
419 these distinctions is essential if networks are to be used rigorously and transparently across
420 scales.

6 Concluding Remarks

1. **Network representations encode different processes:** Different network representations capture distinct assumptions, data structures, and ecological processes; understanding the interplay between a network's structure and the processes it encodes is critical for determining which questions it can address.
2. **Network representations are not interchangeable:** There is no universally optimal network representation. The utility of a network depends entirely on how well its underlying assumptions and data align with the intended scale and process of analysis.
3. **Explicit assumptions are essential for evaluation:** Explicitly articulating the assumptions behind network assembly facilitates a more critical evaluation of network suitability and inferential power. It is important that we move beyond the uncritical and default reliance on conventional network representations in favour of understanding the consequences of selecting a specific representation or reconstruction/modelling approach.
4. **A unified framework improves application and progress:** The framework presented here provides a structured basis for comparing network representations and evaluating their suitability across conceptual, methodological, and applied contexts. Establishing this standard is essential for preventing the misinterpretation of network data and for addressing foundational questions in biodiversity science.

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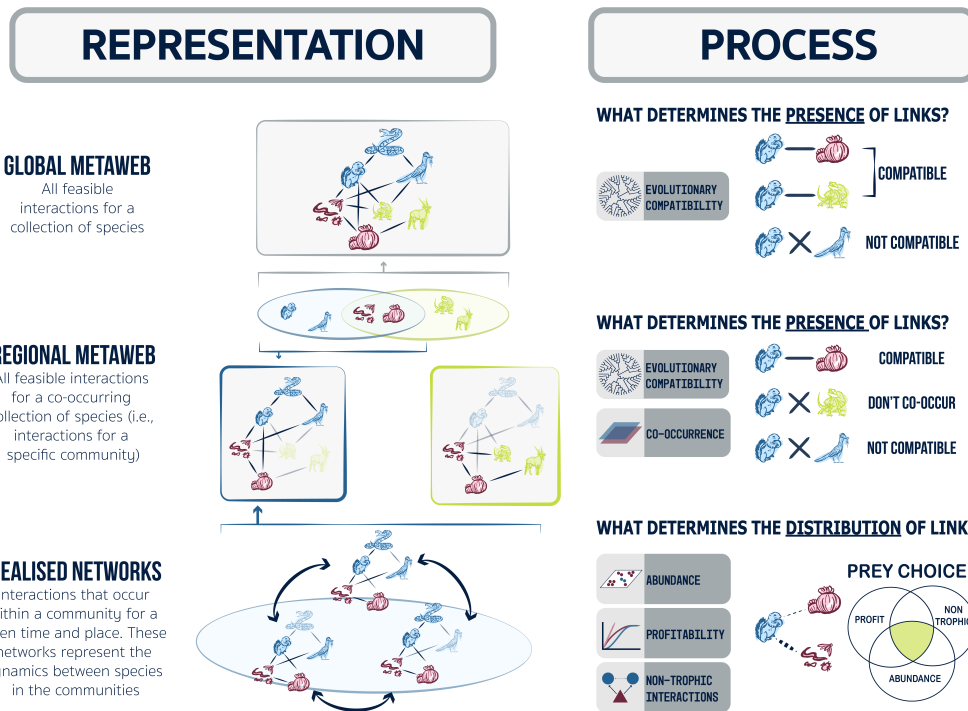


Figure 1: Aligning the processes that determine interactions (right) with different network representations (left). A **global metaweb** captures all feasible interactions among a species pool. Restricting this network by species co-occurrence yields **regional metawebs**, which differ in species composition. Species occurring in both regions are shown in red, whereas region-specific species are shown in blue and yellow. **Realised networks** represent subsets of regional metawebs expressed in specific spatial and temporal contexts. Their structure is shaped not only by co-occurrence, but also by community-level processes such as abundance, diet choice, and non-trophic interactions.