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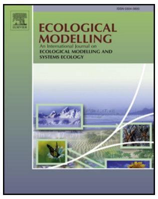

Review

Bibliometric review of ecological network analysis: 2010–2016

Stuart R. Borrett[a,b,*], Laura Sheble[b,c], James Moody[b,d], Evan C. Anway[a]

[a] Department of Biology and Marine Biology and Center for Marine Science, University of North Carolina Wilmington, Wilmington, NC 28403, United States
[b] Duke Network Analysis Center, Social Science Research Institute, Duke University, Durham, NC 27708, United States
[c] School of Information Sciences, Wayne State University, Detroit, MI 48202, United States
[d] Department of Sociology, Duke University, Durham, NC 27708, United States

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ABSTRACT

Ecological Network Analysis (ENA) combines modeling and analysis used to investigate the structure, function, and evolution of ecosystems and other complex systems. ENA is applied to network models that trace the movement of thermodynamically conserved energy or matter through the system. Investigators use ENA to answer a range of questions such as the following. What is the impact of fishing on the marine food web? Which species control the flux of nitrogen in an estuary? What is the ecological relationship among species in the food web when direct and indirect influences are considered? Would a proposed regulation make a city more sustainable? The field has grown since its inception in the 1970s, but it has rarely been systematically reviewed. This absence of reviews likely hinders the development of the field as a whole, obscures the diversity of its applications, and makes it difficult for new investigators to learn, develop, and apply the techniques. The objective of the work presented in this paper was to systematically review ENA research published in 2010 through 2016 to (1) identify the topic diversity, (2) expose methodological development, (3) highlight applications, and (4) assess collaboration among ENA scholars. To accomplish this, we used a combination of bibliometric, network (e.g., social network), and feature analyses. Our search identified 186 records. A topic network built from the bibliographic records revealed eight major topic clusters. The largest groups centered on food webs, urban metabolism, and ecosystem theory. Co-author analysis identified 387 authors in a collaboration network with eight larger components. The largest component contained 56% of the authors. This review shows ENA to be a topically diverse and collaborative science domain, and suggests opportunities to further develop ENA to better address issues in theoretical ecology and for environmental impact assessment and management.

1. Introduction

Ecological Network Analysis (ENA) is used to investigate ecosystem structure and functioning (Hannon, 1973; Jørgensen, 2007; Patten et al., 1976; Ulanowicz, 1986), and is one component of the broader field of network ecology (Borrett et al., 2014; Proulx et al., 2005). ENA techniques have been applied to characterize food web organization (Baird et al., 1998; Bondavalli and Ulanowicz, 1999; Pezy et al., 2017; Rakshit et al., 2017), assess ecosystem maturity or status (Christensen, 1995; Ulanowicz, 1980), trace biogeochemical cycling in ecosystems (Christian and Thomas, 2003; Small et al., 2014), and characterize the sustainability of urban metabolisms and other socio-ecological systems (Fan et al., 2017; Zhang, 2013; Zhang et al., 2009). Responding to the need for ecosystem-based management and recognizing the ability of ENA to characterize the whole ecosystem, multiple papers have called for the increased use of ENA to guide ecosystem assessment and management (Dame and Christian, 2006; de Jonge et al., 2012; Longo et al., 2015; Zhang, 2013). This push includes the use of ENA system metrics as indicators of good environmental status in the EU Marine Strategy Framework Directive (European Parliament and Council of the European Union, 2008). To prepare for this anticipated increase in ENA applications for environmental decision-making, to help advance the field, and to better enable new investigators to learn, develop and apply the ENA approach, we reviewed publications in the field between 2010 and 2016.

ENA studies are distinguished from other types of network analyses in ecology by both the type of network model used and the collection of analyses applied to interrogate the system. In ENA, the network model follows the flow of energy or nutrients through the ecosystem (Fath et al., 2007; Hannon, 1973; Wulff et al., 1989). These models use a single thermodynamically conserved tracer so that the networks function like resource-distribution maps. Network nodes represent species, functional groups, or non-living resource pools, and the directed edges indicate the transfer of the resources between nodes (e.g., eating,

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[*] Corresponding author at: Department of Biology and Marine Biology, University of North Carolina Wilmington, Wilmington, NC 28403, United States.
E-mail address: borretts@uncw.edu (S.R. Borrett).

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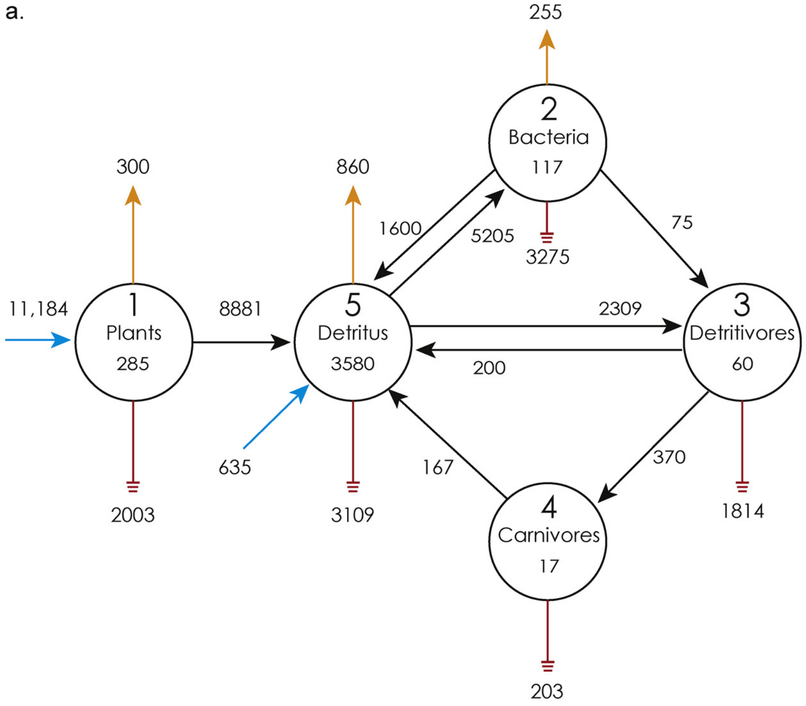

b.

$$\mathbf{F}=\begin{bmatrix}0&0&0&0&8881\\0&0&75&0&1600\\0&0&0&370&200\\0&0&0&0&167\\0&5205&2309&0&0\end{bmatrix},\ z^T=\begin{bmatrix}11184\\0\\0\\0\\635\end{bmatrix},\ e=\begin{bmatrix}300\\255\\0\\0\\860\end{bmatrix},\ r=\begin{bmatrix}2003\\3275\\1814\\203\\3109\end{bmatrix}$$

$$X=\begin{bmatrix}285\\117\\60\\17\\3579\end{bmatrix},\ \text{living}=\begin{bmatrix}\text{TRUE}\\\text{TRUE}\\\text{TRUE}\\\text{TRUE}\\\text{FALSE}\end{bmatrix}$$

Fig. 1. The Cone Spring ecosystem model is a common example of the network model type used for Ecological Network Analysis (Williams and Crouthamel, unpublished). Here the model is shown in both its diagram (redrawn from Ulanowicz, 1986) (a) and matrix (b) representations. The flow matrix $\mathbf{F}_{\mathrm{nxn}}$ is oriented from row to column (*i*→j). The inputs (z), exports (e), respirations (r), and storage or biomass (X) values are shown as separate vectors. The living vector has logical values (TRUE or FALSE) that indicted whether the corresponding node is living, which is an important distinction for some ENA algorithms such as Mixed Trophic Impacts.

excretion, death). The Cone Spring model of energy flow through the aquatic ecosystem (Williams and Crouthamel, unpublished; Ulanowicz, 1986) is a frequently used example due to its simplicity (Fig. 1). Multiple methods exist to build this type of model including a phenomenological energy or nutrient budget approach (Ulanowicz, 1986), the use of linear inverse modeling methods (Saint-Béat et al., 2013b; van Oevelen et al., 2010; Vézina and Pace, 1994; Vézina and Platt, 1988), bioenergetics modeling as implemented in the Ecopath software (Christensen and Walters, 2004; Polovina, 1984), and the construction of dynamic simulation models (Fath et al., 2007; Kazanci, 2007; Moore and de Ruiter, 2012; Patten et al., 1976).

Given this type of energy or material flow model, ENA scientists then apply a distinctive set of network analyses to these models. Building on previous work (Borrett and Lau, 2014; Fath and Borrett, 2006; Fath and Patten, 1999; Ulanowicz and Wolff, 1991), we have categorized the analyses into six related groups based on their analytic goals and underlying mathematics (Fig. 2): structure, flow, storage, environ, control, and impact analyses. For example, the structural analyses focus on the binary network topology and often count the number of different types of pathways (e.g., walks) among the nodes (Borrett et al., 2007; Borrett and Patten, 2003; Patten, 1985a). The flow and storage analyses include approaches built directly on economic input-output analyses (Barber et al., 1979; Finn, 1976; Hannon, 1973; Latham, 2006; Matis and Patten, 1981; Szyrmer and Ulanowicz, 1987) as well as an information diversity framework (MacArthur, 1955; Rutledge et al., 1976; Ulanowicz, 1986, 1980). The environ, control, and impact analyses are derived from the flow and storage analyses, often leveraging the input and output perspectives. Most of these analyses generate whole network descriptors of the system organization and function (Borrett and Lau, 2014; Kazanci and Ma, 2015) such as cycling (Finn, 1980, 1976) and flow efficiency and system robustness (Fath, 2015; Goerner et al., 2009; Patricio et al., 2004; Ulanowicz et al., 2014). While the analyses can be applied to a single model, it is often effective to use the networks as a response variable (Christian et al., 2005; Memmott, 2009) to compare two or more models of different systems (Baird et al., 1991; Borrett et al., 2016; Christensen, 1995) or the same system at different times or under different conditions (Christian and Luczkovich, 1999; Heymans et al., 2002; Ray, 2008; Whipple et al., 2014).

ENA has a long history of development (Fasham, 1985; Hannon, 1973; Patten et al., 1976; Platt et al., 1981; Ulanowicz, 1980; Wulff et al., 1989). Pinpointing a specific origin point for what we call ENA is

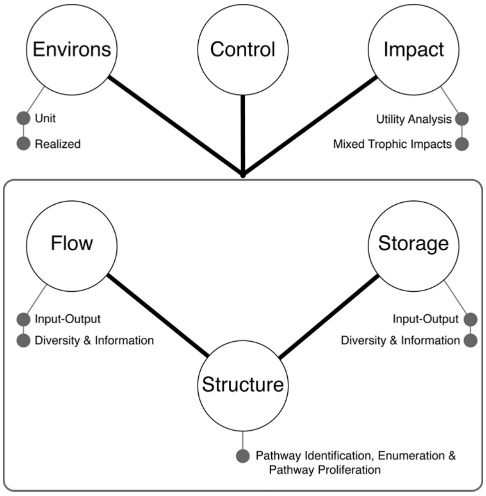

Fig. 2. Organizing framework for Ecological Network Analyses. The core analyses can be grouped into three related areas based on their emphasis: structure (topology), flow (geometry), and storage (i.e., biomass) analyses, each of which includes both input and output oriented methods. Three groups of analyses build on the core analyses including the environ, control, and impact analyses (encompassing both Utility Analysis and Mixed Trophic Analysis).

difficult because network ideas have been used in ecology for many years (MacArthur, 1955; Margalef, 1963; Patten and Witcamp, 1967; Summerhayes and Elton, 1923); however, the introduction of macroeconomic input–output analysis methods is a clear transition point (Hannon, 1973). Despite this history, there are few systematic reviews of ENA related research. Most previous reviews focused on ENA methods, tracing the derivation from flow analyses, input-output analyses, and information theory (Allesina and Ulanowicz, 2004; Barber et al., 1979; Fath and Borrett, 2006; Kay et al., 1989; Latham, 2006; Ulanowicz, 2005). This focus was necessary because of the large number and complexity of different analyses that are part of ENA (Fig. 2). Fath and Patten (1999) include a review of the methodologies and embedded it in a description of the intellectual development of the core ideas from the *environ theory* perspective originated by Patten (1981, 1978). The most comprehensive explanation of the core ENA ideas for the development and use of ENA to characterize ecosystems from a food web perspective were presented by Ulanowicz (1997, 1986). Several collections present illustrations of applying ENA to investigate aquatic ecosystems (Belgrano, 2005; Wulff et al., 1989). Given the importance of reviews to advance a field (Leitch, 1959; Noguchi, 2006; Sheble, 2017), this lack of recent and comprehensive reviews may be an impedance to the development and application of ENA. It also likely makes it more difficult for new investigators to quickly learn the approach and apply it.

The goal of the work presented here was to provide a high-level systematic review and assessment of the state of Ecological Network Analysis for the 2010–2016 period. To accomplish this, we used a bibliometric approach (Borrett et al., 2014; Edelmann et al., 2017; Moody and Light, 2006). Specifically, our objectives were to (1) identify major topics in ENA both in terms of theoretical developments and practical applications, (2) characterize the collaboration networks of teams working on science related to ENA, (3) determine the key references used by the community for this work, and (4) summarize key features of the analyses. Given the historical development and use of ENA, we expected to find a large number of investigations of aquatic (primarily marine) ecosystems with a strong food web component (Dame and Patten, 1981; Hannon, 1973; Wulff et al., 1989); however, we also anticipated finding an increasing use of ENA to investigate urban metabolism and industrial systems (Kennedy et al., 2011; Zhang, 2013). We also suspected that the collaboration networks would have distinct clusters based on research topics or methodological approaches.

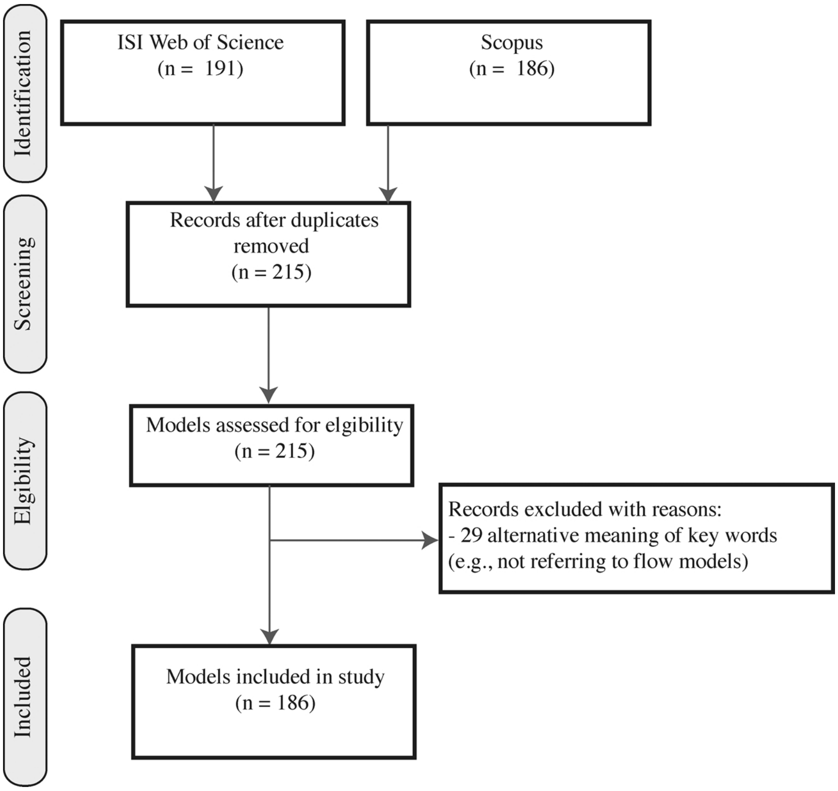

Fig. 3. Information flow for ENA publication identification and selection adapted from the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines.

2. Methods

2.1. Corpus selection

To identify recent ENA publications, we searched the Web of Science (WoS) and Elsevier Scopus (Scopus) databases for relevant publications between 2010 and 2016 (ending on November 17, 2016). Our search focused on three key terms: "Ecological Network Analysis," "Network Environ Analysis," and "Ecosystem Network Analysis." We excluded articles discovered only due to the terms "Business Ecosystems Network Analysis" and "Molecular Ecological Network Analysis" because preliminary screening indicated that articles identified by these terms did not match the target literature (Fig. 3). Publications were identified if our key terms occurred in the record title, abstract, or keywords. Following the initial identification step, we scanned the resultant titles and abstracts for relevance to the targeted ENA literature and eligibility for this study. For each eligible article, we collected the available bibliographic information including title, authors, abstract, keywords, publication year, source (i.e., the journal conference, or book of publication), and sources cited. We included search results from both WoS and Scopus to increase the likelihood of detecting the relevant literature and reduce known individual database biases and issues (Calver et al., 2017; Pautasso, 2014); we selected not to use Google Scholar due to its tendency to include less relevant items for our study (e.g., R help files, course documents), challenge of cleaning the data, and other known database issues (Calver et al., 2017; Jasco, 2009; Meho and Yang, 2007).

2.2. Network models & analyses

To investigate the literature identified, we constructed two different bibliographic network models (Borgatti et al., 2018; Börner, 2010; Edelmann et al., 2017; Moody and Light, 2006; van Eck and Waltman, 2011) and manually categorized important features of each paper. First, we constructed a co-term network to identify the key topics in this literature. Second, we built a coauthorship network to characterize the collaborating teams of scientists conducting this work. Third, we reviewed the papers for select key features including the system-of-interest, whether a new model was presented, and the methods of network construction and analysis.

2.2.1. Topics

To identify the topic structure of the corpus, we built a similarity network of the publications based on co-word frequency. Nodes in this network are the papers and edges indicate a similarity in words used in the title, abstract, and keywords. Edges are weighted by the similarity of their term co-occurrence using the standard tf-idf formulation (Börner et al., 2003), which discounts the similarity of common terms and favors more rare terms. To help clarify the strongest relations, we retained only those edges that were in the top 10% of the similarity value distribution. We then exported this network to PAJEK (Batagelj and Mrvar, 1998) for layout and clustering.

Network layout was done using the Fruchterman-Reingold (FR) algorithm that aims to maximize the correlation between network geodesic distance (shortest path between nodes) and point distance in the layout space (i.e. physical distance between each pair in the figure), thereby highlighting the natural clusters and contours of the topic space (Fruchterman and Reingold, 1991). We fed the resulting coordinates from the network layout to a two-dimensional kernel density smoothing procedure to generate the contours. The topics that label the contour map were identified by network clustering using the Louvain method (Blondel et al., 2008). After a search of the parameter space, we determined that a resolution parameter of 1.75 provided a balance between solution stability and detail (we also examined a coarser solution with broadly similar results). We then identified the 5 most heavily (tf-idf) weighted terms with which to label the cluster centroids in the figure. We placed authors at the centroid of the papers they have authored.

To characterize the shared knowledge foundations, we also determined the common citations in each topic cluster. Common citations were defined as one of the top 10 publications most frequently cited in each cluster, with a minimum requirement of at least 5 citations from within the cluster.

2.2.2. Collaboration

We investigated the collaboration structure among ENA researchers through a co-authorship network built from the identified publications. In this network, nodes represent individual investigators and the edges are weighted by the number of works co-authored. As with topics, we used PAJEK to generate a layout, with the figure restricted to those with at least 2 publications for clarity. We used the Kamada-Kawai layout algorithm (Kamada and Kawai, 1989), which, like the FR layout used in the term network, seeks to minimize the distance between screen distance and geodesic distance but, unlike the FR layout, adds a node-overlap restriction to avoid overlap. This layout is adjusted by hand to array disconnected components in a compact manner. Nodes are sized proportional to the sum of their ties to other nodes (i.e. weighted degree) and color represents connected component membership.

2.3. Feature analysis

To further describe the state of ENA, we conducted a more detailed feature analysis of the corpus. Each paper was inspected to determine (1) if the paper introduced a new model of a system or analyzed previously published models, and then (2) classified the type of ecosystem considered (Food web & biogeochemical cycling, Agroecosystem, Hydrologic, and Urban, Industrial, & Economic). We then considered the ENA methods. We categorized the network construction methods as being primarily based on a phenomenological or budgeting approach, more specifically using the Ecopath modeling technique, Linear Inverse Modelling, or other methods like simulation models. We also counted the number of papers that applied the general categories of ENA methods (Fig. 2), as well as whether or not the study included sensitivity or uncertainty analyses to support their results.

3. Results

3.1. Publication volume & sources

Our search of the WoS and Scopus databases yielded 215 unique records (Fig. 3). We excluded 29 of these publications because an initial review of the title and abstracts indicated that the authors used the key terms in ways other than to indicate the type of ecological network modeling and analyses desired. For example, Ivens et al. (2016) used the term Ecological Network Analysis to refer to their network study of ant community co-occurrence and ant-plant interactions. This use of the term is more general than the historic focus on ecosystems that we targeted for this corpus. We discovered and excluded several papers that used this more general meaning (e.g., Tu et al., 2015; Valverde et al., 2015; Zhao et al., 2016), which has alternatively been referred to as "Network Ecology" (Borrett et al., 2014) and "Ecological Networks" (Ings et al., 2009). After this initial screening process, 186 unique records remained (listed in Appendix A in Supplementary material).

The publication rate appears to be fairly steady with an average of 26 publications per year (± 7.5 SD) between 2010 and 2016 (Fig. 4a), including 3 papers accepted for publication in 2016 but published in 2017. These records included 144 journal articles, 10 book chapters, 22 conference papers, and 10 journal articles marked as reviews by WoS or Scopus. The reviews were typically focused on other domains and included ENA techniques in their consideration (Chen et al., 2013; Loiseau et al., 2012; Longo et al., 2015; Zhang, 2013). The records were published in 60 distinct sources, including high-impact journals such as

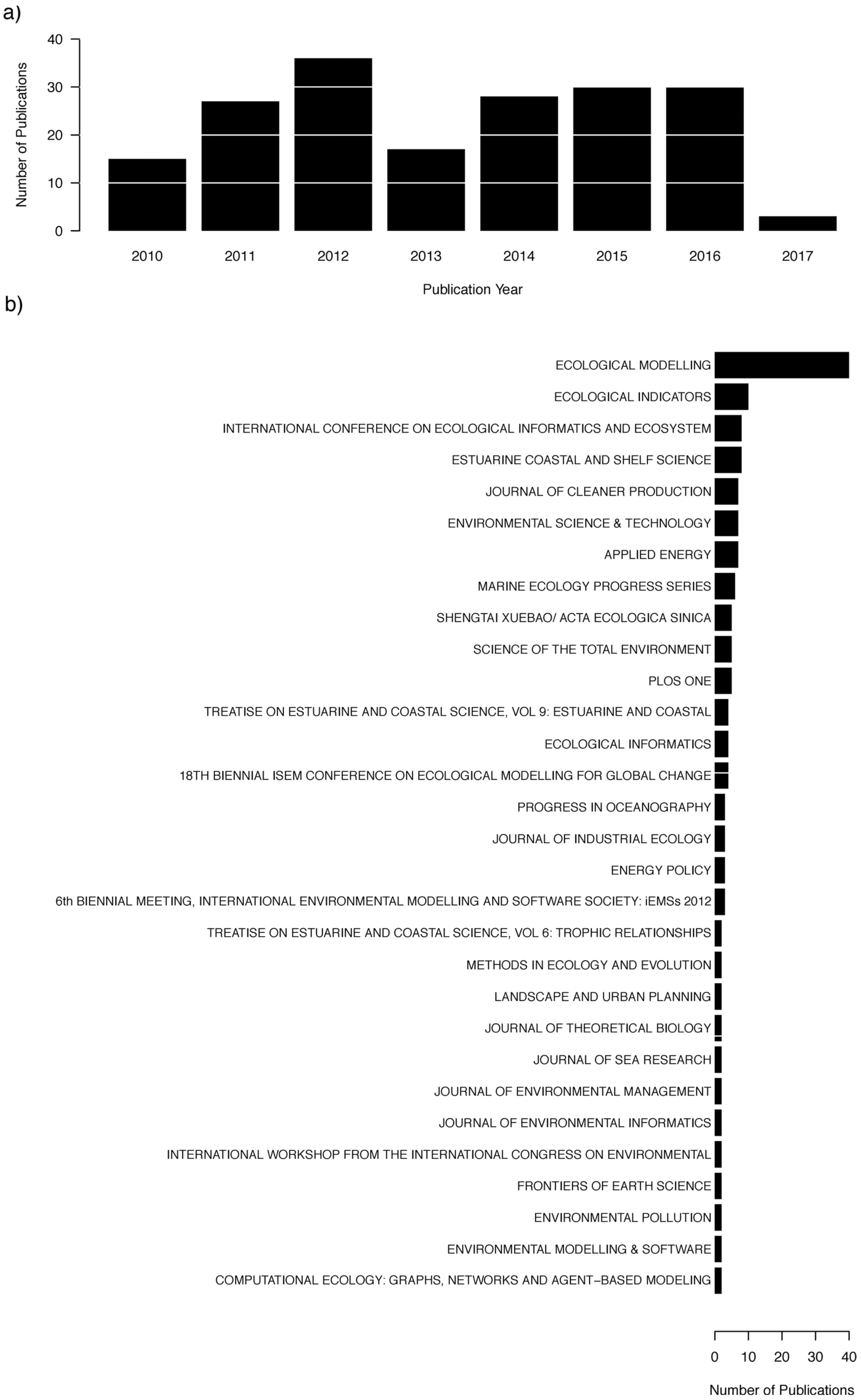

Fig. 4. Publication (a) and source (b) frequency in the 2010–2016 corpus of Ecological Network Analysis publications.

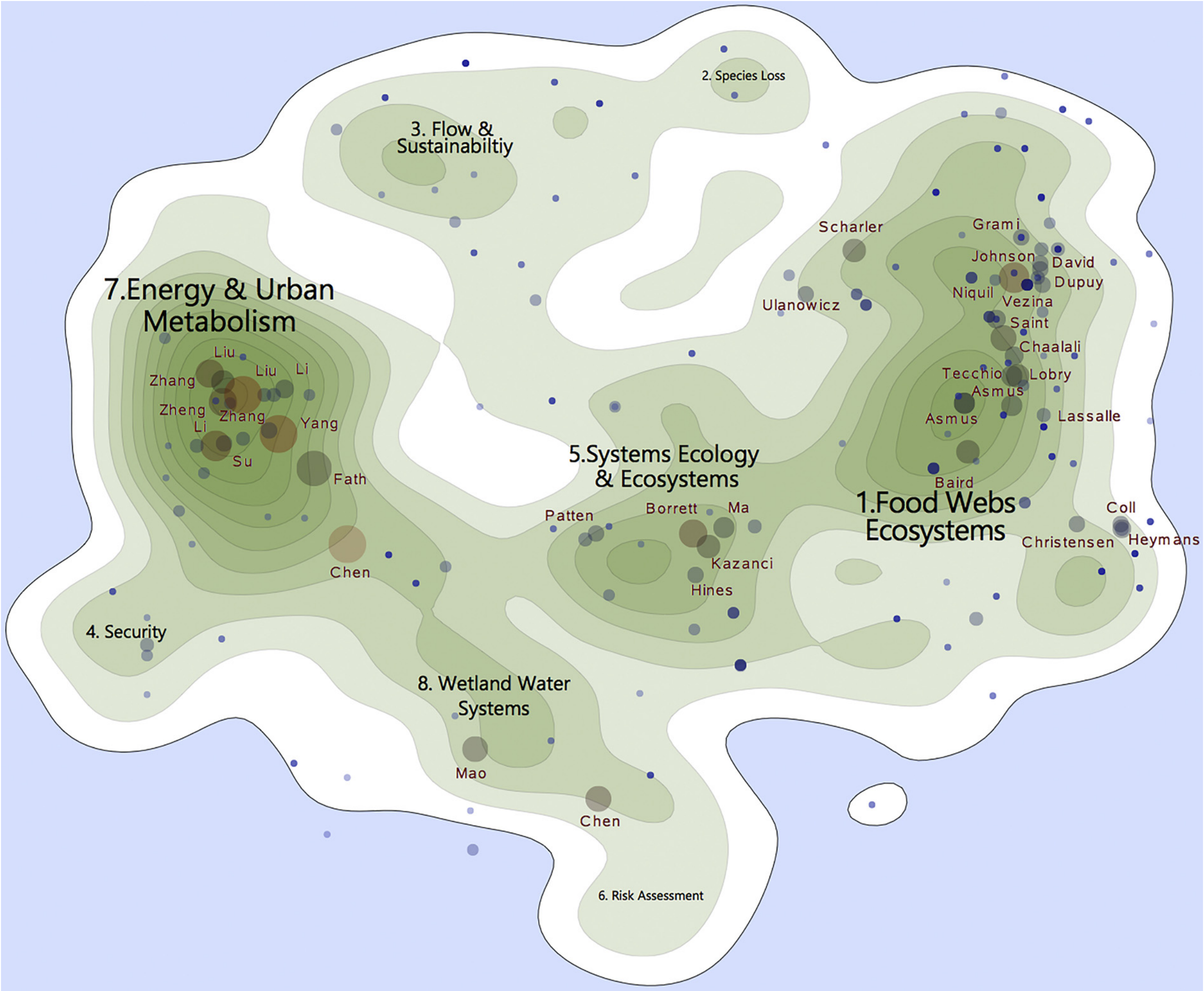

Fig. 5. Contour plot of the topic network in which nodes are papers and network edges indicate a co-term similarity. Peaks indicate topic clusters, which are labeled with cluster numbers and descriptive terms. Selected author names were placed at the centroid of the papers they authored. Greater detail about each cluster can be found in Tables 1 and 2.

Applied Energy, Ecological Indicators, Ecology Letters, Environmental Modeling & Software, Environmental Science & Technology, Functional Ecology, Marine Ecology Progress Series, and Methods in Ecology and Evolution. The majority of papers were published in the international journal Ecological Modelling (22%), with the second most common outlet being Ecological Indicators (5%, Fig. 4b). These publication outlets represent a diverse set of WoS categories including Ecology, Environmental Engineering, Environmental Science, Marine and Freshwater Ecology, and Oceanography.

3.2. Topics

Analysis of the co-term network revealed eight main topic clusters (Fig. 5). The largest cluster (n = 55) focused on food webs and general ecosystem analysis (Cluster 1). Frequently used terms include *food web*, *ecosystem*, *trophic*, *estuary*, *biomass*, *impact*, and *flow*. The most common authors in the cluster include D. Baird, B. Saint-Béat, H. Asmus, R. Asmus, J. Heymans, N. Niquil, and S. Tecchio (Table 1). In this cluster, the set of common authors was identified as 100% unique because they don't appear as common authors in the other topic clusters. While not part of the set of most common authors, the centroid of U. Scharler and R. Ulanowicz's publications appear on the edge of this cluster (Fig. 5). A scan of the papers included in this cluster showed that many are focused on assessing coastal and marine food webs including the Sylt-Romo Bight (Baird, 2012; Baird et al., 2012, 2011), the Baltic Sea (Tomczak et al., 2013), the Humboldt current (Neira et al., 2014), the Seine estuary (Tecchio et al., 2015), the Nador lagoon in Morocco (Bocci et al., 2016), temporarily open estuaries in South Africa (Scharler, 2012), and the intertidal Brouage mudflat (Saint-Béat et al., 2014). Part of the work in this cluster is motivated by efforts to apply ENA indicators to determine good ecological status for management as defined in the EU Marine Strategy Framework Directive (Bocci et al., 2016; Brigolin et al., 2014; Chaalali et al., 2015). There is a general sense that the results of ENA can be used for ecosystem and fisheries management (Longo et al., 2015), and efforts are underway to identify the best whole-network metrics to summarize the ecosystem status.

There are also a number of papers in this cluster focused on improving and extending ENA techniques. For example, Lee et al. (2012, 2011) showed how to combine ENA modeling and analysis with other techniques such as stable isotope enrichment and structural population models to enhance the model construction processes and strengthen the scientific discoveries. Chiu and Gould (2010) suggested the use of Baysean inference to improve the network model construction and Chaalali et al. (2016) developed a method to combine ecological niche modeling with LIM network construction techniques. Further work investigated how the physical characteristics of an ecosystem may influence ENA results (Niquil et al., 2012), and showed how to use ENA to trace and assess the negative impacts of a toxin as opposed to the more common use for the positive impacts of energy and nutrients (Taffi et al., 2015, 2014).

Table 1
Most common authors in eight topic clusters of Ecological Network Analysis inferred from 186 publications from 2010 through 2016.

Author		Cluster							
	Total	1. Food Webs; Ecosystems	2. Species Loss	3. Flow & Sustainability	4. Security	5. Systems Ecology; Ecosystems	6. Risk Assessment	7. Energy & Urban Metabolism	8. Wetland Water Systems
Bin Chen	5			X	X		X	X	X
Brian Fath	5			X	X		X	X	X
Meirong Su	4			X	X		X	X	
Zhifeng Yang	4			X	X			X	X
Yan Zhang	3			X	X			X	
Shaoquing Chen	3			X			X		X
Gengyuan Liu	2			X	X				
Stuart Borrett	2			X		X			
Aurelie Chaalali	1	X							
Blanche Saint-Béat	1	X							
Daniel Baird	1	X							
Geraldine Lassalle	1	X							
Harald Asmus	1	X							
Jeremy Lobry	1	X							
Johanna Jacomina Heymans	1	X							
Nathalie Niquil	1	X							
Ragnhild Asmus	1	X							
Samuele Tecchio	1	X							
Gaston E Small	1		X						
Jacques C Finlay	1		X						
Jiang Zhang	1		X						
Lingfei Wu	1		X						
Robert W Sterner	1		X						
Ali Zharrazi	1			X					
Antonio Bodini	1			X					
Mingqi Zhang	1				X				
Weiwei Lu	1				X				
Yan Hao	1				X				
Ying Fan	1				X				
Andria Salas	1					X			
Bernard Patten	1					X			
Caner Kazanci	1					X			
David Hines	1					X			
Ge Ying	1					X			
Michael Freeze	1					X			
Jie Chang	1					X			
Qianqian Ma	1					X			
Stuart Whipple	1					X			
Guillaume Junqua	1						X		
Roux Philippe	1						X		
Loiseau Eleonore	1						X		
Veronique Bellon-Maurel	1						X		
Hong Liu	1							X	
Hongmei Zheng	1							X	
Shengsheng Li	1							X	
Yanxian Li	1							X	
Delin Fang	1								X
He Chen	1								X
Honghan Chen	1								X
Lijuan Cui	1								X
Ursula M Scharler	1								X
Xufeng Mao	1								X
Total		10	5	10	10	10	8	9	10
% unique		100%	100%	20%	40%	90%	50%	44%	60%

The second largest cluster of papers (n = 46) is focused on urban metabolism and the interaction of socio-economic and natural ecosystems (Cluster 7). Terms such as *energy*, *metabolism*, *utility*, *economic sectors*, *Beijing*, and *relationship* are common. Authors with large contributions to this cluster include B. Chen, B. Fath, Z. Yang, Y. Zhang (Table 1). Papers in this cluster investigate alternative aspects of the urban metabolism of cities like Beijing (Chen and Chen, 2015; Liu et al., 2010,b, Zhang et al., 2016a,b), compare socio-economic regions (Zhang et al., 2016d), and evaluate the effective integration and pollution reduction of eco-industrial parks (Lu et al., 2015, 2012, Zhang et al., 2015a,b). Several papers in this cluster apply the ENA Utility Analyses (Fig. 2) to determine the net or integral relationships among the socio-economic sectors and Control Analyses to determine which sectors exert the most control on the system dynamics (Chen et al., 2015; Guo et al., 2016; Liu et al., 2011a; Lu et al., 2015; Xia et al., 2016; Zhifeng et al., 2014). There are also comparisons of ENA results to other analytical tools such as energy or material flow analysis, and more traditional input–output analyses (Chen and Chen, 2015; Liu et al., 2010).

The third largest cluster (n = 26) includes a set of papers that focused on systems theory, general ecosystem properties, and the ENA methods (Cluster 5). Common authors include S. Borrett, B. Patten, C. Kazanci, D. Hines, S. Whipple, and Q. Ma. Several papers in this cluster investigate evidence for hypothesized general properties of ecosystems (Borrett, 2013; Borrett and Salas, 2010) such as the dominance of indirect effects in ecosystems (Borrett et al., 2010; Fann and Borrett, 2012; Ma and Kazanci, 2013; Min et al., 2011b; Salas and Borrett, 2011). This cluster also includes several papers focused on the development of methods and software. These papers include a software tool (NCNA) for constructing and analyzing network models focused on human dominated nitrogen biogeochemical networks (Min et al., 2011a), updates to the web-based EcoNet software (Schramski et al., 2011), and the introduction of a new R package for ENA called enaR (Borrett and Lau, 2014). This cluster also has a clear connection to the environ concept and theory (Patten, 1978) as a formal approach to studying environments (Kaufman and Borrett, 2010; Schramski et al., 2011; Whipple et al., 2014). While most of the papers in this cluster analyze previously published models, there are two new models presented: a Ukranian pastoral food web (Buzhdygan et al., 2012) and a pair of models for nitrogen biogeochemistry in the Cape Fear River Estuary (Hines et al., 2015, 2012).

Papers in the fourth largest cluster (Cluster 3, n = 22) exhibited a mix of theory, method development, and applications, but there was a general theme of assessing system sustainability from the perspective of the energy or matter flows. Terms that link papers in this cluster include *sustainability*, *performance*, *indicator*, *information*, *diversity*, and *robustness*. Examples of work in this cluster include an assessment of the resiliency of the Heiha River Basin and the trade-offs it experienced between system efficiency and redundancy (Kharrazi et al., 2016), and an assessment of the success of mixed crop and livestock systems that, from a nitrogen-flow perspective, found a low degree of integration in the systems (Stark et al., 2016). There are also a number of ENA applications to urban (Bodini, 2012; Bodini et al., 2012; Chen et al., 2010a), industrial (Layton et al., 2016a), and economic systems (Huang and Ulanowicz, 2014). There are again papers to improve the ENA methods, including work to revise some analyses so as not to require a steady-state assumption (Schaubroeck et al., 2012) and to better understand the sensitivity of the whole-network metrics to model perturbations (Mukherjee et al., 2015), both of which remain important issues for the field.

The remaining four clusters in the co-term network range in size from 19 to 4 papers. Cluster 8 (n = 19) is built around terms such as *water*, *wetland*, *basin*, *control*, *utility*, and *management*. Research in this cluster includes the trace of physical water exchanges in wetlands such as the Baiyangdian Basin (Mao et al., 2015, 2010; Yang and Mao, 2011), analyses of virtual water trade when considering the water embedded in economic products such as agricultural crops (Fang and Chen, 2015; Mao and Yang, 2012; Yang et al., 2012), and investigations of the energy-water nexus (Duan and Chen, 2017; Wang and Chen, 2016; Yan and Chen, 2016). Papers in Cluster 6 (n = 8) share distinctive terms such as *risk* and *risk assessment*. Much of this work is an application of ENA to assess environmental risk of economic development projects such as dam construction (Chen et al., 2011, 2010b). Cluster 4 (n = 7) is joined by terms like *energy security*, *supply*, and *stability* and includes work like a systems assessment of a liquid natural gas distribution system in a region (Lu et al., 2016; Shaikh et al., 2016). The smallest cluster (n = 4; cluster 2) is linked by terms such as *rate*, *remove*, and *lake*, but the internal topics are less coherent. For example, there is an investigation of nitrogen cycling in the Laurentian Great Lakes (Small et al., 2014) that is more like the biogeochemistry models and analyses we have seen in other clusters, as well as an effort to link allometric principals to ecological flow networks (Zhang and Wu, 2013).

To better understand the similarities and differences among the topic clusters, we identified the most commonly cited papers in each of the network clusters (Table 2). Twelve papers were commonly cited in more than one cluster, indicating their broader impact across the ENA domain. The most frequently cited source is a review paper that captures both the early intellectual development of the field and summarizes several of the common methods (Fath and Patten, 1999). While this paper was key for multiple clusters, it was not a common citation of the largest cluster (#1) focused on food webs. Three sources were common citations in three of the co-term clusters. These include one comprehensive monograph on ecosystem organization with a strong trophic perspective (Ulanowicz, 1986), an expository paper that provides more detail about methods to build the core ecosystem network models (Fath et al., 2007), and an early example of applying ENA to investigate urban water metabolism (Zhang et al., 2010a). Ulanowicz (1986) was influential in the large food webs cluster (#1), the flow and sustainability cluster (#3), and the systems ecology cluster (#5), but is not as commonly cited in the second largest group focused on urban metabolism (#7). In fact, 56% of the highly cited literature in the food web cluster was unique to this cluster, and 80% of the Risk Assessment cluster was distinct. The two oldest papers commonly cited were Odum’s (1969) “Strategy of Ecosystem Development,” and Wolman’s (1965) “The Metabolism of Cities.” Further, there were three papers from the 1970s that were still influencing the field (Finn, 1976; Hannon, 1973; Patten, 1978). Thirty-five out of the 47 highly cited sources appear to be influential in only one cluster, and may provide insight to some of the important differences among the clusters. For example, two papers on the Ecopath software (Christensen and Pauly, 1992; Christensen and Walters, 2004) and one on using inverse methods (Vézina and Platt, 1988) were commonly cited only in the food web cluster, which may be an indicative of a difference in the tools and methods of this cluster.

3.3. Collaboration structure

We identified 347 unique authors of the 186 papers in the corpus. These authors are the nodes of the collaboration network (Fig. 6), which identifies 8 main collaborative components. The largest component (n = 195, 56.2%) includes authors that were associated with both the food web topic cluster (#1) and the urban metabolism topic cluster (#7). Within this component, several smaller working groups appeared due to the higher frequency of co-authorship. For example, there appeared to be a strong collaboration amongst Y. Zhang, Z. Yang, H. Zheng, G. Liu, M. Su, B. Chen, S. Chen, and B. Fath. There also appeared to be a strong working group that includes N. Niquil, B. Saint-Béat, J. Lobry, G. Lasalle, A. Chaalali, and S. Tecchio. Within this component, there were three more weakly linked subcomponents. Co-authorship among D. Baird, B. Fath, and U. Scharler created a bridge between two elements, and a co-authorship with S. Tecchio created the second bridge into a subcomponent with J. J. Heymans. The next largest component (n = 20) included C. Kazanci, Q. Ma, B. Patten, and S. Borrett. The third largest component (n = 15) included R. Ulanowicz and it constructed from two papers. While several distinct components emerged in our period of observation with some apparently stronger and productive working groups, these data suggest a generally well-connected collaboration structure.

As is common in science collaboration networks, the collaborator degree distribution of ENA in our corpus appears exponential. The median number of collaborators was 6, while the mean number of collaborators was 9.3. However, some investigators were highly collaborative. For example, within our corpus N. Niquil had 96 co-authors; B. Saint-Béat was the second most collaborative with 61 co-authors in the corpus. This high co-authorship is despite the fact that the most co-authors on a single paper was 26.

The author addresses indicate that ENA work is distributed among 31 countries (Fig. 7). The countries with the most frequent contributions include Austria, China, France, and the United States of America.

3.4. Feature analysis

New models were presented in 103 (55%) of the papers discovered, and the number in each type of system varied from year to year (Fig. 8).

Table 2
Commonly cited references in eight Ecological Network Analysis topic clusters discovered in 186 publications from 2010 through 2016.

Title	Citation	Total	1. Food Webs; Ecosystems	2. Species Loss	3. Flow & Sustainability	4. Security	5. Systems Ecology; Ecosystems	6. Risk Assessment	7. Energy & Urban Metabolism	8. Wetland Water Systems
Review of the foundations of network environ analysis	Fath and Patten (1999)	6			X	X	X	X	X	X
Growth and Development: Ecosystems Phenomenology	Ulanowicz (1986)	3	X		X		X			
Ecological network analysis: network construction	Fath et al. (2007)	3			X	X			X	
Ecological network analysis of an urban water metabolic system: Model development, and a case study for Beijing	Zhang et al. (2010a)	3				X			X	X
The strategy of ecosystem development	Odum (1969)	2	X		X					
Quantitative methods for ecological network analysis	Ulanowicz (2004)	2	X		X					
The Comparative Ecology of Six Marine Ecosystems	Baird et al. (1991)	2	X				X			
Measures of ecosystem structure and function derived from analysis of flows	Finn (1976)	2			X		X			
Ecological network analysis of an urban energy metabolic system: Model development, and a case study of four Chinese cities	Zhang et al. (2010b)	2				X			X	
A MATLAB® function for Network Environ Analysis	Fath and Borrett (2006)	2					X			X
The structure of ecosystems	Hannon (1973)	2						X	X	
Towards a sustainable use of water resources: a whole-ecosystem approach using network analysis	Bodini and Bondavalli (2002)	2							X	X
Comparative study on the trophic structure, cycling and ecosystem properties of four tidal estuaries	Baird and Ulanowicz (1993)	1	X							
ECOPATH II — a software for balancing steady-state ecosystem models and calculating network characteristics	Christensen and Pauly (1992)	1	X							
Ecosystem maturity — towards quantification	Christensen (1995)	1	X							
Ecopath with Ecosim: methods, capabilities and limitations	Christensen and Walters (2004)	1	X							
Food web dynamics in the ocean. I. Best-estimates of flow networks using inverse methods	Vézina and Platt (1988)	1	X							
WAND: an ecological network analysis user-friendly tool	Allesina and Bondavalli (2004)	1			X					
Quantifying the sustainability of economic resource networks: An ecological information-based approach	Ulanowicz et al. (2009)	1			X					
An hypothesis on the development of natural communities	Ulanowicz (1980)	1			X					
Quantifying sustainability: Resilience, efficiency and the return of information theory	Ulanowicz et al. (2009)	1			X					
Civil unrest in North Africa—Risks for natural gas supply?	Lochner and Dieckhöner (2012)	1				X				
Symmetrical overhead in flow networks	Ulanowicz and Norden (1990)	1				X				
Liberalisation and the security of gas supply in the UK	Wright (2005)	1				X				
The Seasonal Dynamics of The Chesapeake Bay Ecosystem	Baird and Ulanowicz (1989)	1					X			
Analysis of Energy Flows in an Intertidal Oyster Reef	Dame and Patten (1981)	1					X			
Flow Analysis of Models of the Hubbard Brook Ecosystem	Finn (1980)	1					X			
Dominance of Indirect Causality in Ecosystems	Higashi and Patten (1989)	1					X			
Systems Approach to the Concept of Environment	Patten (1978)	1					X			
An ecosystem model for assessing ecological risks in Québec rivers, lakes, and reservoirs	Bartell et al. (1999)	1						X		

(*continued on next page*)

Table 2 (*continued*)

Title	Citation	Total	1. Food Webs; Ecosystems	2. Species Loss	3. Flow & Sustainability	4. Security	5. Systems Ecology; Ecosystems	6. Risk Assessment	7. Energy & Urban Metabolism	8. Wetland Water Systems
Ecological network analyses and their use for establishing reference domain in functional assessment of an estuary	Christian et al. (2009)	1						X		
Effects of Nutrient Recycling and Food-Chain Length on Resilience	DeAngelis et al. (1989)	1						X		
Network analysis in perspective: comments on “WAND: an ecological network analysis user-friendly tool”	Fath (2004b)	1						X		
Estimating ecosystem risks using cross-validated multiple regression and cross-validated holographic neural networks	Findlay and Zheng (1999)	1						X		
Risk, Uncertainty in Risk, and the EPA Release Limits for Radioactive Waste Disposal	Helton (1993)	1						X		
Application of Bayesian network to the probabilistic risk assessment of nuclear waste disposal	Lee and Lee (2006)	1						X		
Probe into the method of regional ecological risk assessment—a case study of wetland in the Yellow River Delta in China	Xu et al. (2004)	1						X		
Applying Ecological Input-Output Flow Analysis to Material Flows in Industrial Systems: Part I: Tracing Flows	Bailey et al. (2004)	1							X	
Network synergism: Emergence of positive relations in ecological systems	Fath and Patten (1998)	1							X	
The Metabolism of Cities	Wolman (1965)	1							X	
Ecological network and emergy analysis of urban metabolic systems: Model development, and a case study of four Chinese cities	Zhang et al. (2009)	1							X	
Network mutualism: Positive community-level relations in ecosystems	Fath (2007)	1								X
Ecological network analysis for water use systems: A case study of the Yellow River Basin	Li et al. (2009)	1								X
Quantifying the sustainability of water use systems: Calculating the balance between network efficiency and resilience	Li and Yang (2011)	1								X
The water environs of Okefenokee swamp: An application of static linear environ analysis	Patten and Matis (1982)	1								X
Indirect effects and distributed control in ecosystems: Distributed control in the environ networks of a seven-compartment model of nitrogen flow in the Neuse River Estuary, USA—Steady-state analysis	Schramski et al. (2006)	1								X
Indirect effects and distributed control in ecosystems: Distributed control in the environ networks of a seven-compartment model of nitrogen flow in the Neuse River Estuary, USA—Time series analysis	Schramski et al. (2007)	1								X
			9 56%	0	10 40%	7 43%	10 50%	10 80%	10 40%	10 60%

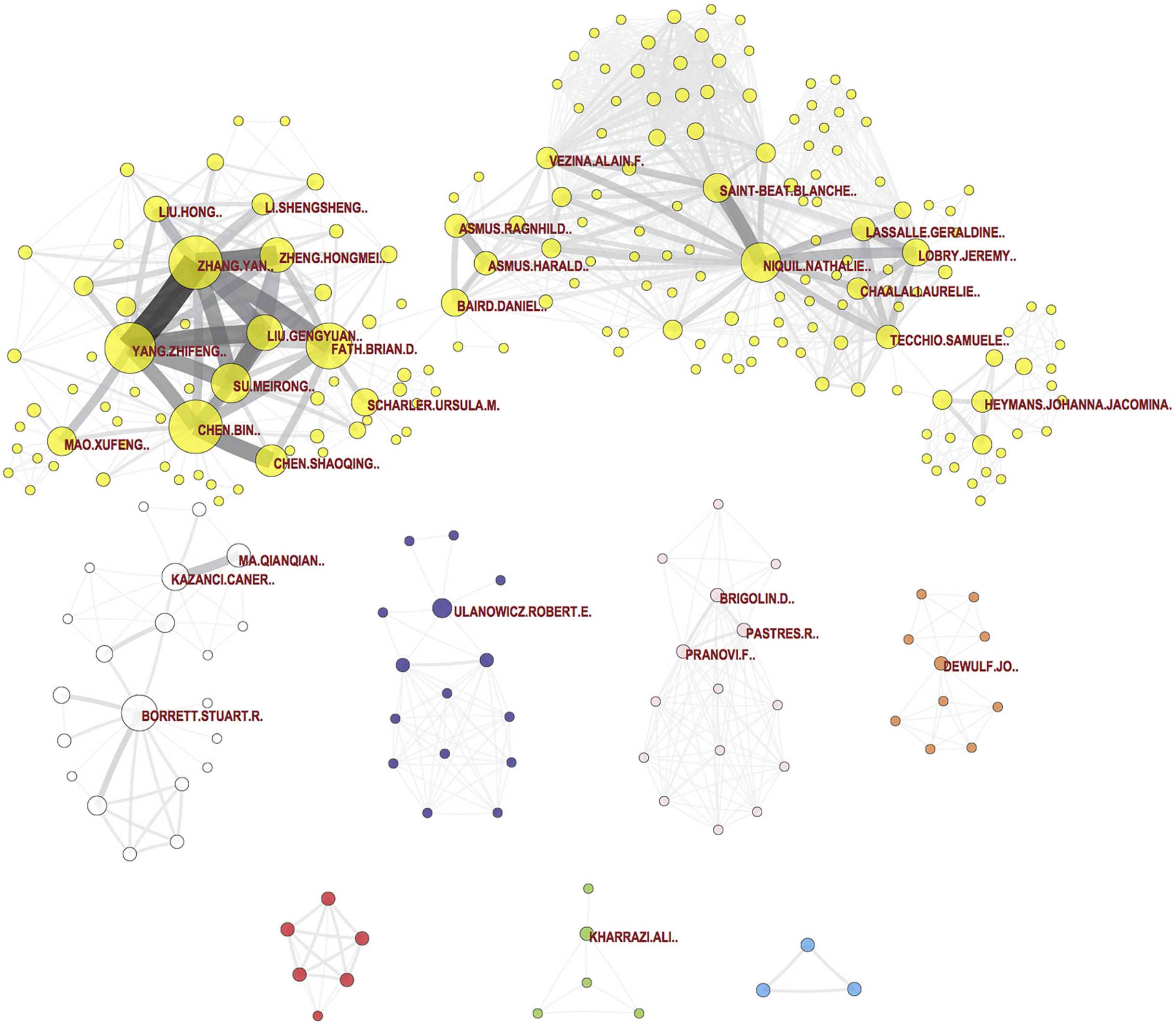

Fig. 6. Coauthorship network for the Ecological Network Analysis publications from 2010 through 2016. In this network model, nodes are authors and edges indicate the number of coauthored publications.

In alignment with the previous results, the food web and biogeochemical cycling ecosystem models, and the urban, industrial, and economic models were most frequent. Over our observation window, the number of new urban, industrial, and economic models surpassed the number of new food web and biogeochemical cycling ecosystem models.

The most frequently reported analyses, other than number of nodes or edges, across all types of systems were the structure analyses in 106 papers (57%). Flow analyses, including both the input–output analyses (98 papers, 53%) and information-based analyses (67 papers, 36%) including ascendency metrics (Table 3), were also common. The control analysis and impact methods (utility analysis and mixed trophic impacts) were used more frequently in papers investigating urban, industrial and economic models. Only 33 papers (18%) included a sensitivity or uncertainty analysis of the results presented.

4. Discussion

Two principal findings result from our analysis of the ENA publications between 2010 and 2016. First, while there are a variety of topics being investigated with this approach, the majority fall either into a cluster focused on food webs or a second cluster focused on the sustainability of socio-ecological systems including studies of urban metabolism. The majority of the food web models investigated aquatic and primarily marine ecosystems, and examined the structure and internal relationships among the ecosystem species or assessed how they differ due to time, space, or changes in specific drivers like an anthropogenic impact. We also discovered a few terrestrial ecosystem applications, including one to assess the sustainability of agricultural systems.

While there is a long history of ENA development and applications tied to trophic studies, the recent applications to socio-economic and socio-ecological systems is an important element of the field. Investigators are finding many creative ways to apply ENA. A second principal finding is the strong collaborative nature of the field. Within our observation window, the majority of authors were linked into a single large component. Our results depend on the specific time period observed, but the key finding is that the authors in the domain are currently highly collaborative and well connected.

When evaluating the quality of a bibliometric review, it is essential to consider the success of the search in identifying the relevant literature. It is possible to have both errors of commission (including papers that really do not belong in the target set) and errors of omission (missing papers in the literature that do belong in the set). Due to our initial screening and subsequent feature analysis, we are confident that our corpus does not contain major errors of commission. We included conference proceedings in our corpus (12%) to better capture the state of the field by being more inclusive in the type of scholarship included.

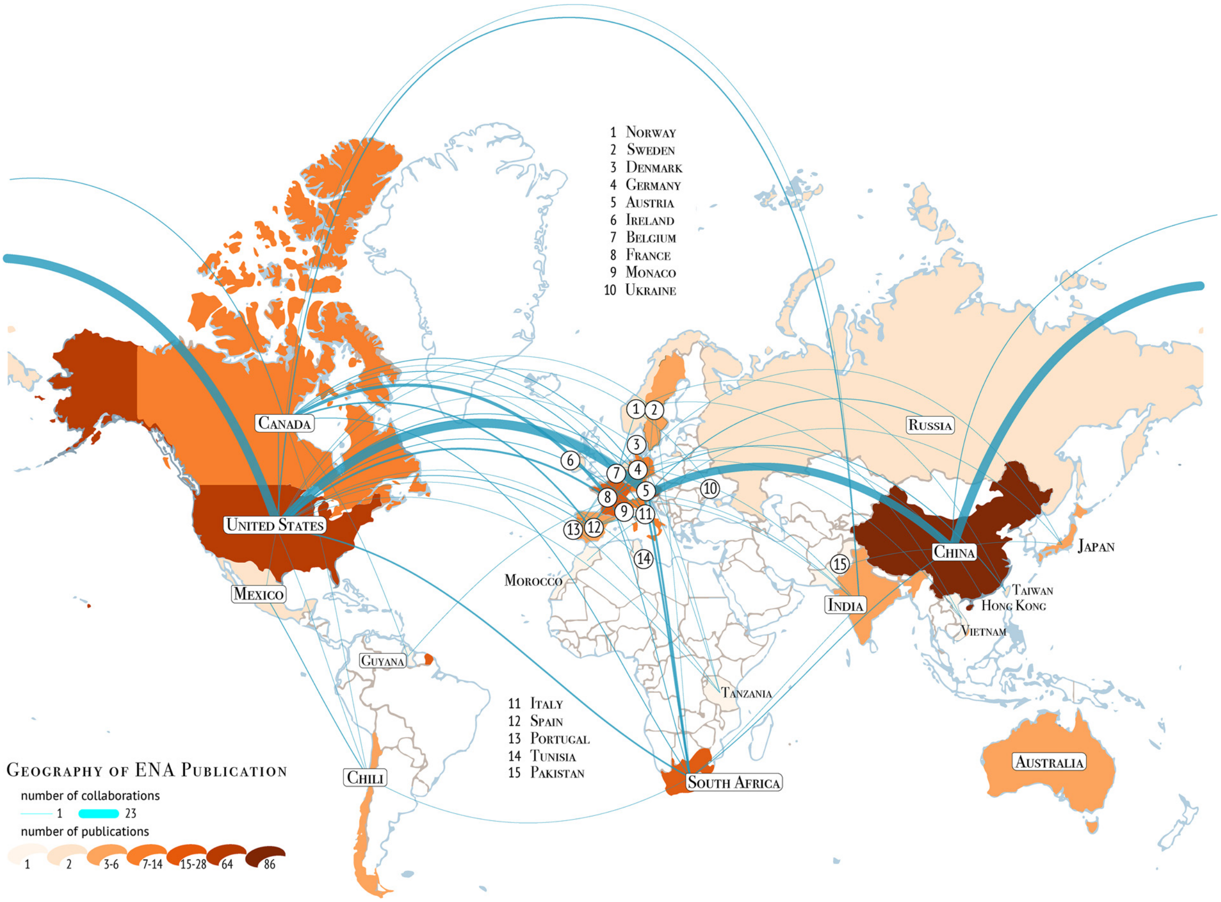

Fig. 7. Geography of Ecological Network Analysis publications from 2010 to 2016 showing the number of publications by authors in each country along with the number of collaborations.

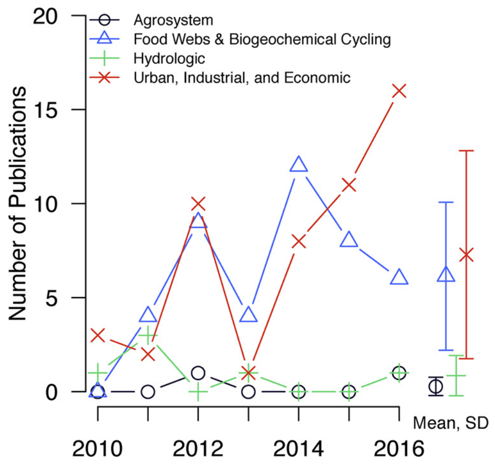

Fig. 8. Number of Ecological Network Analysis papers that introduced a new model each year, classified by system type.

This might have introduced a bias to the results, as some conference papers may be turned into similar journal articles that are also included in the corpus. This potential double counting would be a type of error of commission and would inflate the importance of the topic or author contribution. A review of the author and titles of the corpus indicates that only one conference proceedings was clearly a duplicate (Layton et al., 2016a, 2015). Thus, we expect that the effect of this potential double-counting was minimal.

It is more difficult to assess errors of omission. To increase our likelihood of identifying the relevant literature and decrease errors of omission, we included searches of both the WoS and Scopus databases. However, we are confident that we missed identifying some number of relevant papers. For example, our search failed to find a study applying ENA methods to investigate the ecosystem stoichiometry (C, N, P) of the Twin Cays barrier reef ecosystem in Belize (Scharler et al., 2015), as well as an application of ENA to investigate the performance of economic supply chains (Allesina et al., 2010). We also failed to find a couple of papers by Kharrazi et al. (2016, 2014, 2013) that applied the information based ascendency flow analysis of ENA. In each of these cases, (1) the work was an application of the ENA methods to specific systems, (2) the papers appear to be written for applied audiences, and (3) the papers were missed because the authors did not include the targeted search phrases in their keyword lists, titles, or abstracts. In addition, we estimated that we missed 14 papers published in 2016 due to finalizing our search for this analysis on Nov. 17, 2016 (9 were conference papers published in Energy Procedia). Despite these important omissions, given our working knowledge of the field and an informal comparison of our results to those found by Google Scholar, we suspect that our error of omission rate was small.

4.1. ENA insights

A number of insights emerge from this work about the practice of using ENA, which we consider in three groups: model construction, analysis, and applications.

4.1.1. Model construction

The first step in any application of ENA is to construct the network model. As noted in the introduction, there are multiple ways to construct an appropriate model to be analyzed with ENA (Fath et al., 2007;

Table 3
Number of publications that performed selected categories of Ecological Network Analyses by system category.

ENA Type	Food web & Biogeochemical cycling (n = 71)	Urban, industrial, & economic (n = 63)	Hydrologic (n = 7)	Agroecosystem (n = 2)	Other (n = 43)	Total (n = 186)
Structure	50 (70%)	43 (68%)	7 (100%)	1 (50%)	5 (12%)	106 (57%)
Flow (Input-Output)	58 (82%)	26 (41%)	4 (57%)	2 (100%)	8 (19%)	98 (53%)
Flow (Information[a])	42 (59%)	14 (22%)	5 (71%)	2 (100%)	4 (9%)	67 (36%)
Storage	8 (11%)	.	1 (14%)	.	2 (5%)	11 (6%)
Utility or Mixed Trophic Impacts	12 (17%)	35 (56%)	3 (43%)	.	2 (5%)	49 (26%)
Control	1 (1%)	10 (16%)	2 (29%)	.	.	13 (7%)
Environ	7 (10%)	1 (2%)	1 (14%)	.	.	9 (5%)
Sensitivity or Uncertainty Analysis	25 (35%)	4 (6%)	.	.	4 (9%)	33 (18%)

[a] Includes calculation of information based metrics like Ascendency, Overhead, Capacity, derived ratios, and robustness.

Wulff et al., 1989), many of which are apparent in the literature we reviewed. These model construction methods include building nutrient or energy budgets using phenomenological approaches (Hines et al., 2015, 2012; Scharler, 2012; Ulanowicz, 1986; Xia et al., 2017) or employing theoretical energetic constraints for food webs (Banerjee et al., 2016; Heymans et al., 2011; Tomczak et al., 2013), linear inverse modeling (Niquil et al., 2011; Saint-Béat et al., 2013b; Small et al., 2014; Taffi et al., 2015; Tecchio et al., 2016; van Oevelen et al., 2010; Vézina and Pace, 1994), and creating more mechanistic dynamic models and simulations (Baird, 2011; Lee et al., 2012). Different methods may be more common or appropriate for different applications. For example, the energetic and trophic constraints built into Ecopath models may work well for food webs, but they are typically not appropriate for urban metabolism models. Regardless of the method used, creating ecosystem networks is still a model construction process that should follow modeling best practices (Haefner, 2005; Jørgensen and Bendoricchio, 2001; Schmolke et al., 2010) including a clear evaluation of the model quality both in terms of model structure and the analytic results (Dame and Christian, 2008, 2006; Deehr et al., 2014).

Sensitivity and uncertainty analyses assist with model evaluation and enable investigators to make stronger inferences about the system analyses. Our review shows that applications of these techniques are becoming more common in ENA. These analyses have two main forms. The first form focuses on the initial conceptual model and considers the impact of issues like node aggregation (lumping) on the ENA results. This aggregation may occur when researchers have limited species-specific data for food webs and therefore group species into functional groups (e.g., large phytoplankton, bacteria). For example, several studies have found that ENA indicators were sensitive to different node aggregation schemes, and especially to the representation of detritus and other forms of non-living resource pools in food web ecosystem models (Abarca-Arenas and Ulanowicz, 2002; Allesina et al., 2005; Baird et al., 2009; Johnson et al., 2009). For example, Fath et al. (2013) discovered that some network metrics were less affected by their aggregation scheme for the Sylt-Rømø Bight model, while other metrics exhibited larger differences. The aggregation problem is an old one in ecological modeling (Cale et al., 1979; Gardner et al., 1982), and one that yields few simple guidelines. Despite the potential influence of aggregation issues, Fath et al. (2007) argued that for ENA applications to be most useful as a systems analysis tool, it is essential to include all components of the ecosystem in the model – even if this means creating aggregated functional groups.

A second form of sensitivity and uncertainty analysis considers the network structure largely fixed and focuses on the uncertainty in the flux magnitude estimations (e.g., model parameterization) (Ayers and Scharler, 2011; Guesnet et al., 2015; Hines et al., 2018, 2015; Kones et al., 2009). This is largely accomplished by selected flux perturbations to an initial model using a Monte Carlo approach (Bodini et al., 2012; Heymans et al., 2016; Salas and Borrett, 2011) or using Monte Carlo methods coupled to a modeling procedures such as a regionalized sensitivity analysis (Borrett and Osidele, 2007) or linear inverse modeling (Chaalali et al., 2016; Guesnet et al., 2015; Kones et al., 2009; Pacella et al., 2013) to sample the space of plausible network model parameterizations. These analyses have been used to show that ENA whole-network metrics tend to be more constrained than the estimated network uncertainty, and that some indicators are more robust (less sensitive) to this uncertainty than others (Kaufman and Borrett, 2010; Kones et al., 2009).

The development and application of methods to perform sensitivity and uncertainty analyses for ENA studies is a critical step to evaluating the quality of the models and analytical results. It is also essential to make ENA more useful for ecosystem assessment and environmental management applications because investigators can make stronger inferences about a selected network metric compared to a threshold (Borrett et al., 2016; Hines et al., 2018, 2016) or the differences between systems being compared with ENA (Ayers and Scharler, 2011; Hines et al., 2018, 2015; Saint-Béat et al., 2013a).

4.1.2. *Analyses*

ENA is a set of related analytical tools that build upon ideas in the broader area of network science (Brandes et al., 2013; Newman, 2010), including social network analysis (Wasserman and Faust, 1994), economic Input–Output methods (Hannon, 1973; Leontief, 1966), and information theory (Rutledge et al., 1976; Ulanowicz, 1986). One challenge of using ENA is that there are a large number of different methods that have developed over its more than four decades of development. The advantage of this method diversity, however, is that there is greater flexibility and choice. One way that reviews (such as this one) might help advance the field is by (1) focusing on methods (rather than topic), (2) highlighting the applications of the methods, and (3) identifying characteristics of how different ENA models were implemented. We hope that through this elucidation, the choices researchers must make will become more clear.

Another way that reviews contribute is by formalizing the boundaries and linkages between methods, characterizing the extent to which they vary, and identifying tools for implementation. To that end, Fig. 2 presents a conceptual model of different groups of methods in ENA that builds on previous categorizations (Fath and Patten, 1999). At the base are a collection of structural methods that typically ignore the edge weights and include classic food web descriptors like connectance (i.e., network density). Few of the ENA structural methods are unique to the field; most are shared in common with other domains in network science. However, the pathway proliferation concept underlies many of the other ENA methods (Borrett et al., 2007; Borrett and Patten, 2003; Patten, 1985b). Flow analyses builds on the structural analyses and considers the edge weights (Finn, 1976; Gattie et al., 2006; Kay et al., 1989; Latham, 2006; Patten et al., 1976; Ulanowicz, 1986). Flow methods can be classified into two types: methods that build directly on economic Input–Output techniques (Fath and Patten, 1999; Finn, 1976; Patten, 1985b; Patten et al., 1976; Szyrmer and Ulanowicz, 1987; Ulanowicz and Kemp, 1979) and a set of analyses that draw on information theory, which includes the ascendency set of analytics

(Hirata and Ulanowicz, 1984; Patricio et al., 2004; Ulanowicz, 1980). Our review suggests that flow analyses are the most commonly used methods in our corpus. Storage analyses are mathematically very similar to flow analyses, but also account for node weights to represent the amount of energy or matter stored in a node (Barber, 1978; Fath and Borrett, 2006; Fath and Patten, 1999; Schramski et al., 2011; Ulanowicz and Abarca-Arenas, 1997). In many ecosystem models storage is equivalent to the biomass of the species or functional group. These methods are much less often used in our corpus.

The environ, control, and what we are calling impact methods (Fig. 2) build upon the flow or storage analyses. The specific environ methods operationalize Patten's environ concept for investigating the input and output environs of the system members (Patten, 1981, 1978), which have been used to investigate the ecological niche concept (Patten and Auble, 1981) and to quantify the coupling of steps in biogeochemical cycling (Hines et al., 2015). Control analyses indicate which nodes in a network exert more or less control upon the other node's flow across the network (Chen and Chen, 2015; Dame and Patten, 1981; Fath, 2004a; Hines et al., 2016; Schramski et al., 2007, 2006). The impact methods focus on the net or integral pairwise impact of one species in the network on another, and were well used in our corpus (23%). This includes mixed trophic analysis (González et al., 2016; Ulanowicz and Puccia, 1990) and a similar but more general analysis termed utility analysis (Fath and Patten, 1998; Patten et al., 1991; Zhang et al., 2016c). Scharler and Fath (2009) provide a detailed comparison of these closely related impact methods.

4.1.3. Applications

This review highlights the adaptable nature of ENA. The modeling approach and analyses have been applied to a wide variety of system types and used to address a variety of kinds of questions from theoretical issues to applications to specific ecosystems. The field launched with a strong trophodynamic emphasis (Belgrano, 2005; Dame and Patten, 1981; Finn, 1976; Hannon, 1973; Wulff et al., 1989) that continues today as ENA network metrics are being considered as indicators to assess marine food web status (Bocci et al., 2016; Brigolin et al., 2014; Chaalali et al., 2016; Heymans and Tomczak, 2016; Tomczak et al., 2013). Several papers have investigated the power of indirect interactions to alter the net relationships among species in the food webs (Banerjee et al., 2016; Lassalle et al., 2011; Rodríguez-Zaragoza et al., 2016), which seem to become more positive when the model traces essential resources in food webs or biogeochemical cycling (Borrett et al., 2016). However, creative applications of ENA demonstrate that it can be used to trace the negative effects of toxins as well (Taffi et al., 2015). The methods are also being used to assess the functioning and sustainability of technical, economic, and socio-ecological systems. For example, investigators have used ENA ideas to determine if designing industrial networks using ecosystem principles lead to more sustainable industries (Layton et al., 2016a,b,c). Others have used ENA as a tool to investigate the energy–water nexus in socio-ecological systems (Duan and Chen, 2017; Wang and Chen, 2016; Yan and Chen, 2016). In fact, applications to socio-ecological systems (Chen et al., 2015; Guo et al., 2016; Liu et al., 2011b; Zhang et al., 2016d) grew faster than applications to food webs in our study period (Fig. 8). The individual applications are interesting on their own, and collectively this review illustrates a broad number of ways to use the ENA tools. We suspect that these uses will grow as creative scientists continue to develop and explore the tool set.

4.2. Collaboration

The coauthorship network shows that the investigators in this domain are highly collaborative. These collaborations have clusters that tend to be focused on specific topics, and the work groups tend to have a spatial component that may influence the outcomes (de Bont and Lachmund, 2017); however, there are also many collaborations that extend beyond these working groups. Those authors who appear in multiple work groups function as social bridges that enable the diffusion of ideas and innovations. Further, the data intensity and diversity of technical expertise required to successfully apply ENA may encourage larger and more varied teams of scientists.

The observed co-authorship structure has a strong temporal component and informs us about the collaborative structure within the observation window (2010–2016). If we were to extend our observation period, we would expect to see several of the smaller components join with the giant component. For example, Ulanowicz has coauthored papers with Baird (Baird and Ulanowicz, 1989; Ulanowicz and Baird, 1999), Scharler (Fath et al., 2007; Ulanowicz and Scharler, 2008), and Niquil (Niquil et al., 1999) in the past. Similarly, Fath coauthored a number of papers with Patten before our observation window (Borrett et al., 2007; Fath et al., 2004; Fath and Patten, 1999, 1998). More recent papers would also join the subcomponent with Borrett to authors in the largest component (Hines et al., 2018; Rakshit et al., 2017). Similarly, two of the ENA papers we initially missed in our search would have joined two of the smaller components to the largest author component. The Scharler et al. (2015) paper would have linked the author cluster with Ulanowicz, and the Kharrazi et al. (2013) connects the component with Kharrazi.

The core conclusions from this view of collaboration is that this science community is relatively tight-knit in this domain. Thus, we expect that ideas and innovations propagate quickly across the community. This is reinforced by the finding that some authors are the most common across several topic clusters (Table 1). Despite this connectivity, it is important to notice that (1) clear common working groups are still apparent within the components, and (2) the large food web topic cluster does not have a common author that appears in the other topic clusters. A limitation of this study is that it does not show how well connected this community is to the broader domains of network ecology, or general ecology, environmental sciences, or network science.

4.3. Challenges & opportunities for ENA

While the use of network models and concepts continues to grow by about 0.2% per year throughout the ecological literature (Borrett et al., 2014; Lau et al., 2017), the publication rate for ENA appears fairly steady between 2010 and 2016. The growth in network ecology is driven by the application of network ideas to a variety of different complex ecological problems. These applications include showing how genotypic variation in a foundational species like the narrowleaf cottonwood tree can determine the community composition of macroarthropods that live on the tree (Lau et al., 2016), revealing the small overlap in Venus flytrap (*Dionaea muscipula*) prey and pollinators (Youngsteadt et al., 2018), finding the ecological significance of animal social networks (Kurvers et al., 2014), and considering how organisms move in space (Dale and Fortin, 2010; Jacoby and Freeman, 2016; Saura et al., 2014). While there are clearly some new and interesting applications of ENA and more opportunity for expansion, the field has had over 44 years to mature. In addition, the model type is more restrictive than many other network models (e.g., it traces a single thermodynamically conserved currency such as carbon or nitrogen). This restriction provides the analysis more power, but limits the kinds of system to which the approach may apply. Other issues that may be hindering the potential of ENA include the lack of systematic and critical reviews, the large volume of original data required, and the large and complex sets of analyses that make it difficult for new investigators to know which method to apply when and for what purpose.

Two additional issues may be impeding the development of the science around ENA: language barriers and the requirements for "tacit knowledge." Naming conventions may present challenges to the use and dissemination of ENA. For example, scientists within the ENA field conceptualize the phrase 'Ecological Network Analysis' and the acronym ‘ENA’ to mean a specific set of approaches, measures, and data expectation. It is unclear if these ideas penetrate into the larger community of ecologists and environmental scientists. One indicator that this may not be the case is that while searching the literature for this study, we observed that the term ‘ecological network analysis’ is increasingly being used more generically by scientists beyond the community cited here. This generic use may dilute the power of ‘ecological network analysis’ as a key-term. However, we advocate strongly that the community continue to use the Ecological Network Analysis phrase as a key-term in its publications as it will assist with finding the relevant literature, which may promote an ease of communication and research (Sheble et al., 2016). At a more detailed level within the lexicons of ENA research, there remains a jumble of terminology and mathematical notation, with the same or similar concepts expressed in different ways with different types of ENA approaches. In some cases, it appears that the software tools as well as publication texts propagate linguistic differences. There is opportunity to streamline terminology to facilitate the continued use of the approach, expose similarities in approaches, and more cohesively communicate to a wider audience the commonalities that enable researchers well-versed in ENA to recognize strong similarities amongst this family of methods. This task could be assisted with additional reviews and synthesis papers, and translation aids that enable an extent of multilingualism, much in the way that some scientists develop levels of comfort with both network and graph theory.

The second impediment concerns the hidden knowledge embedded in ENA practice. ENA is like many newer procedurally-oriented research practices in that it is most often learned in the contexts of laboratories and research teams or through mentorships (Leahey, 2008). Both the methods and the intricacies of decisions made and options available are transmitted from mentors to learners tacitly through the experience of working on a project (Klemmer et al., 2006; Polanyi, 1967). To counter challenges imposed by irregular naming conventions and transmission of methodological knowledge primarily in the practice of research, it could be helpful for ENA researchers to question, work to codify, and write about research and data practices for broader audiences. For example, researchers could write for more general ecology journals, journals targeting complex network modeling and analysis, and those that target more application- and education-oriented audiences.

Another challenge, and thus opportunity for ENA research, is focused on the large number of network metrics produced by the analyses (Borrett and Lau, 2014; Kazanci and Ma, 2015; Lau et al., 2017). Each metric was constructed to describe a selected feature of the systems, and many appear to relate the system state in the DIPSR framework (Burkhard and Müller, 2008). However, the large number of metrics can be overwhelming (e.g., the *get.ns()* function in the enaR software returns 82 whole-network metrics), and we know from both the underlying mathematics and statistical analyses (Borrett and Osidele, 2007; Kazanci and Ma, 2015) that not all of the metrics are provide independent information about the system. While in some theoretical work and applications it will continue to be useful to have the full range ENA network metrics, it might also be useful to identify a smaller subset that provide a user or manager with more robust and independent information. Participants at the “Use of coastal and estuarine food web models in politics and management: The need for an entire ecosystem approach to prevent crises” workshop held at the Alfred Wegener-Institute Helmholtz-Zentrum fur Polar und Meeresforschung in Sylt, Germany (Sept. 2017) considered this issue. However, even if the community can identify a key subset of metrics, there remains the challenge of constructing strong indicators from these metrics (Dale and Beyeler, 2001). For example, we generally do not have clear or consistent expectations (with supporting evidence) as to how the metrics should or do respond to different stressors (Luang et al., 2014; Ludovisi and Scharler, 2017).

Is ENA up to the task of environmental assessment and guidance of management? It has solid theoretical foundations and this review shows that this foundation is being built upon by a dedicated and cohesive community of scientists developing and applying the science in a diversity of ways. This is a promising start. However, there remains a need for the community to collaboratively build and consistently follow best practices for model construction (Fath et al., 2007) including rigorous model evaluation and the application of sensitivity and uncertainty analyses that enable stronger inferences. There is also effort required to transform network metrics from system state descriptors into good indicators that have clear meaning for management with known and reliable responses to changes in the system state (Dale and Beyeler, 2001). Given the findings of this review, we are optimistic for the future of Ecological Network Analysis.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecolmodel.2018.04.020.

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