

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

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Abstract: Ecological networks provide a critical framework for understanding the architecture of biodiversity and predicting ecosystem responses to environmental change. However, the application of network ecology is often hindered by a lack of clarity regarding the assumptions inherent in different network representations. Here, we present a hierarchical framework that distinguishes between ‘metawebs’ (representing the fundamental feasibility of interactions) and ‘realised webs’ (representing interactions expressed in specific spatiotemporal contexts). We contrast our conceptual approach with recent data-centric reviews, focusing instead on the theoretical gradients that govern network construction. We identify five core processes that drive the transition from potential to realised interactions: evolutionary compatibility and co-occurrence, which define the feasibility of links; and abundance, diet choice, and non-trophic interactions, which determine their realisation. Furthermore, we map these processes onto a methodological spectrum of network construction, distinguishing between inductive approaches (*e.g.*, trait-matching and stochastic models) that infer structure from observation, and deductive approaches (*e.g.*, neutral and optimal foraging models) that generate structure from mechanistic first principles. By making explicit the assumptions and scale-dependent processes underpinning these different representations, this framework clarifies the scope of inference possible with each approach, ultimately facilitating more robust predictions of biodiversity dynamics in the anthropocene.

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

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¹ 1 Introduction

² At the heart of modern biodiversity science are a set of concepts and theories about species
³ richness, stability, and function, which have been discussed since the foundational work of
⁴ Elton (2001), Lindeman (1942), and MacArthur (1955) and more recently Loreau & de
⁵ Mazancourt (2013). These relate to the abundance, distribution, functions, and services
⁶ that biodiversity provides. Network representations of interactions among organisms are
⁷ increasingly argued to be an asset to understanding and predicting the impacts of multiple,
⁸ simultaneous stress on biodiversity (*e.g.*, foundational studies on food web structure and
⁹ robustness: Cohen et al. (1990); Martinez & Dunne (1998); Dunne et al. (2002); Simmons
¹⁰ et al. (2021)). Documenting interactions between and among taxa is thus one of the
¹¹ fundamental building blocks of community ecology and provides a powerful abstraction and
¹² platform for mathematical and statistical modelling of biodiversity to make predictions,
¹³ and to mitigate and manage threats (Windsor et al., 2023).

¹⁴ However, there is a growing discourse around limitations to the interpretation and applied

15 use of networks, which have been recognised since early discussions of sampling effort
16 and aggregation in food webs (Cohen et al. (1990); Polis (1991); Martinez (1991); recent
17 discussions: Dormann (2023); Blüthgen (2010)). Against this, it is important to evaluate
18 the value and the limitations of the various network conceptualisations and how these relate
19 to biodiversity concepts, such as community structure or ecosystem function (Blüthgen
20 & Staab, 2024). In this perspective we aim to provide an overview of different **food**
21 **web** representations, particularly how each representation embeds assumptions about the
22 processes that determine interactions (Section 3) about the levels of organization at which
23 this occurs (*i.e.* the biological, ecological, spatial/temporal scales) and the way in which
24 we construct the resulting networks (Section 4).

25 Fundamentally, we are talking about an intersection of the type of data used to construct
26 a network and the underlying theory as to what drives the resolution and occurrence of
27 interactions among species in those data. We still lack a clear explanation of the different
28 assumptions and scale dependent processes that underpin network construction alongside
29 extensive discussions about the challenges relating to data collection and observation
30 (Blüthgen & Staab, 2024; Brimacombe et al., 2023, 2024; Dunne, 2006; Martinez &
31 Dunne, 1998; Moulatlet et al., 2024; Pimm, 1984; Polis, 1991; Pringle & Hutchinson, 2020;
32 Saberski et al., 2024). Such an understanding should deliver an acceleration in capacity
33 to more effectively predict the impact of multiple stressors on biodiverse communities.

34 In their recent work, Gauzens et al. (2025) showcased a 2+2 decomposition of networks
35 around aggregated versus species level resolution of nodes and around potential and realised
36 links among the nodes. Their review delivers valuable insight into the methodologies used
37 to collect and manage data among the node and link differentiation. It also delivers an
38 overview of the scale and types of questions that are associated with each category of
39 differentiation.

40 Here we provide a complementary perspective focused on concepts, models, and theory,
41 in contrast to the data driven breakdown in Gauzens et al. (2025) (*e.g.*, their Tables 1
42 and 2). Our approach delivers a hierarchical perspective on network construction based
43 on a gradient from feasibility, capturing the concept of metawebs and Gauzen et al's
44 'potential' webs, through to realised webs as in Gauzens' et al. In contrast to their 2
45 + 2 decomposition (their Fig 1), our perspective showcases nested ecological scales and
46 processes that derive from shifts in the assumptions and theories embedded along this
47 gradient. This includes classic ecological 'aggregations' such as functional/phylogenetic

48 groups through to species, populations and individuals, unique perspective on how space
49 and time intersect with node and link resolution, refined insight into which networks are
50 derived by induction vs. deduction and a revealing of a core transition between assumptions
51 about how links are derived based on evolutionary vs. ecological theories.

52 In the following sections we provide a scene-setting review of nodes and edges (links) in
53 networks before aligning various processes that determine interactions with the different
54 network representations. Ultimately, we provide a unique perspective on the nested
55 hierarchy of processes that govern transitions from meta-webs to realised webs. We finish
56 with a refined and nuanced alignment of models/representations and key questions in
57 biodiversity science in the anthropocene.

58 **2 Setting the Scene: The Not So Basics of Nodes and 59 Edges**

60 Ecological networks serve multiple uses, representing an ‘object’ from which inferences
61 can be made. While many aspects of community structure can be analysed without
62 networks (*e.g.*, through trait distributions or abundance patterns) networks provide a
63 formal framework for capturing the organisation of interactions among species. The study
64 of network structure and topology has a long history in ecology, rooted in early theory on
65 energy flow (Lindeman, 1942; Odum, 1968), and later extended to questions of robustness,
66 stability, and complexity (Brose et al., 2006; Dunne et al., 2002; May, 1972; Montoya
67 et al., 2006; *e.g.*, Pimm, 1984). More recent work has built on this foundation to link
68 network structure to ecosystem functioning, persistence, and dynamical behaviour (Danet
69 et al., 2024; Pilosof et al., 2017; *e.g.*, Schneider et al., 2016). Networks are therefore
70 commonly treated as response variables in tests of ecological theory and statistical models
71 of the generative processes that give rise to observed structure, and are widely used to
72 compare communities across environmental gradients or through time (*e.g.*, Hao et al.,
73 2025; Pecuchet et al., 2020). They also provide a platform for evaluating downstream
74 responses to perturbations, including secondary extinctions and robustness to species loss
75 (*e.g.*, Dunne et al., 2002; Keyes et al., 2021, 2024; Staniczenko et al., 2010), as well as
76 for implementing dynamical process that inference about stability, ecosystem function,
77 invasions, climate change, contaminants, and extinction cascades (Curtsdotter et al., 2019;
78 *e.g.*, Delmas et al., 2017; Terry et al., 2025). Against this backdrop of multiple research
79 agendas, the definition of ‘edges’ and ‘nodes’, and the levels of organisation at which they

80 are defined, take many forms (Moulatlet et al., 2024; Poisot, Stouffer, et al., 2016), each of
81 which encode a series of assumptions within a network. Here we introduce a perspective
82 on these baseline assumptions.

83 **2.1 How do we define a node?**

84 While nodes are conventionally described as representing species, in practice they may
85 correspond to a range of taxonomic and non-taxonomic units, including sub-species,
86 genera, or families, as well as trophic species (*e.g.*, Yodzis (1982); Williams & Martinez
87 (2000)), feeding guilds (*e.g.*, García-Callejas et al., 2023), or life-stage-specific subsets of
88 species (*e.g.*, Clegg et al., 2018). These choices reflect differences in the level, type, and
89 consistency of resolution at which networks are constructed, rather than aggregation *per se*.
90 In many cases, aggregation is applied explicitly on top of more highly resolved—or unevenly
91 resolved—data to address particular questions, as in the construction of trophic species,
92 and the underlying data may remain available for alternative analyses. Nevertheless,
93 representing nodes at coarser or mixed resolutions can limit taxon-specific inference (*e.g.*,
94 whether species *a* consumes species *b*), bias estimates of degree distributions—particularly
95 generality and vulnerability—and complicate downstream analyses such as extinction or
96 invasion dynamics, where species identity and the consequences of loss may be obscured
97 (Beckerman et al., 2006; Clegg et al., 2018). At the same time, there are clear justifications
98 for using aggregated representations when the distribution of interactions among functional
99 or trophic units is more informative than species-level detail, for example when analysing
100 extinction patterns across feeding guilds (Dunhill et al., 2024). More broadly, issues of
101 resolution, scale, and sampling have long been recognised as central to the construction
102 and interpretation of food webs (Dunne, 2006; *e.g.*, Martinez & Dunne, 1998).

103 **2.2 What is captured by an edge?**

104 In order to break down the definitions of an edge, it is important to introduce the concept
105 of *potential* versus *realised* links: potential links reflect feasibility while realised links are
106 connected to flux of some currency (typically energy; see below for more detail). Links
107 within food webs are thus a representation of either potential links between species Pringle
108 (2020) or fluxes within a system *e.g.*, energy transfer or material flow as the result of
109 the feeding links between species (Lindeman, 1942; Proulx et al., 2005). Edges can thus
110 correspond to different ‘currencies’ (Gauzens et al., 2025). There are also a myriad of ways
111 in which the links themselves can be specified. Links between species can be treated as

112 present or absent (*i.e.*, binary), may be defined as probabilities (Banville et al., 2025; Poisot,
113 Cirtwill, et al., 2016) or by continuous functions which further quantify the strength of an
114 interaction (Berlow et al., 2004). How links are specified thus requires intersecting both
115 the currency being modelled and their specification. For example, feasibility is unlikely
116 to accommodate flux, but does align with binary or probability representations. Taking
117 a food web that consists of links representing feasible interactions among a collection of
118 species will be meaningless if one is interested in understanding the flow of energy through
119 the network as the links are not environmentally/energetically constrained.

120 2.3 Network representations

121 Against these definitions of nodes and edges, networks fall into two major ‘types’: metawebs,
122 traditionally defined as all the *potential* interactions for a specific species pool (Dunne,
123 2006); and realised networks, which is the subset of interactions in a metaweb that are
124 *realised* for a specific community at a given time and place. The fundamental differences
125 between these two network representations are the spatial and temporal scale at which
126 they are constructed, and the associated processes that are assumed to drive patterns at
127 these scales.

128 A metaweb is, at its core, a list of *feasible* interactions between pairs of species. The
129 feasibility for a given pair is derived from the complementarity of their traits, typically
130 aligned with feeding. Feasibility can be further refined by *co-occurrence* leading to
131 the transition from a *global* to *regional metaweb*. Metawebs thus provide a means to
132 identify evolutionary plausible links, regionally plausible interactions, the set of ecologically
133 impossible, *i.e.*, forbidden, links (Jordano, 2016b), and ultimately a definition of the
134 plausible *complete* diet of a species (Strydom et al., 2023).

135 In contrast, realised networks are typically localised in space and time, with links contingent
136 on species co-occurrence, environmental conditions, and mechanisms of diet choice. As a
137 result, the presence or absence of a link reflects species behaviour, such that even when
138 a realised network is represented as a binary matrix, each edge implies an underlying
139 function describing interaction strength. A realised network is therefore not a simple
140 downscaling of a metaweb based on finer spatial or temporal resolution. Rather than
141 being obtained by filtering feasible interactions through co-occurrence alone, realised webs
142 capture the processes that govern whether interactions are expressed and how energy
143 flows through a community. In this sense, the definition of an edge shifts from one of

144 feasibility to one of realised choice and consequence, centred on energy acquisition and
145 transfer. Consequently, a metaweb and a realised network constructed from the same set
146 of species may share node composition yet differ structurally, because they are constrained
147 by fundamentally different rules governing link presence. This distinction has important
148 implications for interpretation: links absent from a metaweb can be treated as truly absent
149 in terms of feasibility, whereas links absent from a realised network should instead be
150 interpreted as context-dependent absences arising from environmental, behavioural, or
151 community-level constraints.

152 **3 From Nodes and Edges to Process and Constraints**

153 In the previous section we discussed how the definition of nodes and edges, representing
154 different scales and processes, lead to the concept of a metaweb and a realised web. The
155 fundamental take-homes are that nodes vary in their resolution, edges vary in what kind
156 of process they represent and the intersection of these, defined by meta- vs. realised webs,
157 underpins distinct lines of inquiry and constraints on the type of inference we can make
158 with networks. Here we reveal five core constraints across evolutionary and ecological
159 scales that further delineate the transition from meta- to realised webs, exposing processes
160 that determine the nature of links among nodes: evolutionary compatibility, co-occurrence,
161 abundance, diet choice, and non-trophic interactions Figure 1.

162 [Figure 1 about here.]

163 **3.1 Processes that determine the feasibility of an interaction**

164 Evolutionary compatibility and co-occurrence are the two principal processes that ‘act’ at
165 the species pair of interest and define feasibility. The scale of inference and set of processes
166 embodied in these two constraints typically combine to define a ‘list’ of interactions that are
167 viable/feasible and defined strictly as present/absent. Reflecting on the previous section,
168 nodes are typically species and rules defining edges are defined by trait complementarity
169 (phylogenetic) and/or co-occurrence. Here we provide more insight into each process.

170 **Evolutionary compatibility**

171 This constraint is defined by shared (co)evolutionary history between consumers and
172 resources (Dalla Riva & Stouffer, 2016; Gómez et al., 2010; Rossberg et al., 2006; Segar et
173 al., 2020) which is manifested as ‘trait complementarity’ between two species (Benadi et

174 al., 2022). In this body of theory, the consumer has the ‘correct’ set of traits that allow it
175 to acquire and consume the resource. Interactions that are not compatible are defined as
176 forbidden links (Jordano, 2016b); *i.e.*, they are not physically possible and will *always* be
177 absent within a network.

178 Networks do not properly arise from models based on this constraint. Instead, interacting
179 species pairs are defined and these are represented as binary (possible vs forbidden)
180 or probabilistic (Banville et al., 2025). For example, in the metaweb constructed by
181 Strydom et al. (2022) probabilities are quantified as the confidence of a specific interaction
182 being *possible* between two species. A network constructed on the basis of evolutionary
183 compatibility is conceptually aligned with a ‘global metaweb’, and gives us information as
184 to the global feasibility of links between species pairs despite the fact that they do not
185 co-occur (see Figure 1).

186 (Co)occurrence

187 The co-occurrence of species in both time and space is a fundamental requirement for an
188 interaction between two species to occur (at least in terms of feeding links). Although
189 co-occurrence data alone is insufficient for building an accurate and ecologically meaningful
190 representation of *feeding links* (Blanchet et al., 2020), it is still a critical process that
191 determines the possible realisation of a feeding. Knowledge on the co-occurrence of species
192 allows us to spatially constrain a global metaweb to reflect regional metawebs (Dansereau,
193 Barros, et al., 2024). In the context of Figure 1 this would be the metawebs for regions
194 one and two.

195 We reinforce that these two constraints don’t deliver a network *per se*, but a list of feasible
196 species pairs. Although it is possible to build a network from the list of interactions
197 generated by these constraints, it is important to be aware that the structure of this
198 network is not constrained by any community context: just because species are able to
199 interact does not mean that they will (Caron et al., 2024; Poisot et al., 2015).

200 3.2 Processes that realise networks

201 In contrast to the above, here we highlight three processes that influence the *realisation* of
202 an interaction between species and thus form the conceptual basis for realised networks.
203 As we show in Figure 1, a ‘truly realised’ network is the product of properties of the
204 community (**abundance** and **non-trophic interactions**) and the individual (**diet**
205 **choice**). This represents a conceptual shift from considering the feasibility for species

206 pairwise interactions to considering the edge as a representation of energy flow. Such
207 a transition requires information about how the community, the environment and the
208 individual *constraints* network topology as defined by consumer choice (Quintero et al.
209 (2024), Section 2.3)

210 **Abundance**

211 Abundance as a realising process emerges from a null model for energy acquisition:
212 organisms feeding randomly will consume resources in proportion to their abundance
213 (Stephens & Krebs, 1986). Here, abundance of different prey species influences the
214 distribution of links in a network (Vázquez et al., 2009) by defining a preference linked to
215 individuals among species meeting (Banville et al., 2025; Poisot et al., 2015). Abundance
216 data (linked to a derived metaweb) delivers a foundation ruleset that can define the
217 distribution and strength of links. Of note, however, is that such abundance constrained
218 interactions are not necessarily contingent on there being any compatibility between
219 species (E. Canard et al., 2012; Momal et al., 2020; Pomeranz et al., 2019).

220 **Diet choice**

221 It is well established that consumers make more active decisions than eating items in
222 proportion to their abundance (Stephens & Krebs, 1986). Ultimately, consumer choice
223 is underpinned by an energetic cost-benefit framework centered around profitability and
224 defined by traits associated with acquisition and consumption of a resource (Smith et al.,
225 2021; Wootton et al., 2023). Energetic constraints are invoked to construct networks in
226 a myriad of ways (e.g., Beckerman et al., 2006; Cherif et al., 2024; Pawar et al., 2012;
227 Portalier et al., 2019).

228 In contrast to metaweb ‘construction’ from a list of pairwise interactions, these methods
229 deliver a realised web directly and as an emergent property of node behaviour. We also
230 here make a distinction, developed below, with models like the Niche Model (Williams
231 & Martinez, 2000), where diet choice is implicit in its probabilistic network generating
232 function, but it is working to replicate the *expected* structure of the network, and this
233 structure does not emerge from node-based rules. Note that we select diet choice as a term
234 to capture rules linked to optimal foraging (Pyke, 1984) and metabolic theory (Brown et
235 al., 2004); it is a sensible ‘umbrella concept’ for capturing the energetic constraint on of
236 the distribution and strength of interactions.

237 **Non-trophic interactions**

238 We include non-trophic interactions (see Miele et al., 2019) here not as a determinant
239 of links, but a modifier of them - they are the community context above and beyond
240 co-occurrence and abundance. Non-trophic interactions include competition for space,
241 predator interference, refuge provisioning, recruitment facilitation as well as non-trophic
242 effects that increase or decrease mortality. These interactions specifically modify either
243 the realisation or strength of trophic interactions (Golubski & Abrams, 2011; Ings et al.,
244 2009; Kamaru et al., 2024; Pilosof et al., 2017; Staniczenko et al., 2010) and represent
245 direct (e.g., predator *a* outcompetes predator *b*) and indirect (e.g., mutualistic/facilitative
246 interactions) mechanisms.

247 Some interactions, such as pollination, occupy an intermediate position in this framework,
248 as they combine trophic components (e.g. resource consumption) with non-trophic effects
249 that influence reproduction, recruitment, and population persistence (Bascompte &
250 Jordano, 2007; Holland et al., 2002; Sauve et al., 2016). They operate on the realisation
251 of a network by altering the fine-scale distribution and abundance of species and relative
252 contributions of direct and indirect effects to biomass, persistence, stability and the
253 functioning of the communities (Buche et al., 2024; Kéfi et al., 2012, 2015; Miele et al.,
254 2019).

255 4 Network construction

256 The above five processes are central to understanding the assumptions inherent in building
257 different types of networks. Each of the processes, or combinations thereof, deliver a
258 unique set of boundary conditions on what a network represents and can be used for. Here
259 we build on the introduction of these five processes to further categorise the approaches to
260 constructing networks. In doing so also introduce more detail on a variety of methodologies
261 used to construct networks.

262 4.1 Why construct networks?

263 Networks are a representation of biodiversity. In a perfect world, we might know about
264 all interactions. However, the empirical collection of interaction data is both costly and
265 challenging to execute (Jordano, 2016a, 2016b; Poisot et al., 2021). In the absence of
266 robust empirical data, we construct models that facilitate interpolation and gap-filling of
267 existing empirical datasets (e.g., Biton et al., 2024; Dallas et al., 2017; Poisot et al., 2023;
268 Stock et al., 2017), predict the feasibility of interaction among pairs of species, or directly

269 predict network structure (see Strydom et al., 2021 for a broader discussion).

270 They are unique in delivering more than just estimates of species richness. As noted in
271 the introduction, a network embodies the organising structure of biodiversity and allows
272 numerous opportunities for ‘downstream’ analysis, including the comparison of structures,
273 estimation of energy flux or extinction dynamics and ultimately form the structural inputs
274 to dynamical systems models that facilitate ecological and conservation relevant inference
275 about productivity-diversity-stability-function relationships (Danet et al., 2024) in space
276 and time. But making such inferences requires careful attention to one or more of the
277 processes discussed in Section 3.

278 4.2 Construction through induction

279 Constructing feasible or realised networks can be framed as an ‘inductive reasoning’
280 process where insight and generalisation arises from a set of observations and relationships.
281 Inductive reasoning as a foundation for network construction is implemented at node
282 and network levels. When applied at the node level, species-specific networks are created
283 and judged by their association with expected feeding interactions. When applied at the
284 network level, networks are judged by their structural properties.

285 4.2.1 Species specific networks: construction through node level induction

286 Constructing feasible networks and facilitating the interpolation or gap-filling of existing
287 empirical datasets on sets of species interactions can be framed as an ‘inductive reasoning’
288 process where insight and generalisation arises from a set of observations and relationships
289 about feeding. All methods in this inference space rest on a set of three assumptions:
290 there are a set of ‘feeding rules’ that underpin interaction feasibility (Morales-Castilla et
291 al., 2015); these rules are phylogenetically conserved (Bramon Mora et al., 2018; Dalla
292 Riva & Stouffer, 2016); and they can be specified by matching the traits between consumer
293 and resource.

294 Evolutionary compatibility and co-occurrence constraints have been critical to the con-
295 struction of ‘first draft’ networks for communities for which we have no interaction data
296 (Strydom et al., 2022). They are also central to interpolation in data poor regions and
297 predicting interactions for ‘unobservable’ communities *e.g.*, prehistoric networks (Dunhill
298 et al., 2024; Fricke et al., 2022; Yeakel et al., 2014) or future, novel community assemblages
299 (Van der Putten et al., 2010). Furthermore, they have the capacity to evaluate a role of

300 interactions among species relative to their distribution by accounting for the role of the
301 environment and the role of species interactions (Albouy et al., 2014; Gravel et al., 2019;
302 Higino et al., 2023; Pollock et al., 2014). There are substantial data requirements for
303 these approaches including expert knowledge, species traits and phylogenetic relationships
304 and/or interaction data on related species or communities.

305 Feeding rules are defined in multiple ways. The determination of the feeding rules can be
306 defined *a priori* based on expert knowledge opinions. Typically this is done on a ‘trait
307 matching’ basis. An example are the paleo food web models of Shaw et al. (2024) and
308 Roopnarine (2017) that specify a series of rules for a set of traits and interactions deemed
309 feasible if all conditions are met. Alternatively the body size ratio between the consumer
310 and resource is often used (e.g., Gravel et al., 2013; Rohr et al., 2010), with the idea that
311 consumers will only utilise a resource with a body size is less than or equal to their own
312 (Brose et al., 2019; Yodzis & Innes, 1992), although it is broadly acknowledged that many
313 herbivores (such as insects) violate these assumptions (Valdovinos et al., 2023). However,
314 work from Van De Walle et al. (2023) seems to suggest that adding morphological traits
315 in addition to body size ratio improves model performance.

316 Rules are also defined by correlating real world interaction data with suitable ecological
317 proxies for which data is more widely available (e.g., traits) using some sort of binary
318 classifier (see Pichler et al. (2020) for an overview). These include generalised linear
319 models (e.g., Caron et al., 2022), random forest (e.g., Llewelyn et al., 2023), trait-based
320 k-NN (e.g., Desjardins-Proulx et al., 2017), and Bayesian models (Cirtwill et al., 2019;
321 e.g., Eklöf et al., 2013).

322 Finally, graph embedding uses the structural features of a known network to infer the
323 position of species in an unknown network through the decomposition of the interaction
324 onto the embedding space. This decomposition relies on a combination of ecological proxies
325 (e.g., traits) in conjunction with known interactions to infer the latent values of species,
326 which can then be mapped onto decomposition of a known network. See Strydom et al.
327 (2023) for a detailed review of methods and Strydom et al. (2022) for a specific example.

328 4.2.2 Species agnostic networks: construction through structure induction

329 Networks in this category are generated using rules that create non-random networks
330 that reflect some minimal empirical knowledge of ecological networks. These can be
331 used in a variety of ways, for example comparing the structure of realised networks to

332 quantify relative deviations from the model structure. They are also used as a way to
333 generate ‘realistic’ food web structures that are used for dynamical or other analyses.
334 The determination of links between species is only implicitly linked to properties of the
335 nodes. This means these networks are usually not species specific. Although these models
336 are data input light, often requiring only species richness and an estimate of the number
337 of expected links, they make clear assumptions regarding what the expectations are for
338 network structure. These are some of the most commonly used network generation tools
339 (e.g., the Niche model; Williams & Martinez (2000)). There are two sub-categories of
340 these species agnostic networks.

341 Stochastic network models use a probabilistic rule-set about diet choice and niche breadth
342 to reflect fundamental ideas of foraging biology. These models that are based on the
343 compartmentalisation and acquisition of energy for species at different trophic levels
344 (Allesina & Pascual, 2009; Krause et al., 2003) and that network structure can be
345 determined by distributing interactions along single dimension [the ‘niche axis’; Allesina
346 et al. (2008)]. Typically these models parametrise some aspect of the network structure
347 (although see Allesina & Pascual, 2009 for a parameter-free model). These models include
348 the most commonly used network generator, the Niche model (Williams & Martinez,
349 2000), as well as the original Cascade model (Cohen et al., 1990) and the derived Nested
350 hierarchy model (Cattin et al., 2004). These models often form the basis for dynamic
351 models e.g., the allometric trophic network (Brose et al., 2006; Schneider et al., 2016) and
352 bioenergetic food web models (Delmas et al., 2017).

353 4.3 Construction through deduction

354 In contrast to the above approaches centred on feasibility, realised networks via methods
355 reflecting abundance and diet choice typically rely on deductive reasoning and have a
356 unique agenda to those above. In contrast to the inductive methods, inference about a
357 realised network follows from a set of premises defining generative processes, often referred
358 to as mechanisms. Typically, models that embed abundance and diet choice constraints
359 reference theory that allows inference about the distribution and strength of interactions.
360 Such models are ‘network topology generators’ and have a strong representation in research
361 comparing network structures along environmental gradients and delivering inference about
362 extinctions and energy flux. They also provide the structural backbone for dynamical
363 systems modelling to address questions about stability-structure-productivity-function
364 relationships, secondary extinction dynamics, species invasion and climate change. There

365 are two broad groups of models in this deductive category.

366 **4.3.1 Species-specific networks**

367 These models capture the behaviour of the nodes by explicitly taking into account the
368 properties of the different species in the community. Which means that there is a degree of
369 variance in which links are predicted between species unlike the more ‘static’ predictions
370 made by inductive models. However, these networks are ‘costly’ to construct in real world
371 settings (requiring data about the entire community, as it is the behaviour of the system
372 that determines the behaviour of the part) and also lack the larger diet niche context
373 afforded by metawebs.

374 Neutral networks are built on the assumption that foraging decisions are tied *only* to the
375 abundance of species within the community (E. F. Canard et al., 2014; Krishna et al.,
376 2008). Here links are solely determined by the relative abundance of the different species
377 in the community. Although it is highly unlikely that abundance is the only determinant
378 of interactions work by Pomeranz et al. (2019) showcases how these neutral processes
379 can be used in conjunction with inductive models to construct more refined/localised
380 networks.

381 There is a broader group of models that focus on determining interactions in terms of
382 energetic constraints on diet breadth, often using the ratio of consumer-resource bodysize as
383 a proxy for capturing the energetic constraints of feeding. Models such as those developed
384 by Portalier et al. (2019) and Woottton et al. (2023) are similar to the mechanistic
385 approaches discussed in Section 4.2, however instead of determining interactions based on
386 mechanistic feasibility it is rather constrained by the energetic cost of predation. Note
387 that although these models do not place any explicit constraints on the expected structure
388 of the network, the links should still be considered as ‘realised’ owing to the energetic
389 constraint placed on links. A different subset of diet models (*e.g.*, Beckerman et al.,
390 2006; Petchey et al., 2008) use a diet choice approach, however similar to the stochastic
391 network models they also embed assumptions on network structure. Thus these models
392 predict both interactions and network structure simultaneously, although they would
393 benefit in being refined by more explicitly accounting for trait-based (*i.e.*, feasibility)
394 parameterisation (Curtsdotter et al., 2019).

395 5 Making Progress with Networks

396 The motivation to leverage network ecology in conservation ecology, environmental risk
397 assessment and natural resource management stems from a shift away from species/popu-
398 lation specific measures of the effects of stress and disturbance to community level metrics
399 of these impacts. These metrics, such as resilience and more generally stability, ecosystem
400 function and biodiversity *per se*, are natural properties of networks. This suggests that
401 modern conservation, risk assessment and resource management requires robust network
402 tools to support decision making.

403 This is also true in the disciplines of ecology and environmental science and their focus
404 on abundance, distribution, functions and services that biodiversity provides (Loreau &
405 de Mazancourt, 2013). Major questions remain, for example, about stability-diversity-
406 productivity relationships, the impacts of extinctions and invasions and the impacts of
407 multiple stressors operating at multiple ecological scales. A network approach to answering
408 these types of questions specifically allows us to evaluate how environmental gradients and
409 anthropogenic stress map through direct and indirect effects among species in a complex
410 community and reveal fundamental patterns and understanding of processes in the natural
411 world.

412 In order to effectively use networks to aid us in answering questions about conservation/risk
413 assessment/management and core ecological theory, we need to be mindful that we are
414 mapping the *correct* network representation to the question of interest (Gauzens et al.,
415 2025). Notably, there are certain questions that cannot be answered using specific network
416 representations as the scale of the question of interest is fundamentally misaligned with
417 either the process captured by a specific network representation Section 3.1, the underlying
418 data that is used to construct it Section 4 or both of these factors.

419 Here we discuss and map the different network representations shown in Figure 1 to
420 ‘appropriate’ research questions and agendas see also 1. We also highlight some of the key
421 methodological challenges that currently limit our conceptualisation of a ‘network’ and
422 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

| Net- work Rep- resen- tation | Example Research Question | Representative Studies |
|--|--|---|
| Global Metaweb | How will novel communities respond <i>e.g.</i> , extinction, turnover, invasion and rewilding \checkmark | Gravel, Albouy, et al. (2016); Dunne et al. (2002) |
| | Diet-based conservation focusing not only on the target species but the species it might depend on for food resources Δ | Rooney & McCann (2012); Curtsdotter et al. (2011) |
| | Rewiring capacity/potential of species by looking at the <i>entire</i> diets of species Δ | Gilljam et al. (2015); Staniczenko et al. (2010); Su et al. (2024); Marjakangas et al. (2025) |
| | Eco-Evolutionary dynamics and how they relate to the conservation and origination of feeding strategies \times | Poisot et al. (2015); Baskerville et al. (2011) |
| Re- gional | Applied use potential of questions highlighted for global metawebs at the management scale <i>e.g.</i> , a protected area Δ | Albouy et al. (2014); Pellissier et al. (2018) |
| Metaweb | Refinement/extension of species distribution models by incorporating co-occurrence and species associations <i>e.g.</i> , predator and prey \checkmark | Araújo & Luoto (2007); Kissling et al. (2012) |

Net-
work
Rep-
resen-
tation

| | Example Research Question | Representative Studies |
|-----------------------|--|--|
| Re- alised webs | The allocation of multiple stressors across networks Δ | Crain et al. (2008); Beauchesne et al. (2021) |
| | Temperature threshold to community collapse Δ | O'Gorman et al. (2019); Petchey et al. (2010) |
| | Extinction and persistence after harvesting/invasion/extinction \checkmark | Allesina & Tang (2012); Yodzis (2001) |
| | Stability-diversity-productivity-function \checkmark | Thébault & Fontaine (2010); Rooney & McCann (2012) |
| | Explicitly tying ecosystem level processes and nutrient flows to networks \times | Moore et al. (2004) |
| | Meta communities and the idea of meta-network-communities Δ | Gravel, Massol, et al. (2016); Gilarranz et al. (2017) |

⁴²³ **5.1 Key Eco-Evo-Conservation Questions**

⁴²⁴ **5.1.1 Global Metawebs**

⁴²⁵ The interactions in global metawebs are not constrained by the realisation of specific
⁴²⁶ community assemblages (or species co-occurrence). These networks provide a platform
⁴²⁷ for answering questions that assume interactions *could* occur between species (feasibility)
⁴²⁸ or where the potential diet breadth of species is required. Examples of appropriate
⁴²⁹ research questions at this scale includes those about *hypothetical* or *novel* communities and
⁴³⁰ interactions under future climate change scenarios, or the potential 'position' of an invasive
⁴³¹ (or re-introduced) species within a network (Hui & Richardson, 2019). This scale is also
⁴³² appropriate for a particular class of questions related to the potential (eco-evolutionary)
⁴³³ rewiring capacity of species, and how this may help inform on the opportunities for
⁴³⁴ persistence of species within new community assemblages (Marjakangas et al., 2025). The
⁴³⁵ implicit focus on feasibility in these examples highlights that global metawebs are linked

436 to strong proxies for targets and mechanisms of evolutionary change. This offers a network
437 scale for modelling ecological-evolutionary dynamics and the role that both evolutionary
438 history, natural selection, and phenotypic plasticity shapes the diet breadth of species.

439 **5.1.2 Regional Metawebs**

440 Regional metawebs are conceptually a spatially constrained global metaweb. They make
441 explicit the co-occurrence between species. Against this backdrop, they are conceptually
442 aligned with similar questions to those posed above, with the added focus on a community
443 facing, real-world, challenge. Additionally, regional metawebs can and have been used
444 to refine and constrain species distribution model predictions, giving us more refined
445 range maps (García-Callejas et al., 2023) or community composition under climate change
446 scenarios, even at global scales (Hao et al., 2025).

447 However we must exercise a high degree of caution when comparing structures among
448 regional metawebs, whether discrete collections or along environmental gradients. At this
449 scale, where the network embeds the assumptions of feasibility, the link distribution is
450 not meaningfully constrained by environmental factors (see Section 2.2) and it is vital to
451 disentangle structural change *per se* from the multiple processes that might determine
452 species turnover (*e.g.*, β - diversity).

453 **5.1.3 Realised networks**

454 Realised network are the most representative of what comes to mind when people think of
455 networks, and more specifically how we can use them to help inform on larger biogeographic
456 processes (Thuiller et al., 2024). This is partially because of the popularity and legacy of
457 generative network models (like the Cascade and Niche model) which produce realised
458 network representations, and represent the ideal ‘currency’ for which to understand the
459 constraints placed on interactions/network structure by the broader community and
460 environmental context. This change in currency and context affords us the opportunity to
461 ask questions that revolve around major ecological theory - *e.g.*, community stability and
462 resilience, biodiversity dynamics, ecosystem function, structure-function relationships -
463 and around major conservation and climate change global challenges - *e.g.*, temperature
464 change, extinction dynamics, invasion impacts and reintroductions/rewilding.

465 Realised networks embody an explicit focus on the link between network structure to
466 ecosystem function. Because the structure of realised webs are isolated from turnover

467 processes they allow us to think about the propagation of change (across both time and
468 space) which allows us to ask questions about the persistence of communities and how
469 they respond to perturbations or stressors (at both the level of the node as well as the
470 modification of links). For example in Section 5.1.1 we discuss how global metawebs
471 can inform us as to the rewiring *capacity* of a species, a realised network however would be
472 better suited to capture the rewiring of networks over time as a response to changes in
473 the environment or community.

474 Although the recent boom in the availability of long-term observation data is allowing us
475 to unpack decades of insights for stability-diversity-productivity relationships for more
476 complex communities (Danet et al., 2024) or to evaluate the impacts and efficacy of
477 re-introductions (Wooster et al., 2024), we need to be mindful that empirical interaction
478 data is typically accumulated over time and so it compresses the transient nature of the
479 interactions between species (Polis, 1991). Thus we need to apply a degree of caution
480 when using empirical data to construct realised networks - although there is scope to think
481 about developing methods that will allow us to modify metawebs in such a way that their
482 structures become more aligned with realised webs (see the next section).

483 5.2 Key methodological challenges

484 As noted above, the three types of networks help highlight longstanding methodological
485 challenges that affect our ability to increase both precision and accuracy of inference
486 derived from the questions we highlight above. Here we review some of these challenges
487 and opportunities that are arising to mitigate them.

488 **Understanding what empirical data represents:** Ultimately, knowing what is
489 right/precise/correct in an ecological network requires robust data. What does it mean
490 when we ‘observe’ an interaction be that directly (predator actively feeding on prey) or
491 indirectly via *e.g.*, gut or isotope analysis. A network constructed with empirical data will
492 most likely still represent an ‘accumulation’ of feeding data making it conceptually more
493 closely aligned with the idea of a metaweb.

494 **The validation of network structure:** Progress has been made in the development of
495 tools and approaches of assessing how well a model recovers pairwise interactions (Poisot,
496 2023; Strydom et al., 2021), but we still lack a clear set of guidelines for benchmarking
497 the ability of models to recover structure (Allesina et al., 2008; Tylianakis et al., 2010).
498 This makes it challenging to assess if models are capturing network structure accurately,

499 especially if one wants to use empirical data as the ‘testing set’. Specifically, can we use a
500 network constructed using long-term interaction observation data (*i.e.*, conceptually a
501 metaweb) to assess the accuracy of a modelled (*I don’t know how I feel about this word*),
502 realised network? Additionally one needs to think about *what* aspect of accurate/precise
503 network construction is the most important - is it the structure or ability to correctly
504 predict pairwise links? In the case of attempting to construct a metaweb it is important
505 that one is accurately recovering both links that are truly present and absent, however in
506 the case of realised webs it is perhaps not that clear. Is it sufficient to correctly recover
507 structure *e.g.*, connectance or do the pairwise links also need to be correct?

508 **Transitioning between metawebs and realised webs:** Currently most approaches
509 to modelling realised networks fail to explicitly account for any form of evolutionary
510 constraint (although see Van De Walle et al. (2023) and Wootton et al. (2023)) and
511 we need to develop either an ensemble modelling approach (Becker et al., 2022; Terry
512 & Lewis, 2020) or tools that will allow for the downsampling of metawebs into realised
513 networks, (*e.g.*, Roopnarine, 2006).

514 Importantly we need to think critically how the creation of either an ‘ensemble network’ or
515 downsampled metaweb might change the underlying ‘currency’ of a network and thus the
516 underlying definition of the edge *e.g.* the downsampling approach developed by Roopnarine
517 (2006) structurally constrains the network to structurally look like a realised web, but the
518 links do not represent prey choice *per se*.

519 Having a well developed framework as well as ‘fluidity’ to allow us to scale up between
520 meta- and realised food webs lays the groundwork for us to actively begin the integration
521 of food webs into the classical metacommunity-metaecosystem space (Massol et al., 2011)
522 as well as ecosystem level processes (Liu et al., 2025). That being said developments in the
523 community-ecosystem space should be intentional about articulating a firm distinction as
524 to what defines a ‘network’ as a unit, as well as defining the logical (spatial and temporal)
525 boundaries between networks (Fortin et al., 2021).

526 **Making networks more tractable in applied spaces:** There is a disconnect when
527 it comes to effectively using networks in applied spaces. This is probably at least in
528 part related to the challenges with delineating ‘boundaries’ between networks, and how
529 these relate to ‘management units’ and scales in addition to a limited interpretability
530 of network metrics, specifically how this can be applied to conservation targets/indices
531 (Dansereau, Braga, et al., 2024). In order to address these shortcomings we need to make

532 an effort to more efficiently map the form (structure) of a network to its function in order
533 to identify how this can effectively be integrated into policy to make it meaningful and
534 actionable (O'Connor et al., 2025), all while remaining mindful to ensure that we identify
535 the appropriate analytical tools and network representation (Pellissier et al., 2018).

536 Taken together, these challenges highlight three overarching messages. (i) Network
537 representations are inseparable from the data and assumptions used to construct them;
538 (ii) validation and benchmarking must be explicitly aligned with the intended network
539 type and question; (iii) greater conceptual clarity is needed when transitioning between
540 metawebs and realised networks, particularly in applied contexts. Explicitly articulating
541 these distinctions is essential if networks are to be used both rigorously and transparently
542 across scales.

543 6 Conclusion

544 Having a clear understanding of the interplay between network representations and the
545 processes that they are capable of encoding is critical if we are to understand exactly
546 which networks can be used to answer which questions. A central message of this synthesis
547 is that network representations are not interchangeable, and that their utility depends
548 explicitly on the assumptions, data, and processes they are intended to capture. As we
549 highlight in Section 5 the different network representations have different potential uses
550 and it should be clear that there is no ‘best’ network representation but rather a network
551 representation that is best suited to its intended purpose. By formalising the assumptions
552 and mechanisms underlying different network constructions, we provide a framework for
553 evaluating when and how particular representations are appropriate. This framework
554 aims to prevent the unintentional misuse or misinterpretation of networks. It also offers
555 a starting point for developing improved approaches to the applied use of networks in
556 addressing questions that are pressing both within the field and across broader biodiversity
557 science.

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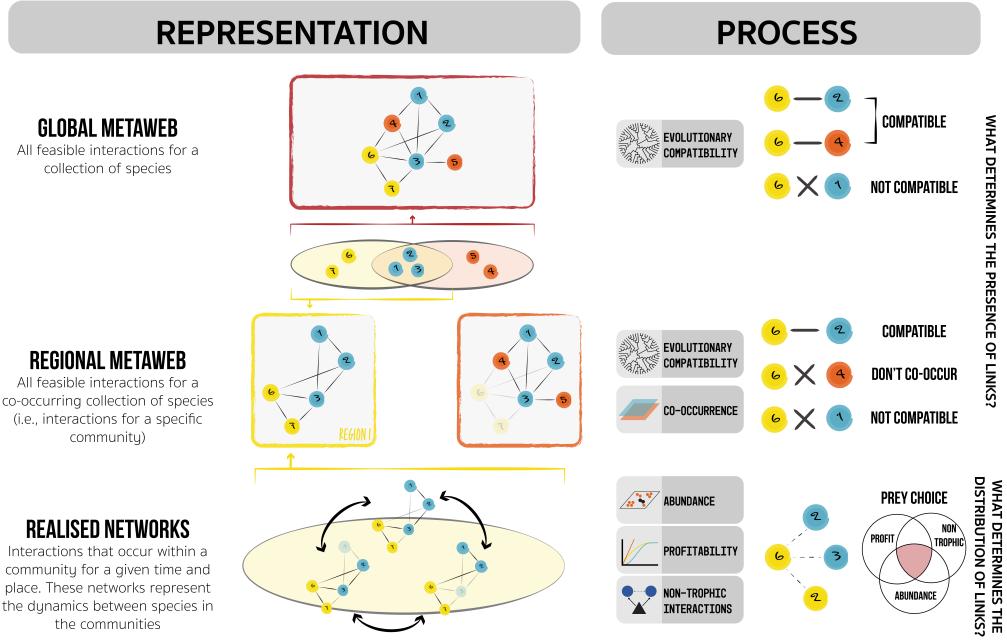


Figure 1: Aligning the various processes that determine interactions (right column) with the different network representations (left column). First, we start with a **global metaweb** this network captures all possible interactions for a collection of species in the global context. However, within the global environment different species occur in different regions (region one = yellow and region 2 = orange), and it is possible to construct two different metawebs (**regional metawebs**) for each region by taking account for the co-occurrence of the different species - as shown here we have two regions with some species that are found in both regions (blue) and others endemic to either region one (yellow) or region two (orange). However, even within a region we do not expect all interactions to be realised but rather that there are multiple configurations of the regional metaweb over both space and time. The ‘state’ of the different **realised networks** is ultimately influenced not just by the co-occurrence of a species pair but rather the larger community context such as the abundance of different species, maximisation of energy gain, or indirect/higher order interactions.