

Ecological Network Metrics: Opportunities for Synthesis

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Abstract

Network ecology provides a systems basis for approaching ecological questions, such as factors that influence biological diversity, the role of particular species or particular traits in structuring ecosystems, and long-term ecological dynamics (e.g. stability). Whereas the introduction of network theory has enabled ecologists to quantify not only the degree, but also the architecture of ecological complexity, these advances have come at the cost of introducing new challenges, including new theoretical concepts and metrics, and increased data complexity and computational intensity. Synthesizing recent developments in the network ecology literature, we point to several potential solutions to these issues: integrating network metrics and their terminology across sub-disciplines; benchmarking new network algorithms and models to increase mechanistic understanding; and improving tools for sharing ecological network research, in particular “model” data provenance, to increase the reproducibility of network models and analyses. We propose that applying these solutions will aid in synthesizing ecological subdisciplines and allied fields by improving the accessibility of network methods and models.

Keywords: Network ecology, systems analysis, computational methods, metrics, benchmarking, data provenance

28 **1 Introduction**

29 Interactions are at the heart of ecology and drive many of its key questions. What are
30 the roles of species interactions in ecological systems? When and why is biological
31 diversity important? What factors influence the long-term dynamics of ecosystems?
32 These are all questions with a long history in ecology (Cherrett, 1989; Council, 2003;
33 Lubchenco et al., 1991; Sutherland et al., 2013) that are not addressed in isolation.
34 Points of intersection include the relationship between diversity and stability (May,
35 2001, 2006); the identity and role of species that are the main drivers of community
36 structure (Paine, 1966, e.g. keystone species), ecosystem engineers (Jones et al.,
37 1994), or foundation species (Dayton, 1972; Ellison et al., 2005); and the causes and
38 consequences of introducing new species into existing assemblages (Baiser et al., 2008;
39 Simberloff and Holle, 1999). Furthermore, “systems thinking” has been a persistent
40 thread throughout the history of ecology (Margalef, 1963; Odum and Pinkerton,
41 1955; Patten, 1978; Patten and Auble, 1981; Ulanowicz, 1986), dating back at least to
42 Darwin’s *Origin of Species* in his famous pondering of an entangled bank (Bascompte
43 and Jordano, 2014; Golley, 1993). The application of network theory has provided
44 a formal, mathematical framework to approach systems (Bascompte and Jordano,
45 2014; Proulx et al., 2005) and led to the development of network ecology (Borrett
46 et al., 2014; Patten and Witkamp, 1967; Poisot et al., 2016b).

47 Network ecology can be defined as the use of network models and analyses to
48 investigate the structure, function, and evolution of ecological systems at many scales
49 and levels of organization (Borrett et al., 2012; Eklöf et al., 2012). The influx of
50 network thinking throughout ecology, and ecology’s contribution to the development
51 of network science highlights the assertion that “networks are everywhere” (Lima,
52 2011). And, as one would expect, the field has grown rapidly, from 1% of the primary
53 ecological literature in 1991 to over 6% in 2017 (Fig. 1A). Some examples include:
54 applying network theory to population dynamics and spread of infectious diseases
55 (May, 2006); description and analysis of networks of proteins in adult organisms
56 (Stumpf et al., 2007) or during development (Hollenberg, 2007); expanding classical
57 food webs to include parasites and non-trophic interactions (Ings et al., 2009; Kéfi
58 et al., 2012); investigating animal movement patterns (Lédée et al., 2016) and the
59 spatial structure of metapopulations (Dubois et al., 2016; Holstein et al., 2014);
60 connecting biodiversity to ecosystem functioning (Creamer et al., 2016); identifying
61 keystone species (Borrett, 2013; Zhao et al., 2016); and using social network theory
62 in studies of animal behavior (Croft et al., 2004; Fletcher et al., 2013; Krause et al.,
63 2003; Sih et al., 2009). Further, ideas and concepts from network ecology are being
64 applied to investigate the sustainability of urban and industrial systems (Fang et al.,

65 2014; Layton et al., 2016; Xia et al., 2016) and elements of the food-energy-water
66 nexus (Wang and Chen, 2016; Yang and Chen, 2016).

67 Over the past 15 years, re-occurring themes for moving network ecology for-
68 ward have emerged from reviews, perspectives, and syntheses (e.g. Bascompte, 2010;
69 Borrett et al., 2014; Poisot et al., 2015; Proulx et al., 2005). In this paper, we
70 examine areas where the network approach is being applied to address important
71 ecological questions and identify both challenges and opportunities for advancing
72 the field. Among these are the need for shifting the focus toward mechanisms rather
73 than observations, and increasing the resolution (e.g. individuals or traits as nodes
74 and weighted edges of different interaction types) and replication of network models
75 across different ecosystems and time (Ings et al., 2009; Poisot et al., 2016*b*; Wood-
76 ward et al., 2010). After a brief primer of key concepts from network ecology, we
77 discuss the following topics as they relate to these issues: the proliferation of ter-
78 minology for ecological metrics with the increasing application of network methods;
79 fully exploring the underlying assumptions of models of mechanistic processes for
80 generating network structure; and the need for improved sharing and reproducibility
81 of ecological network research and models. Although these topics are not new, the
82 combination of the influx of metrics and theory and rapid increases in the computa-
83 tional intensity of ecology are creating novel challenges. With respect to these issues,
84 we discuss recent advances that should be explored as tools to aid in a more effective
85 integration of network methods for synthesis across ecological (sub)disciplines.

86 **2 A primer of ecological networks: models and** 87 **metrics**

88 Prior to the introduction of network methods in ecology, the primary way of study-
89 ing interactions was limited to detailed studies of behaviors and traits of individual
90 species important to interactions, or of relationships between tightly interacting pairs
91 of species (Carmel et al., 2013). Some ecologists were advancing whole-system meth-
92 ods (Lindeman, 1942; Odum, 1957); however, quantifying interactions is costly, as
93 compared to surveys of species abundances. This has created a significant barrier to
94 studying interactions at the scale of entire communities, either at the scale of indi-
95 viduals or species pairs, because the number of interactions becomes intractable. For
96 instance, even if one assumes that only pairwise interactions occur among S species,
97 the number of possible pairs is $S(S-1)/2$. Local assemblages of macrobes often have
98 $10^1 - 10^2$ species, and microbial diversity can easily exceed 10^3 OTUs (Operational
99 Taxonomic Units).

100 This complexity of ecological systems is one reason there is a long tradition in
101 community ecology of studying interactions within small subsets of closely-related
102 species (e.g. trophic guilds) and using dimensionality reducing methods based on
103 multivariate, correlative approaches (Legendre et al., 2012). While some approaches
104 to studying subsets of species incorporate the underlying pattern of direct and in-
105 direct links (e. g., modules, (sensu Holt, 1997; Holt and Hoopes, 2005), the ma-
106 jority do not. Such limitations repeatedly have led to calls for the application of
107 “network thinking” to ecological questions (e.g. Golubski et al., 2016; Ings et al.,
108 2009; Jacoby and Freeman, 2016; Patten and Witkamp, 1967; Proulx et al., 2005;
109 QUINTESSENCE Consortium et al., 2016; Urban and Keitt, 2001). There are now
110 many resources for learning about network ecology and network theory in general,
111 and we point the reader in the direction of excellent reviews in this area (Bascompte
112 and Jordano, 2007; Borrett et al., 2012; Brandes et al., 2013; Ings et al., 2009; Proulx
113 et al., 2005) and more comprehensive introductions (Brandes et al., 2005; Estrada,
114 2015; Newman, 2010).

115 Network ecology employs network theory to quantify the structure of ecological
116 interactions. All networks consist of sets of interacting nodes (e.g. species, non-
117 living nutrient pools, habitat patches) whose relationships are represented by edges
118 (e.g. nutrient or energy transfers, pollination, movement of individuals). Conceptu-
119 ally, a network is a set of things or objects with connections among them. Stated
120 mathematically, a network is a generic relational-model comprised of a set of objects
121 represented by nodes or vertices (N) and a set of edges (E) that map one or more
122 relationships among the nodes, $G = (N, E)$. A canonical ecological example of a net-
123 work is a food-web diagram, in which the nodes represent species, groups of species,
124 or non-living resources, and the *edges* map the relationship who-eats-whom.

125 The analysis of networks is inherently hierarchical, ranging from the entire net-
126 work down to individual nodes and edges. Depending on the characteristics and level
127 of detail of the information provided for a given model, there is a large number of
128 network analyses and metrics that can be used to characterize the system at multiple
129 levels (similar to Hines and Borrett, 2014; Wasserman and Faust, 1994), including:
130 (1) the whole network level (i.e., the entire network), (2) the sub-network level (i.e.,
131 groups of two or more nodes and their edges), and (3) the individual node or edge
132 level (Fig. 2).

133 Network-level metrics integrate information over the entire set of nodes and edges.
134 For example, the number of nodes (e.g., the species richness of a food web) and
135 the density of connections or connectance are both network-level statistics used to
136 describes the overall complexity of a network and have been investigated by ecologists
137 for over 40 years (Allesina and Tang, 2012; May, 1972).

138 Sub-network level analyses focus on identifying specific subsets of nodes and
139 edges. There are a variety of groups that have different names (e.g., module, motif,
140 cluster, clique, environ) and different methods for measurement. Sub-networks often
141 represent more tractable and meaningful units of study than individual nodes and
142 edges on the one hand or entire networks on the other. For example, in landscape
143 and population ecology, the preferential movement of individuals and genes (edges)
144 between habitat patches (nodes) has implications for conservation of populations and
145 the design of preserves (Calabrese and Fagan, 2004; Fletcher et al., 2013; Holt and
146 Hoopes, 2005). Also, both nodes and edges can be divided into classes. An example
147 of this is the bipartite graph, in which interactions occur primarily between, rather
148 than within, each class or “part” of the community. A bipartite network has only
149 two classes of nodes, such as in a pollination network in which the community is
150 divided into plants being pollinated and insects that do the pollination (Petanidou
151 et al., 2008). In this network, edges representing pollination visits can only map
152 between two nodes in the different classes.

153 Metrics at the individual node or edge level quantify differences in relative impor-
154 tance. Whether we are interested in an individual or species that transmits disease,
155 species whose removal will result in secondary extinctions, or key habitat patches
156 that connect fragmented landscapes, identifying important nodes is a critical com-
157 ponent of network analysis. Another type of node or edge-level metric classifies
158 nodes or edges according to their roles within a network. This classification can use
159 information from differing levels. Additionally, nodes and edges can have variable
160 characteristics. Edges can be weighted and they can map a directed relationship
161 (as opposed to a symmetric or undirected relationship). For example, in ecosystem
162 networks, the edges show the directed movement of energy or nutrients from one
163 node to another by some process like feeding, and the edge weight can indicate the
164 amount of energy or mass in the transaction (Baird and Ulanowicz, 1989; Dame and
165 Patten, 1981). Nodes also can be weighted (e.g. size of individual, population size,
166 biomass of a given species). Lastly, network models are flexible enough to accommo-
167 date variation in edge types and relationships among edges (e.g. hypergraphs), but
168 analysis of these more complicated models is challenging and has only begun to be
169 applied in ecology (e.g. Golubski et al., 2016).

170 **3 Resolving network metrics**

171 The application of network theory defines an explicit mathematical formalism that
172 provides a potentially unifying set of terms for ecology and its inter-disciplinary
173 applications (QUINTESENCE Consortium et al., 2016). Ironically, the develop-

174 ment of ecological network metrics has had an opposing affect. One reason for this
175 is that introductions have occurred in multiple sub-disciplinary branches (Fig. 1B)
176 (Blüthgen, 2010; Borrett et al., 2014; Carmel et al., 2013). Having separate research
177 trajectories can facilitate rapid development of ideas and the process of integration
178 can lead to novel insights (Hodges, 2008). At the same time, these innovations in
179 network ecology have come at the cost of the “rediscovery” of the same network met-
180 rics and subsequent description of them with new terms. This has led to different
181 metrics with similar purposes existing in separate areas of ecology (Table 1).

182 Ecological studies using network approaches draw from a deep well of general net-
183 work theory (Newman, 2003, 2006; Strogatz, 2001). Ecologists broadly use network
184 concepts, techniques, and tools to: (1) characterize the system organization (Borrett,
185 2013; Croft et al., 2004; Ulanowicz, 1986); (2) investigate the consequences of the
186 network organization (Borrett et al., 2006; Dunne et al., 2002; Grilli et al., 2016); and
187 (3) identify the processes or mechanisms that might generate the observed patterns
188 (Allesina and Pascual, 2008; Fath et al., 2007; Guimarães et al., 2007; Poisot et al.,
189 2016*b*; Ulanowicz et al., 2014; Williams and Martinez, 2000). The unnecessary pro-
190 liferation of network metrics is exemplified by “connectance” (C), which is used by
191 food-web ecologists to mean the ratio of the number of edges in the network divided
192 by the total number of possible edges. Elsewhere in the network science literature,
193 this measurement is referred to as network density (Newman et al., 2001). As an-
194 other example, what ecosystem ecologists have described as “average path length”
195 (total system through-flow divided by the total system input) (Finn, 1976) also has
196 been called network aggradation (Jørgensen et al., 2000). In economics, average path
197 length is known as the multiplier effect (Samuelson, 1948).

198 Another kind of redundancy is the creation and use of multiple statistics that
199 measure the same or very similar network aspects. A clear example of this is inher-
200 ent in the proliferation of centrality measures to indicate node or edge importance.
201 Network scientists have shown that many centrality metrics are correlated (Jordán
202 et al., 2007; Newman, 2006; Valente et al., 2008). Likewise, Borrett and Osidele
203 (2007) found that nine commonly reported ecosystem network analysis metrics co-
204 varied in 90 plausible parameterizations of a model of phosphorus biogeochemical
205 cycling for Lake Lanier, GA, but that all these metrics were associated strongly with
206 only two underlying factors. However, even a perfect correlation does not mean
207 that two metrics have identical properties, and they still may diverge in different
208 models. Therefore, it is important to have mathematically based comparisons of
209 metrics (Borgatti and Everett, 2006; Borrett, 2013; Kazanci and Ma, 2015; Ludovisi
210 and Scharler, 2017). It is incumbent on network ecologists to establish clearly the
211 independence and uniqueness of the descriptive metrics used.

212 From the perspective of the broader field of ecology, the proliferation of con-
213 cepts, terms, and metrics is not a new issue (e.g. Ellison et al., 2005; Tansley, 1935).
214 Ecologists have a long history of using network concepts and related models in mul-
215 tiple subdomains (e.g, metapopulations, matrix population models, community co-
216 occurrence models, ecosystems) without fully recognizing or capitalizing on the sim-
217 ilarities of the underlying models. Each subdomain has constructed its own concepts
218 and methods (occasionally borrowing from other areas), and established its own jar-
219 gon that impedes scientific development. Previous suggestions for solving this issue
220 have focused on maintaining an historical perspective of ecology (Graham and Day-
221 ton, 2002); Blüthgen et al. (2008) is an excellent example of how this can be done
222 through peer-reviewed literature.

223 One possible approach that would go beyond such a diffuse, literature-centered
224 approach would be to develop a formal ontology of concepts and metrics. An on-
225 tology is a a set of related terms that are formally defined and supported by as-
226 sertions (Bard and Rhee, 2004). An ontology therefore provides a framework for
227 developing concepts within a discipline and presents the opportunity for more ef-
228 ficient synthesis across disciplinary boundaries. The concept of an ontology is not
229 new, but more rapid sharing of ontologies and their collaborative development have
230 been enabled by the Internet. For example, the Open Biological Ontologies (OBO,
231 <http://www.obofoundry.org>) supports the creation and sharing of ontologies over
232 the web. Currently, there is no OBO for a “network ecology metric” ontology, and
233 as far as we are aware, ontologies have yet to be explored or developed for network
234 metrics.

235 The OBO could provide a platform for harmonizing ecological network metrics,
236 terms, and concepts. Key obstacles to such harmonization include a requirement that
237 network ecologists work within a common framework, and the need for an individual
238 or leadership team to periodically curate the ontology based on new developments in
239 the field. In determining the best course of action, network ecologists could follow the
240 example of how similar OBO projects have been managed in the past. The *FOODON*
241 food role ontology project (<http://www.obofoundry.org/ontology/foodon.html>)
242 contains information about “materials in natural ecosystems and food webs as well
243 as human-centric categorization and handling of food.” It could serve as an example
244 or even the basis of a ecological network metric ontology.

245 4 Benchmarking: Trusting our models of mecha- 246 nisms

247 Inferences about processes in ecological systems have relied in part on the application
248 of simulation models that generate matrices with predictable properties. As discussed
249 in the previous section, the proliferation of network metrics points to the need for
250 the investigation and comparison of how these metrics will behave in the context
251 of different modeling algorithms. Once a metric or algorithm has been chosen, it
252 is tempting apply them widely to empirical systems to detect patterns, but before
253 research proceeds, a process of “benchmarking” with artificial matrices that have
254 predefined amounts of structure and randomness should be used to examine the
255 behavior of the algorithms and the metrics that are applied to them.

256 Benchmarking of ecological models developed from null model analysis in com-
257 munity ecology (Atmar and Patterson, 1993; Connor and Simberloff, 1979; Gotelli
258 and Ulrich, 2012). Null models are specific examples of randomization or Monte
259 Carlo tests (Manly, 2007) that estimate a frequentist P value, the tail probability
260 of obtaining the value of some metric if the null hypothesis were true (Gotelli and
261 Graves, 1996). The aim of a null model is to determine if the structure of an observed
262 ecological pattern in space or time is incongruous with what would be expected given
263 the absence of a causal mechanism. A metric of structure calculated for a single em-
264 pirical data set is compared to the distribution of the same metric calculated for a
265 collection of a large number of randomizations of the empirical data set. The data
266 are typically randomized by reshuffling some elements while holding other elements
267 constant to incorporate realistic constraints. Comparison with a suite of null models
268 in which different constraints are systematically imposed or relaxed may provide a
269 better understanding of the factors that contribute most to patterns in the network
270 (see Box 1). However, the devil remains in the details and there are also a variety
271 of ways to randomize data and impose constraints to construct a useful null model.
272 If the null model is too simplistic, such as a model in which edges and nodes are
273 sampled with uniform probability, it will always be rejected and provide little insight
274 into important ecological patterns, regardless of what metric is used. At the other
275 extreme, if the null model incorporates too many constraints from the data, it will
276 be difficult or impossible to reject the null hypothesis, even though the network may
277 contain interesting structure.

278 In network theory, the Erdos-Renyi (ER, (Erdős and Rényi, 1959)) model is a
279 now-classic example of a model used to generate networks via a random process
280 for creating matrix structure. The ER model is a random graph that starts with an
281 $N \times N$ adjacency matrix of nodes and assigns to it K edges between randomly chosen

282 pairs of nodes. The ER model has been applied in ecology to address questions about
283 the relationship between stability and complexity (May, 1972) and the structure of
284 genetic networks (Kauffman et al., 2003). For example, randomized networks have
285 been used to link motifs (Milo et al., 2002) to network assembly (Baiser et al., 2016),
286 stability (Allesina and Pascual, 2008; Borrelli et al., 2015), and persistence in food
287 webs (Stouffer and Bascompte, 2010).

288 In addition to the random matrix approaches of null and ER models, there are
289 other, more complex algorithms that are used to generate structured matrices. Per-
290 haps one of the best known in network theory is the Barabasi-Albert (BA, Barabási
291 and Albert 1999) model, which adds nodes and edges to a growing network with
292 a greater probability of adding edges to nodes with a higher degree. The BA algo-
293 rithm is similar to ecological network algorithms that generate non-random structure,
294 because of either direct influence or similar processes operating in systems of inter-
295 est. Some of these models include processes of “preferential attachment” in which
296 organisms tend to interact with the same, common species. Food-web modeling algo-
297 rithms also have been developed that use a trait-based approach (e.g. Allesina and
298 Pascual, 2009), consumer-resource models (Yodzis and Innes, 1992), niches (Williams
299 and Martinez, 2000), cyber-ecosystem algorithms (Fath, 2004), and cascade models
300 (Allesina and Pascual, 2009; Allesina and Tang, 2012; Cohen and Luczak, 1992).

301 The statistical behavior of some models and metrics can be understood ana-
302 lytically. For example, the networks generated by the BA algorithm display degree
303 distributions that approximate a power-law distribution, like many real-world “scale-
304 free” networks (Albert et al., 2002). If the network is sparse (i.e. $(K \ll N^2)$), the
305 degree distribution of the network should follow a Poisson distribution. However, as
306 new models and metrics are introduced, new benchmarking should be done and com-
307 pared to previous results. Newman et al. (2016) is one example of how benchmarking
308 can be used for investigating processes operating on ecological networks. Ludovisi
309 and Scharler (2017) advocate the same approach for the analysis of network models
310 in general. The `benchmark` (Eugster and Leisch, 2008) package in R (R Core Team,
311 2017) is a general algorithm-testing software package that provides a useful starting
312 point.

313 **5 Reproducibility: Open-data, Open-source and** 314 **Provenance**

315 As analyses of network models increase in computational intensity, there is a concomi-
316 tant increase in the need for new tools to track and share key computational details.

317 This need is compounded when models incorporate data from multiple sources or
318 analyses involve random processes. The combination of the volume of data and com-
319 putational intensity of studies of ecological networks further increases the burden on
320 ecologists to provide information needed to adequately reproduce datasets, analyses,
321 and results. As the sharing and reproducibility of scientific studies are both essential
322 for advances to have lasting impact, finding easier, faster, and generally more conve-
323 nient ways to record and report relevant information for ecological network studies
324 is imperative for advancing the field.

325 Sharing data and open-source code have become established in ecology, and net-
326 work ecologists are now producing more network models and data (e.g. Fig. 1A).
327 These include not only ecological interaction networks, but also an influx of other rele-
328 vant networks, including ecological genomic networks generated by next-generation,
329 high-throughput sequencing technologies (Langfelder and Horvath, 2008; Zinkgraf
330 et al., 2017). There are now multiple web-accessible scientific databases (e.g. NCBI,
331 Data Dryad, Dataverse) and at least four databases have been constructed specifically
332 to curate ecological network data: including “Kelpforest” (Beas-Luna et al., 2014),
333 “The Web of Life” (Fortuna et al., 2014), “Mangal” ecological network database
334 (Poisot et al., 2015) and the “Interaction Web Database” ([https://www.nceas.
335 ucsb.edu/interactionweb/resources.html](https://www.nceas.ucsb.edu/interactionweb/resources.html)).

336 The increase in ecological network data is linked to an increasing rate of shared
337 analytical code and other open-source software. It is now commonplace for ecologists
338 to have a working knowledge of one or more programming languages, such as R,
339 Python, SAS, MatLab, Mathematica, or SPSS. Multiple software packages exist for
340 doing ecological analyses, including ecological network analyses. In addition to the
341 general network analysis packages available in R, there are at least two packages
342 aimed specifically at ecological network analysis: `bipartite` and `enR`. The former
343 provides functions drawn largely from community ecology (Dormann et al., 2009),
344 whereas the latter provides a suite of algorithms developed in the ecosystem network
345 analysis literature (Borrett and Lau, 2014; Lau et al., 2015).

346 Although, ecology has long had a culture of keeping records of important re-
347 search details, such as field and lab notebooks, these practices put all of the burden
348 of recording “metadata” on the researcher. Manual record-keeping methods, even
349 when conforming to metadata standards (Boose et al., 2007, e.g. EML, see), do not
350 take advantage of the power of the computational environment. Data-provenance
351 methods aim to provide a means to collect formalized information about computa-
352 tional processes, ideally in a way that aids the reproducibility of studies with minimal
353 impact on the day-to-day activities of researchers (Boose et al., 2007). These tech-
354 niques have been applied in other areas of research and could provide an effective

355 means for documenting the source and processing of data from the raw state into a
356 model (Boose and Lerner, 2017).

357 The reproducibility of scientific studies is imperative for advances to have last-
358 ing impact through the independent verification of results. Although this has been
359 an ongoing topic of discussion in ecology (Ellison, 2010; Parker et al., 2016), the
360 need was highlighted by a recent survey finding issues with reproduction of stud-
361 ies across many scientific disciplines (Baker, 2016). There is significant motivation
362 from within the ecological community to move toward providing detailed informa-
363 tion about computational workflows for both repeatability and reproducibility, which
364 includes repetition by the original investigator (Lowndes et al., 2017). It is also im-
365 portant in network ecology for data sources and methods for model construction
366 be standardized and transparent, and that models be curated and shared (McNutt
367 et al., 2016).

368 Collecting details, such as those enabled by data-provenance capture software, is
369 one innovative way forward. These tools have been developing in the computer-
370 science domain for decades; however, only recently have they gained a foothold
371 in ecology (Boose et al., 2007; Ellison, 2010) or the broader scientific community.
372 Although there are many challenges in the development and application of data-
373 provenance principles, multiple software packages do exist for collecting data prove-
374 nance in the context of scientific investigations. Two provenance capture packages
375 exist in R, the `recordr` package associated with the DataOne repository (Cao et al.,
376 2016) and `RDataTracker` (Lerner and Boose, 2014). In addition, although they do
377 not collect formal data provenance, there are methods developed for “literate com-
378 puting” that help to collect code along with details about the code and the intention
379 of the analyses (e.g., the Jupyter notebook project: (Shen and Barabasi, 2014)).

380 For ecological networks, there is software that captures the “data pedigree” of
381 food-web models, but it does not capture data provenance. Data pedigree was ini-
382 tially implemented in the EcoPath food-web modeling package (Guesnet et al., 2015;
383 Heymans et al., 2016) to define confidence intervals and precision estimates for net-
384 work edges. It has been developed further to allow for the use of informative priors
385 in Bayesian modeling of ecological networks. This is done by linking models to the
386 literature sources from which estimates were derived, an approach that is similar
387 to incorporating metadata information within databases of ecological networks. Al-
388 though this approach focuses only on a subcomponent of provenance, this still is a
389 promising way to address the issue that networks, network metrics, and simulation
390 models used to analyze them commonly assume a lack of uncertainty (*cf.* Borrett
391 and Osidele, 2007; Kauffman et al., 2003; Kones et al., 2009), and typically ignore
392 inaccuracy in the empirical data (Ascough et al., 2008; Gregr and Chan, 2014).

393 6 Moving Forward

394 Development and application of new technologies (e.g. sequencing methods and com-
395 putational, data-driven approaches) have the potential to increase both the abun-
396 dance and quality of ecological networks. For the future development of network
397 ecology, there is a pressing need not only to share data and code, but also to integrate
398 and use the large amounts of information enabled by technological advances. For ex-
399 ample, synthetic networks (i.e. networks merging models from different studies, and
400 *sensu* Poisot et al., 2016a) are a promising new direction; however, the structural
401 properties of synthetic networks and the behavior of network metrics applied to them
402 will require careful investigation, including the application of systematic benchmark-
403 ing. Multi-trophic networks provide a precedence for these studies to move forward,
404 but synthesizing models from across many different sources produces new challenges
405 for developing and benchmarking metrics, as well as an opportunity for new tech-
406 nologies, like data provenance, to help establish better connections among studies
407 and researchers.

408 The burgeoning of “open” culture in the sciences (Hampton et al., 2014) also has
409 the potential to serve as a resource for models and a clearinghouse for resolving the
410 validity of metrics, models, and algorithms. First, because code is openly shared,
411 functions used to calculate metrics are open for inspection and, if coded and docu-
412 mented clearly using software “best-practices” (e.g. Noble, 2009; Visser et al., 2015),
413 the code provides a transparent documentation of how a metric is implemented and
414 its computational similarity to other metrics. Second, enabled by the ability to write
415 their own functions and code, researchers can do numerical investigations of the sim-
416 ilarities among metrics. Through comparison of metrics calculated on the same or
417 similar network models, a researcher could at least argue, for a given set of models,
418 that two or more metrics produce similar results. Third, data provenance provides a
419 useful tool to aide in the dissemination and synthesis of network models and increases
420 the reproducibility of ecological network studies, including those documenting new
421 metrics and benchmarking those metrics and associated algorithms for generating or
422 analyzing empirical models. Last, as with data provenance, formalizing ecological
423 network metrics and concepts requires a mathematically rigorous foundation that is
424 developed by the community of researchers working along parallel lines of inquiry.
425 Whether this is done through an ontological approach or some other formalized
426 “clearing-house,” an open process of exchange that integrates multiple perspectives
427 is essential to prevent the rapid dilution of concepts in ecological network research
428 as these concepts continue to proliferate, develop and evolve.

429 Over half a century ago, Robert MacArthur published his first paper on the rela-

430 tionship between diversity and stability, initiating multiple research trajectories that
431 have now become the mainstay of many ecological research programs (MacArthur,
432 1955). The theory that MacArthur applied was based on flows of energy through
433 networks of interacting species. Thus, network theory is at the roots of one of the
434 most widely studied topics in ecology and is now a part of the broader context of
435 integration across many scientific disciplines that is aimed at consilience of theory
436 (Wilson, 1999). The synthesis of ecological concepts through the mathematically
437 rigorous “lingua franca” of network terminology has the potential to unify theories
438 across disciplines. As with previous concepts (e.g. keystone species, foundation
439 species, ecosystem engineer), greater clarity and less redundancy will come about
440 as network methods are used more commonly and researchers compare the mathe-
441 matical and computational underpinnings of the metrics that they are using. With
442 the increased use of these approaches, the network concept has and will continue to
443 serve as a common model that transcends disciplines and has the potential to serve
444 as an inroad for new approaches. With thoughtful dialogue across sub-disciplines
445 and among research groups, further infusion of network theory and methods will
446 continue to advance ecology.

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¹⁰⁰¹ **Author contributions statement**

¹⁰⁰² All authors contributed to the conception, writing and review of the manuscript.

1003 Boxes

1004 *Box 1. Benchmarking Ecological Models* The most basic test is to feed the algorithm
1005 a set of "random" matrices to make sure that the frequency of statistically significant
1006 results is no greater than 5%. Otherwise, the algorithm is vulnerable to a Type I
1007 statistical error (incorrectly rejecting a true null hypothesis). However, specifying a
1008 matrix produced by random sampling errors is not so easy. By definition, if a null
1009 model algorithm is used to generate the random matrices, then no more than 5%
1010 of them should be statistically significant (unless there were programming errors).
1011 For binary matrices, two log-normal distributions can be used to generate realistic
1012 heterogeneity in row and column totals, while still maintaining additive effects for cell
1013 occurrence probabilities (Ulrich and Gotelli, 2010). "Structured" matrices are needed
1014 to test for Type II errors (incorrectly accepting a false null hypothesis), and these
1015 require a careful consideration of exactly what sort of pattern or mechanism the test
1016 is designed to reveal. One approach is to begin with a perfectly structured matrix,
1017 such as one derived from a mechanistic model for generating network structure,
1018 contaminate it with increasing amounts of stochastic noise, and test for the statistical
1019 pattern at each step (Gotelli, 2000). A plot of the P value versus the added noise
1020 should reveal an increasing curve, and will indicate the signal-to-noise ratio below
1021 which the test cannot distinguish the pattern from randomness. Alternatively, one
1022 can begin with a purely random matrix but embed in it a non-random substructure,
1023 such as a matrix clique or a node with extreme centrality. The size, density, and
1024 other attributes of this matrix can be manipulated to see whether the test can still
1025 detect the presence of the embedded structure (Gotelli et al., 2010). Because all
1026 null model tests (and all frequentist statistics) are affected by sample size and data
1027 structure, these benchmark tests can be tailored to the attributes of the empirical
1028 data structures for better focus and improved inference.

1029 Even simple randomization algorithms may require further filters to ensure that
1030 random matrices retain a number of desirable network properties. For example,
1031 Dunne et al. (2002) created random food-web matrices with constant species rich-
1032 ness and connectance, but they discarded webs with unconnected nodes and subwebs
1033 because these topologies were not observed in the empirical webs. A "stub recon-
1034 struction" algorithm builds a topology that is constrained to the observed number
1035 of edges per node (Newman et al., 2001). Each node is assigned the correct number
1036 of edges, and then nodes are successively and randomly paired to create a growing
1037 network. However, this algorithm also generates multiple edges between the same
1038 two nodes, which must be discarded or otherwise accounted for. Maslov and Sneppen
1039 (2002) use a "local re-wiring algorithm" that preserves the number of connections

1040 for every node by swapping edges randomly between different pairs of nodes. This
1041 algorithm is closely analogous to the swap algorithm used in species co-occurrence
1042 analyses that preserves the row and column totals of the original matrix (Connor
1043 and Simberloff, 1979). The more constraints that are added to the algorithm, the
1044 less likely it is that simple sampling processes can account for patterns in the data.
1045 However, some constraints, such as connectivity or matrix density, may inadvertently
1046 “smuggle in” the very processes they are designed to detect. This can lead to the
1047 so-called “Narcissus” effect (Colwell and Winkler, 1984). Finding the correct balance
1048 between realistic constraints and statistical power is not easy (Gotelli et al., 2012),
1049 and there are many potential algorithms that reasonably could be used, even for
1050 simple binary matrices (Gotelli, 2000).

1051 **Tables**

| Sub-discipline | Level | Metric | Concept | Reference |
|----------------|-------|------------------------|--|--|
| General | W | Density | The proportion of possible edges that are actually associated with nodes; called Connectance in Food Web ecology. | |
| General | N | Centrality | Multiple ways to characterize the relative importance of nodes. | Wasserman and Faust (1994) |
| General | N | Degree | Number of edges connected to a given node, which is a type of local centrality. | |
| General | N | Eigenvector Centrality | Global centrality metric based on number of walks that travel through a node | Bonacich (1987) |
| General | W | Centralization | Shape of the frequency distribution of edges among nodes. | Barabási and Albert (1999); Dunne et al. (2002) |
| General | W | Graph diameter | The concentration (versus evenness) of centrality among the nodes. | Freeman (1979) |
| General | W | Modularity | The longest path between any two nodes in a graph. | Barabási et al. (2000); Urban and Keitt (2001) |
| General | G | Motifs | Degree to which edges are distributed within rather than between distinct sets of nodes. | Newman (2010) |
| General | N | Link density | Small sets of nodes with similar distributions of edges. | Milo et al. (2002) |
| Community | N | Temperature | Average number of edges per node. | Martinez (1992) |
| Community | W | Co-occurrence | Measures the nestedness of a bipartite network. | Ulrich and Gotelli (2007) |
| Community | N | Indicator Species | Degree of overlapping spatial or temporal distributions of species relative to a null model. | Gotelli (2000) |
| Community | W | Nestedness | The degree to which the abundance of a taxonomic group responds to an environmental gradient. | |
| Community | W | Evenness | The degree to which interactions can be arranged into subsets of the larger community | |
| Community | W | Diversity | Deviation of the distribution of observed abundances relative to an even distribution among taxonomic groups in a community | |
| Community | W | Richness | Distribution of abundances among taxonomic groups in an observed community | |
| Community | W | Stability | The number of taxonomic groups in a community | |
| Food-Web | N | Removal Importance | The change in the abundances of taxonomic groups across a set of observations | |
| General | N | Connectance | The degree to which removal of a compartment or species produces subsequent removals in the ecosystem. | Borrvall et al. (2000); Dunne et al. (2002); Eklöf and Ebenman (2006); Solé and Montoya (2001) |
| Food-Web | G | Food-chain length | Proportion of realized out of possible edges | Pimm (1982); Vermaat et al. (2009) |
| Ecosystem | W | Finn cycling index | The number of feeding relationships among a set of compartments in a food-web. | Post et al. (2000); Ulanowicz et al. (2014) |
| Ecosystem | G | Environ | Degree to which matter or energy passes through the same set of compartments. | Finn (1980) |
| Ecosystem | N | Throughflow | The sub-network of the probability of movement of energy or matter among compartments generated by a single unit of input (output) into a selected node. | Patten (1978); Patten and Auble (1981) |
| Ecosystem | N | Throughflow Centrality | Amount of energy or matter passing into or out of a node | Finn (1976) |
| General | G | Chain Length | The proportion of energy or matter that passes through a given compartment in an ecosystem. | Borrett (2013) |
| Food-Web | G | Average Path Length | Number of edges between two nodes in a group | |
| Ecosystem | W | Pathway Proliferation | The average number of times a unit of matter or energy travels from one compartment to another before exiting the ecosystem | Finn (1976) |
| Ecosystem | W | Ascendency | Rate of increase in the number of edges between nodes with increasing path length | Borrett et al. (2007) |
| Food-Web | N | Trophic Level | Measures the average similarity in matter or energy flows among compartments in an ecosystem. | Ulanowicz (1986) |
| | | | Ordinal classification of a compartment or taxonomic group based on the relative position in the ecosystem. | Allesina and Pascual (2009); Fath (2004); Williams et al. (2002) |

Table 1: Ecological network metric summary and classification. Level indicates the hierarchy of the metric (W = Whole network, G = Group or sub-network, N = Node). The Sub-disciplines include 'General' network theory, 'Community' ecology, 'Food-web' and 'Ecosystem' ecology. Also available at <https://figshare.com/s/1bf1a7e0a6ee3ac97a4b>

1052 **Figures**

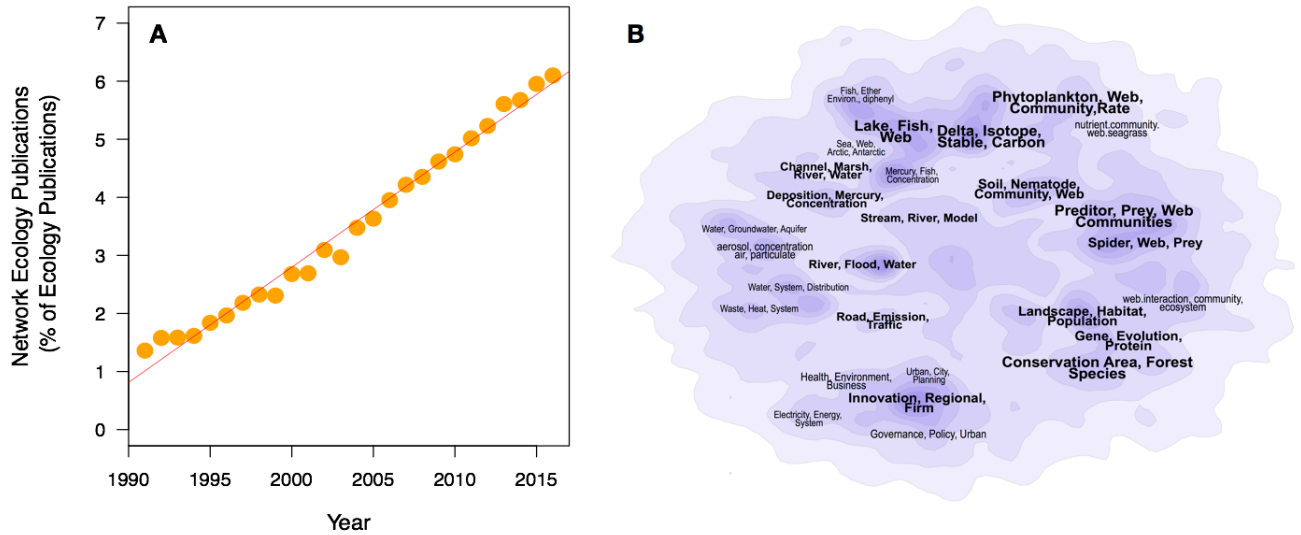


Figure 1: Although systems thinking has been a part of ecology since at least the work of Darwin, network ecology has grown rapidly since the turn of the last century but has been developing in isolated sub-fields. (A) Plot showing the increase in “network ecology” keywords in the literature from 1991 to current (updated search based on Borrett et al., 2014). (B) Contour plot of common topics in network ecology with peaks indicating clusters of related topics. The regions are labeled with the most common terms found in the clusters. From Borrett et al. (2014), reproduced with permission.

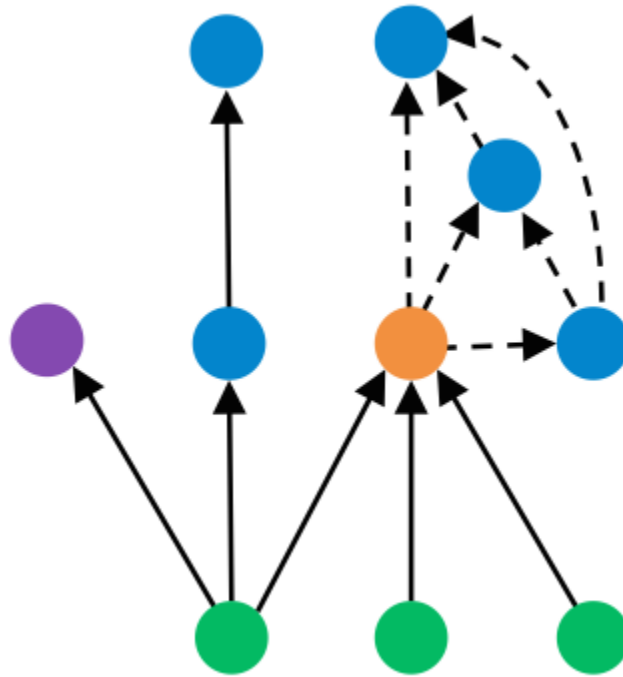


Figure 2: Hypothetical unweighted, directed network showing examples of the four classes of network metrics. *Node Level*: the purple node exhibits low centrality while the orange node exhibits high centrality. *Group or Sub-Network Level*: the blue nodes connected with dashed edges shows a module. *Global or Whole Network Level*: using the edges of all nodes we can measure the connectance of the entire network ($c = \text{edges}/\text{nodes}^2 = 0.12$).