The Review of Ecological Network Indicators in Graph Theory Context: 2014-2019

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Abstract

Ecological Network Analysis (ENA) capability has led to develop a set of indicators. Ecological Network Indicators (ENIs) investigates a range of subject in different context "e.g. Graph theory", which is the origin of variety of questions such as following: What is the geographical distribution of studies and their relationship with each other? On what fields these studies are focused? What graph-based index or indexes have been used in the studies of ecological networks? What are the most widely used indexes in ecological studies?

Accordingly, this study is to investigate the related literature between 2014 and 2019 in the framework of graph theory. To answer the mentioned question, we conducted systematic literature review. To find as many potentially eligible articles as possible, the search was performed multiple times using diverse related keywords. We identified 456 related records. After the screening process, 114 articles were left as the basis of further analysis.

The results indicate that ENA applied mainly in China, USA, France. ENIs is studied more frequently among plants and mammals. We identified about 58 ENIs. But the Probability of Connectivity (PC), Integral index of connectivity (IIC) have been consistently used in most studies. Also, these two indices are used in combination with others ENIs. The outcomes show researchers introduce new indexes every year. The increasing trend of introducing new indicators shows the usability and applicability ENIs. But so far, PC, IIC, and LCP seem to be the most credible graph-based indexes for use in ecological network research. The overall results imply that graph theory as base of ecological network is developing, presents new indicators and opening new dimensions in the study and analysis of connections and communications in ecological networks. It has adequate flexibility to answer questions that may arise in the future in the field of ecological network analysis.

Background

Over the past 20 years, graph theory has been one of the most widely used tools that ecologists have used to study ecological networks (Bishop-Taylor, Tulbure, & Broich, 2018; Ruiz et al., 2014; Tulbure, Kininmonth, & Broich, 2014). This theory is widely used, Due to its high application in providing a functional view of networks and also the lack of need for a lot of data (Calabrese & Fagan, 2004; Foltête, 2018; Galpern, Manseau, & Fall, 2011). Graph theory can be used to simplify complex ecosystems by creating their mathematical representations in the form of easy to understand vertices, edges, and flows in graph structures(Gross & Yellen, 2005). Using the methods and tools provided by graph theory, researchers and especially ecologists can study, understand, and analyze complex environments more effectively and more conveniently.

Over the years, graph theory has been developed and used to analyze many ecological networks of the plant (P. Huang, Du, Yang, & Liu, 2016; Tambosi, Martensen, Ribeiro, & Metzger, 2014), animal species (Meurant, Gonzalez, Doxa, & Albert, 2018; Sahraoui, Foltête, & Clauzel, 2017) and context (Masselink et al., 2017) in both terrestrial (Mikoláš et al., 2017) and aquatic (Stewart-Koster, Olden, & Johnson, 2015) ecosystems (Grech et al., 2018; Urban, Minor, Treml, & Schick, 2009). This study focuses mainly on the habitat network because it focuses more on the ecological connectivity network. There have been several extensive reviews of studies in the field of ecological network analysis. These include the works of Janssen et al. (Janssen et al., 2006), which provided a framework for the study of socio-environmental systems with a focus on interactions between the components of these systems, Saint-Béat et al. (Saint-Béat et al., 2015), which reviewed the theories that link food web structure and performance to the sustainability of ecosystems. Borrett et al. (Borrett, Sheble, Moody, & Anway, 2018), provides a systematic review of studies in the field of ecological network analysis from 2010 to 2016, and Kleinman et al (2019), which identified and described the ecological consequences of discrete forest disturbance events involved in compound interactions. (Kleinman, Goode, Fries, & Hart, 2019).

While graph theory has been used in various areas of ecological analysis for many years (Ernst, 2014b; Hejkal, Buttschardt, & Klaus, 2017; Hofman, Hayward, Kelly, & Balkenhol, 2018; Loro, Ortega, Arce, & Geneletti, 2015; Zhang, Meerow, Newell, & Lindquist, 2019), few studies have been conducted on its application in ecological network sciences. In this regard, we can refer to the research conducted by Brett and his colleagues in 2014 in the field of Network ecologists. Which has documented the emergence of network ecology and identified the diversity of topics discussed in this field, as well as mapping the scientific cooperation between scientists specializing in this field. They have used three terms to identify research, one of which is graph theory (Borrett, Moody, & Edelmann, 2014). In that study, they examined graph theory in a broader format because study aimed was to identify and determine the scope of the network environment. Considering the extensive use of graph theory and graph-based indexes in the field of ecology, the various aspects of this use need to be explored more systematically, and special focus is needed on the concept of graph theory in network analysis in the research. Therefore, this study aimed to investigate the use of graph-based indexes in the studies of ecological networks. For this purpose, given that in recent years the use of graph theory in the ecological network has been growing, with considering that the results

and methods that have been presented in this field recently are updated to be. The authors reviewed the indicators used in such studies, which were published between 2014 and 2019. For achievement to the main aim, the following research questions are specifically addressed: 1- What is the geographical distribution of studies and their relationship with each other? 2. In the field of ecological network, what indicators of graph theory have been used and what are the most widely used indicators? 3- In what domains are these studies focused and Graph theory indicators have been used to study on what species used in studies? This was done by conducting a systematic review of relevant articles published in this period and specifically the studies that have used graph theory.

Methods

Search Process

Considering that systematic review is one of the explicit methods of literature review with widespread use in many fields of science(Amui, Jabbour, de Sousa Jabbour, & Kannan, 2017; Callahan, 2014; Grant & Booth, 2009; Petticrew, 2001; Pham, Paillé, & Halilem, 2019), the authors chose this method for answering the research questions.

The systematic review was started by taking the following steps:

1. A) Defining the time scope of the search as follows: January 2014 - February 2019.
2. B) Selecting the keywords of the search as follows: "Graph Theory", "Ecological Networks", "Fragmentation", "Landscape Connectivity", "Landscape Ecology", "Urban Landscape", and any combination of these terms.

The searched databases were Google Scholar and ISI Web of Knowledge. This search was narrowed to articles written in English in which graph theory has been used in the study of ecological networks.

To find as many potentially eligible articles as possible, the search was performed multiple times, each time with the term "Graph Theory" used as the fixed keyword but combined with one of the following complementary terms: "Ecological networks", "Fragmentation", "Landscape connectivity", "Landscape ecology", "Urban landscape". Finally, the search results were sorted in the descending order of the publication year (from 2019 to 2014).

Selection Process

The eligible articles were selected through the three-phase process used by Mehring et al. (2019). The diagram of this process is illustrated in Figure (1). In the first phase, articles that had the term "graph theory" and one of the complementary keywords ("Ecological Networks", "Fragmentation", "Landscape Connectivity", "Landscape Ecology", "Urban Landscape") in their titles, abstracts, or keywords were listed (duplicate articles were discarded). The number of articles in this phase was 456. After sorting the articles in the order of their publication year, in the second phase, the texts of the articles were examined to be clear whether the articles in the text also deal with graph theory or not? and those articles that were not related to the field of interest and those that had not used graph theory were discarded. This was done to enhance the focus in selecting articles on the subject under study and avoiding mistakes. Because in some researches, although keywords are included in the title, abstract and keywords, they are not used in the research text. Bringing these researches in the results and analysis causes an error in the research and diverts it from the main goal. Eventually, A total of 167 scientific articles were found to meet these criteria. In the third phase, the articles that had not used the graph-based indexes were discarded, leaving 114 articles. These 114 articles had used graph-based indexes for ecological analysis.

Analysis

The grounded theory (GT) was used to reach a simpler and more organized categorization of indexes used in the articles so that the results can be presented and discussed in separate segments. This method involves systematic data collection followed by systematic analysis and simplification of the collected contents (Glaser & Strauss, 2017). The core idea of this method is to gather data about a specific subject through research and then transform the gathered data into concepts and categories through repeated comparison and refinement (X. Li, Du, & Long, 2019). In this study, the software VOS viewer was used for data visualization where needed.

In the analysis of articles, the following were investigated: geographical distribution of studies by country and continent, employed indexes, main indexes, number and composition of employed indexes, novel indexes, ecosystem composition of the use of graph-based indexes, frequency of use of graph-based indexes by the number and type of species, frequency of use of graph-based indexes in different fields of ecology. Although, The relationship between the indicators is investigated using Spearman correlation.

Results

Geographical Distribution of Studies

The use of the graph-based approach in ecological research does not have an even geographical distribution. This approach has been used most frequently in Europe and Asia, followed by North America. Only a limited number of studies in other regions have used this approach.

The results show that the studies using this approach have been limited to 26 countries (Fig. 2). China (16.67%), the USA (13.15%), and France (13.15%) have the highest number of studies. Other countries with a notable number of studies are Spain (6.14%) and Australia and Canada (5.3%). Also, 4.38% of the studies have not been focused on any specific country.

The results also show that researchers from 37 countries have taken part in the reviewed studies. The highest rates of participation are related to researchers from the United States, France, and China with 27%, 20%, and 19%, respectively.

Ecosystem Composition of The Use of Graph-based Indexes in The Field of Ecology

Ecological indexes can be used in the analyses of all types of ecosystems. But as expected, these indexes were mostly used in the study of terrestrial ecosystems (80%). In 15.65% of the reviewed studies, indexes were used to study aquatic ecosystems. The rest of the studies (4.35%) were not focused on any specific ecosystem (Fig. 3).

Indexes

In the 114 reviewed studies, a total of 58 indexes were used 160 times. In these studies, the indexes were used in two ways: 1- individually, 2- combined with other indexes. In terms of frequency of use, some indexes were used for many years, but some others were new and had not been used as frequently. Therefore, this issue was taken into account during the analysis.

Frequency of Use of Graph-based Indexes by the Number and Type of Species

The 114 reviewed studies were categorized from two perspectives: 1- the number of species studied, 2- the type of species studied. Approximately 85.09% of the studies were performed on one species, 6.14% were performed on two species, 4.38% were performed on 3 species, and 0.88% were performed on 5 species. The remaining 3.51% of the studies were general. Table 1 shows the number of single-species studies that were conducted on each type of species. Table 2 shows the number of studies performed on two, three, and five of each type of species.

Table 1
domains of the reviewed studies

Plants	Birds	Reptiles and amphibians	Mammals	Context	Insects	Aquatic animals
34	9	6	29	13	2	4

Table 2
Frequency of the types of species examined in the studies

	Plants	Birds	Reptiles and amphibians	Mammals	Context	Insects	Aquatic animals
studies were performed on two species	*			*			
			*	*			
		*		*			
			*	*			
		*		*			
		*	*				
	*					*	
studies were performed on three species					*	*	*
		*	*	*			
		*	*		*		
		*	*	*			
		*	*	*			
studies were performed on five species	*	*	*	*		*	

The total number of biological domains on which the studies were conducted was 131 (135 if the four general studies are included). To provide a better understanding of the frequency of use of graph theory in the domains of ecological analysis, the distribution of its use in different domains is depicted in Table 1. As the results show, the most frequent domains are animal species with 60.30%, plant species with 28.24%, Context with 11.45%, and general with 2.29%. The studies on animals were divided into five groups: birds (12.98%), reptiles and amphibians (10.69%), mammals (29.01%), insects (3.82%), and aquatic species (3.82%). The studies on plants were divided into two groups: aquatic (0.76%) and terrestrial (27.48%).

Name and Usage Frequency of Employed Indexes

The frequency analysis showed that the studies had used the graph-based indexes 160 times. In terms of frequency of use, the indexes were divided into three categories: 1) widely used, 2) intermittently used, and 3) rarely used. The indexes PC (Probability of Connectivity), IIC (Integral index of connectivity), and LCP (Least-cost-path algorithm) fall in the first category. The most widely used index is PC, which has been used in 30% of the studies. The indexes IIC and LCP are second and third in this ranking with use in 18.75% and 8.12% of the studies respectively. The indexes ECA (Equivalent connected area), SP (Randomized Shortest Path), MGP (Minimal planar graph), NC (Number of components), AWF (Area-weighted flux), NL (Number of links), EC (Equivalent connectivity index), and LSP (Least-cost path), HI (Harary index), which have been used in 2 to 4% of the studies, fall in the second category. The third category includes 47 indexes that each has been used in only one study (Table 4, Table 5).

The index PC has been consistently used in most studies. IIC has been used in the studies published from 2014 to 2017. LCP has been used in various studies published in 2014, 2015, 2016, 2018, and 2019. ECA has been used in 2014, 2016, 2017, and 2018. LSP has been used in 2015, 2018, and 2019. The index NC, with a usage frequency of 1.87%, has been used only in 2017. Other indexes have usage frequencies ranging from 0.5 to 2% and have been used in either 1 or 2 years.

Number	index	Frequency	percent	Number	index	Frequency	percent	Number	index	Frequency	percent
1	PC	48	30%	21	PA	1	0.62%	41	E	1	0.62%
2	IIC	30	18.75%	22	TC	1	0.62%	42	LCP	13	8.12%
3	DNMS	1	0.62%	23	DF	1	0.62%	43	LSP	3	1.87%
4	ED	1	0.62%	24	SDM	1	0.62%	44	HI	2	1.25%
5	ECA	4	2.5%	25	SP	2	1.25%	45	STRG	1	0.62%
6	IV	1	0.62%	26	IM	1	0.62%	46	GED	1	0.62%
7	LCD	1	0.62%	27	MSSN	1	0.62%	47	CAT	1	0.62%
8	RD	1	0.62%	28	GD	1	0.62%	48	EC	2	1.25%
9	GT	1	0.62%	29	NSC	1	0.62%	49	NL	2	1.25%
10	SRM	1	0.62%	30	F	2	1.25%	50	NC	3	1.87%
11	AWF	2	1. 25%	31	SHI	1	0.62%	51	EB	1	0.62%
12	CT	1	0.62%	32	BC	1	0.62%	52	KP	1	0.62%
13	MPG	2	1.25%	33	KPR	1	0.62%	53	KPF	1	0.62%
14	LI	1	0.62%	34	RNG	1	0.62%	54	CI	1	0.62%
15	OP	1	0.62%	35	C	1	0.62%	55	FBC	1	0.62%
16	HG	1	0.62%	36	DPC	1	0.62%	56	IP	1	0.62%
17	SPT	1	0.62%	37	BM	1	0.62%	57	MCA	1	0.62%
18	MCM	1	0.62%	38	GCC	1	0.62%	58	MLT	1	0.62%
19	VIF	1	0.62%	39	PCM	1	0.62%				
20	NV	1	0.62%	40	AWM	1	0.62%				

Frequency of Use of Indexes in Different Domains of Ecological Research

Another topic of interest was the nature of indexes used in each domain of research. The results show that the most widely used indexes in all domains are PC, IIC, and LCP. The authors also examined the frequency of use of graph-based indexes on different species, the results of which are presented in Table 3.

Table 3
Graph theory indicators used in the field of ecology

	Name	Summary mark	Frequency	
1	Probability of Connectivity	PC	30	(Appolloni, Sandulli, Vetrano, & Russo, 2018; Betbeder, Laslier, Hubert-Moy, Burel, & Baudry, 2017; Celine Clauzel, Bannwarth, & Foltete, 2015; Céline Clauzel, Jeliazkov, & Mimet, 2018; Celine Clauzel, Xiqing, Gongsheng, Giraudoux, & Li, 2015; Correa Ayram, Mendoza, Etter, & Pérez Salicrup, 2017; Ernst, 2014a; Foltête, 2018; Foltête, Couval, Fontanier, Vuidel, & Giraudoux, 2016; Foltête, Girardet, & Clauzel, 2014; Girardet, Conruyt-Rogeon, & Foltête, 2015; Gurrutxaga & Saura, 2014; Harris, Dickinson, & Whigham, 2014; He, Huang, Liu, Wang, & Li, 2018; Kang, Minor, Lee, & Park, 2016; Le Roux et al., 2017; W. Li et al., 2017; Liu et al., 2014; Loro et al., 2015; Mikoláš et al., 2017; Pietsch, 2018; Pirnat & Hladnik, 2016; Roy, Bhattacharya, Ramprakash, & Kumar, 2016; Sahraoui et al., 2017; Serret et al., 2014; Sillero, Biaggini, & Corti, 2018; Song & Kim, 2016; Volk, Gattringer, Otte, & Harvolk-Schöning, 2018; Xun, Yu, & Wang, 2017)
2	Integral index of connectivity	IIC	14	(Ayram, Mendoza, Salicrup, & Granados, 2014; Bergsten, Galafassi, & Bodin, 2014; Devi, Murthy, Bijan, & Jha, 2016; Fourie, Rouget, & Lötter, 2015; Goulart, Takahashi, Rodrigues, Machado, & Soares-Filho, 2015; Herrera, Sabatino, Gastón, & Saura, 2017; Ishiyama, Akasaka, & Nakamura, 2014; Ishiyama, Koizumi, Yuta, & Nakamura, 2015; Alex Mark Lechner, Rebecca MB Harris, et al., 2015; Lloyd, Widmeyer, & Neel, 2016; Naicker, Rouget, & Mutanga, 2016; Nogués & Cabarga-Varona, 2014; Ren et al., 2014; Van Looy et al., 2014)
3	Least-cost-path algorithm	LCP	13	(Albert, Rayfield, Dumitru, & Gonzalez, 2017; Álvarez-Romero et al., 2018; Chen et al., 2017; B. Cui, Shao, & Zhang, 2015; Drake, Griffis-Kyle, & McIntyre, 2017; Khosravi et al., 2018; Kong, Yin, Nakagoshi, & Zong, 2010; Alex Mark Lechner, Brown, & Raymond, 2015; Luo et al., 2016; Perkl, Baldwin, Trombulak, & Smith, 2016; Ruppert, Fortin, Gunn, & Martell, 2016; Schaffer-Smith, Swenson, & Boveda-Penalba, 2016; Wu & Lane, 2017; Xiu et al., 2017)
4	Probability of Connectivity, Integral index of connectivity	PC_IIC	9	(N. Cui, Feng, Wang, Li, & Guo, 2018; Dondina, Saura, Bani, & Mateo-Sánchez, 2018; Giannini et al., 2015; P. Huang et al., 2016; Neel, Tumas, & Marsden, 2014; Rappaport, Tambosi, & Metzger, 2015; Rodríguez-Pérez, García, & Martínez, 2014; Tambosi et al., 2014; Ziółkowska, Ostapowicz, Radeloff, & Kuemmerle, 2014)
5	Minimal planar graph or Minimum planar graph	MPG	2	(Foltête & Vuidel, 2017; Prima, Duchesne, Fortin, Rivest, & Fortin, 2018)
6	Probability of connectivity, Equivalent connected area	PC_ECA	1	(Xun, Yu, & Liu, 2014)
7	Dynamic network models	DNMS	1	(Ferrari, Preisser, & Fitzpatrick, 2014)
8	Effective distance	ED	1	(Creech, Epps, Monello, & Wehausen, 2014)
9	Integral Index of Connectivity, Importance value	IIC_IV	1	(Alex M Lechner, Doerr, Harris, Doerr, & Lefroy, 2015)
10	Equivalent Connected Area, Size of a single patch, Probability of connectivity, Transboundary connectivity	ECA_PA_PC_TC	1	(Santini, Saura, & Rondinini, 2016)
11	Dispersal flow	DF	1	(Yu, Liu, Xun, & Shao, 2015)

	Name	Summary mark	Frequency	
12	Species-distribution models	SDM	1	(Mikolajczak et al., 2015)
13	Randomized Shortest Path	SP	1	(Panzacchi et al., 2016)
14	Integrated metrics	IM	1	(Poodat, Arrowsmith, Fraser, & Gordon, 2015)
15	Multi-species spatial network	MSSN	1	(Layeghifard, Makarenkov, & Peres-Neto, 2015)
16	Least-cost path, Euclidean	E_LSP	1	(Bishop-Taylor, Tulbure, & Broich, 2015)
17	Harary index	HI	1	(Niculae, Nita, Vanau, & Patroescu, 2016)
18	Spatio-temporal relational graph, Graph edit distance	STRG_GED	1	(Cheung, Brierley, & O'Sullivan, 2016)
19	Connectivity Analysis Toolkit	CAT	1	(Perkl, 2016)
20	Equivalent connectivity index, Probability of connection index	EC_PC	1	(Dilts et al., 2016)
21	Least-cost distance, Resistance distance	LCD_RD	1	(Avon & Bergès, 2016)
22	Graph-theoretic approaches	GT	1	(Castillo et al., 2016)
23	Spatial-territorial reorganization model	SRM	1	(Mao, Liu, Wang, Tang, & Kong, 2017)
24	Equivalent connected area index	ECA	1	(Ayram, Mendoza, Etter, & Salicrup, 2017)
25	Graph development index	GD	1	(Szmytkie, 2017)
26	Network Structural Connectivity index, Flow analyses, The Shimbel index	NSC_F_SHI	1	(Cossart & Fressard, 2017)
27	Number of links, Number of components ,Integral index of connectivity	NL_NC_IIC	1	(Hejkal et al., 2017)
28	Integral index of connectivity, Probability of connectivity, Highest Number of landscape components	IIC_PC_NC	1	(Gao et al., 2017)

	Name	Summary mark	Frequency	
29	Number of links, Number of components, Harary index, Area-weighted flux, Integral index of connectivity	NL_NC_H_AWF_IIC	1	(Qi, Fan, Ng, Wang, & Xie, 2017)
30	KeyPlayer algorithm	KP	1	(Juliana Pereira & Jordán, 2017)
31	Probability of connectivity, Betweenness centrality	PC_BC	1	(Chaput-Bardy, Alcala, Secondi, & Vuilleumier, 2017)
32	Circuit theory	CT	1	(Crist, Knick, & Hanser, 2017)
33	Probability of connectivity, M-reach-closeness centrality, Fragmentation centrality	PC_KPR_KPF	1	(Juliana Pereira, Saura, & Jordán, 2017)
34	Probability of Connectivity, Equivalent Connectivity	PC_EC	1	(Martensen, Saura, & Fortin, 2017)
35	Relative neighbourhood graph algorithm	RNG	1	(Perry, Moloney, & Etherington, 2017)
36	Cycle Indicator, Leaf Indicator	CI_LI	1	(Mair, Zischg, Rauch, & Sitzenfrei, 2017)
37	Integral Index of Connectivity, the Equivalent Connected Area of the IIC	IIC_ECA	1	(Rehnus, Bollmann, Schmatz, Hackländer, & Braunisch, 2018)
38	Probability of connectivity, Connect	PC_C	1	(J. Huang, He, Liu, Li, & Qian, 2018)
39	Shortest-path, current-Flow-based centrality	SP_FBC	1	(Carroll, Parks, Dobrowski, & Roberts, 2018)
40	The Flux, Area-Weighted Flux, and Probability of Connectivity Index metrics, The Influx Potential, Outflux Potential, Metapopulation Capacity metrics.	F_AWF_PC_IP_OP_MCM	1	(d'Acampora, Higueras, & Román, 2018)
41	Potential Connectivity Model	PCM	1	(Hofman et al., 2018)
42	Relative values of habitat patches for connectivity	DPC	1	(J Pereira, 2018)

	Name	Summary mark	Frequency	
43	Maximum clique analysis	MCA	1	(Brown et al., 2018)
44	The bioenergy-based PANDORA model	BM	1	(Cheng, Liu, Hou, Zhang, & Dong, 2018)
45	Harary graph	HG	1	(Arif et al., 2018)
46	Spatial prioritization tool, Least-cost paths	SPT_LSP	1	(Meurant et al., 2018)
47	Greatest connected component	GCC	1	(Thornhill, Batty, Hewitt, Friberg, & Ledger, 2018)
48	Metapopulation mean lifetime model	MLT	1	(Peterman et al., 2018)
49	Integral index of connectivity, Least-cost path	IIC_LSP	1	(Zhang et al., 2019)
50	Variance inflation factor	VIF	1	(Corro et al., 2019)
51	Edge betweenness, Node value, Integral Index of Connectivity, Area-Weighted Metric	EB_NV_IIC_AWM	1	(Mestre, Ascensão, & Barbosa, 2019)

Table 5
The frequency of use of graph theory theorists in different species

species	Frequency of indicators in different species							
	Plants	Birds	Reptiles and amphibians	Mammals	Context	Insects	Aquatic animals	total
PC	16	7	6	18	2	2	1	52
IIC	16	2	1	8	4	3	2	36
NC	2			1				3
NL	2							2
ECA	1			3				4
MPG				2				2
LCP	3	2	4	7	2		1	19
VIF	1					1		2
SPT		1	1	1				3
SP				1	1			2
MSSN			1				1	2
F				1	1			2
RNG	1			1				2
LSP	1	1	1	1				4
EC		1		2				3
CI		1			1			2
	43	15	14	46	11	6	5	140
Other indexes*	10	7	1	14	11	0	0	43
total	53	22	15	60	22	6	5	183

• This row depicts the cumulative frequency of indexes that only on time is used

Statistical relationships between Indexes

In order to explore the relationship between the indexes, the Pearson correlation is conducted. Because the main indexes frequency was less than two, any statistical analysis was meaningless. Therefore, the correlation was calculated for indexes with equal or more than 2 frequency. As result in Table 6 shows: no specific relationship is considerable. Only a weak and negative relationship is observed between PC and LCP (-0.335). The second meaningful relation is observed between the AWF and F index. Table 7 depicts the significance level alpha.

Table 6
Correlation between Indexes

Variables	CI	ECA	PC	E	LCP	EC	IIC	F	AWF	SP
CI	1	-0.026	0.027	-0.018	-0.055	-0.018	-0.078	-0.018	-0.018	-0.018
ECA	-0.026	1	0.039	-0.026	-0.079	-0.026	0.000	-0.026	-0.026	-0.026
PC	0.027	0.039	1	-0.111	**-0.335**	0.165	-0.095	0.027	0.027	-0.111
E	-0.018	-0.026	-0.111	1	0.138	-0.018	0.078	-0.018	-0.018	-0.018
LCP	-0.055	-0.079	**-0.335**	0.138	1	-0.055	-0.177	-0.055	-0.055	-0.055
EC	-0.018	-0.026	0.165	-0.018	-0.055	1	-0.078	-0.018	-0.018	-0.018
IIC	-0.078	0.000	-0.095	0.078	-0.177	-0.078	1	-0.078	0.078	-0.078
F	-0.018	-0.026	0.027	-0.018	-0.055	-0.018	-0.078	1	**0.491**	-0.018
AWF	-0.018	-0.026	0.027	-0.018	-0.055	-0.018	0.078	**0.491**	1	-0.018
SP	-0.018	-0.026	-0.111	-0.018	-0.055	-0.018	-0.078	-0.018	-0.018	1

Values in bold are different from 0 with a significance level alpha = 0.05

Table 7
p-values (Pearson)

Variables	CI	ECA	PC	E	LCP	EC	IIC	F	AWF	SP
CI	**0**	0.786	0.777	0.849	0.564	0.849	0.415	0.849	0.849	0.849
ECA	0.786	**0**	0.687	0.786	0.410	0.786	1.000	0.786	0.786	0.786
PC	0.777	0.687	**0**	0.246	**0.000**	0.083	0.321	0.777	0.777	0.246
E	0.849	0.786	0.246	**0**	0.148	0.849	0.415	0.849	0.849	0.849
LCP	0.564	0.410	**0.000**	0.148	**0**	0.564	0.062	0.564	0.564	0.564
EC	0.849	0.786	0.083	0.849	0.564	**0**	0.415	0.849	0.849	0.849
IIC	0.415	1.000	0.321	0.415	0.062	0.415	**0**	0.415	0.415	0.415
F	0.849	0.786	0.777	0.849	0.564	0.849	0.415	**0**	**0.0001**	0.849
AWF	0.849	0.786	0.777	0.849	0.564	0.849	0.415	**0.0001**	**0**	0.849
SP	0.849	0.786	0.246	0.849	0.564	0.849	0.415	0.849	0.849	**0**

Discussion

The last decade has seen the growing importance of research into ecological networks, and therefore, the tools used in such research. One of the tools of ecological network analysis is graph theory. Graph theory greatly facilitates the analysis of functional (Iswoyo, Dariati, Vale, & Bryant, 2018) and structural (Koohafkan & Gibson, 2018) connections of the components of ecological networks. This theory can be used to simplify the analysis of relationships in the study of different animals and different ecosystems. In this study, the scientific literature concerning this subject was systematically analyzed in order to provide a better insight into the geographical distribution (Mehring, Mehlhaus, Ott, & Hummel, 2019) of studies that take this approach, the indexes commonly used in these studies, and the ecosystems and species on which these studies have been conducted.

To clarify the issue, as will be discussed below, we first mentioned the domains that have been studied. Then, to better understand the subject, we divided the species based on behavioural states, because by understanding the behavioural states of animals, their communication network can be analyzed. Then, by introducing the indicators, we put the main focus on them, such as: What species are they used for, which indicators have been used together, what is the percentage of use of indicators in studies, what is the dynamics of graph theory in presenting new indicators. Finally, with a better understanding of the position and status of graph theory in ecological network analysis, we will map its future in this area.

Geographical Distribution of the Studies

The examination of the geographical distribution of the use of graph theory in the field of ecology showed that the method is more widely in Europe and North America and also more evenly used across these continents. In Asia, this method has not been commonly used anywhere outside China, which has the world's highest number of studies with this approach (19 studies). What is interesting about these results is the higher concentration of studies conducted in the developed countries, which can be attributed to the higher priority given to ecological sustainability.

These studies have been conducted to examine the extent of habitat communication as well as animal communication, so this indicates that the critical areas in this regard are African, Asian and South America countries. The importance of South America and Africa in biodiversity, as well as the lack of studies on these continents, is a wake-up call for researchers, politicians and the public. Given that in these areas, animal habitats are disappearing one after another, so these results can draw the attention of officials in these countries for more policy and investment on conservation and environmental connectivity, and Also attract the use of new scientific methods in this field.

Species studied

Species diversity in research using graph theory in ecological network analysis is a positive point in the efficiency of graph theory in studies on different species. However, there are some points in the results that need further analysis, for example, graph theory has been used for different species, but the results show a high difference in the frequency of study of the studied species. Which we will discuss in the following.

In the three main categories that were done, most of the graph theory was used for animal species with 79 uses, followed by plants with 37 uses and then litter with 15 uses. The low frequency of studies on the Context in ecological fields and its high difference with the other two categories raised the question of whether graph theory is effective in the study of context connections. Looking at the issues that have been done in these studies, it has been observed that studies in the field of bedding are divided into four categories: water network connections, roads, residential structure and land uses. Studies on connections on water networks are more prominent than other cases that have been studied in various forms such as delta, wetland, river networks. As Na Xiu and colleagues suggest, Only a small number of studies have provided specific approaches or suggestions in geographical distributions (Xiu et al., 2017). Therefore, in the future, researchers can use the capabilities of graph theory in the field of context study or further study the challenges of graph theory in this field.

Animal species have the most use of graph theory so that out of 131 cases studied, 79 cases have been assigned to them. However, it cannot be said that all animals have a relatively similar pattern of movement or share common factors. After classifying animals in groups that have a relatively similar pattern of behavior, it has been observed that the focus of further studies is on mammals, birds, reptiles and amphibians. In the meantime, aquatic animals and insects were each in the margins with 5 frequencies compared to other animal species. Due to the specific characteristics of aquatic animals and insects, there are reasons such as difficult to track, lack of access to the minimum required information, etc., and this may indicate that these species are not attractive to researchers. Given the diversity of species and the importance of aquatic animals and insects, it is hoped that in the future more researchers will use graph theory in the analysis of the ecological network of these two species.

Indexes

Employed Indexes

In the reviewed studies, 58 graph-based indexes have been used 160 times in ecological network analyses. The results show that the indexes PC, IIC, and LCP have the highest frequency of use in these studies. PC, IIC, and LCP can be considered the most popular indexes for research in the field of ecology. It should be noted that the less frequent use of other indexes is not because of their ineffectiveness, but rather because many of them have been introduced more recently and it will take some time for them to become widely recognized and established. Nevertheless, the frequent use of PC, IIC, and LCP suggests that these three indexes can be trusted to yield fairly reliable results in ecological analyses. There are also a small number of old indexes that have not been used as frequently, which indicates that they have not been accepted by the scientific community.

One of the benefits of using graph theory in ecological analyses is that graph-based indexes can be used in combination with each other to study multiple aspects of an ecological network simultaneously. Out of the 114 studies reviewed in this work, 23 had used two

indexes. Of these 23 studies, 9 had used a combination of PC and IIC. This shows that these two indexes can be used together in research in the field of ecological network analysis.

The studies were also examined from the perspective of the composition of species studied. This examination showed that 85.09% of the studies were focused on a single species. Also, 6.14% of the studies (7 studies) were focused on two species. Among these 7 studies, two studies were focused on mammal and reptile-amphibian species(Chaput-Bardy et al., 2017; Drake et al., 2017), two studies on mammal and bird species(J. Huang et al., 2018; Martensen et al., 2017), one study on mammal and plant species(Ruppert et al., 2016), one study on reptile-amphibian and bird species(Pietsch, 2018), and one study on plant and insect species(Corro et al., 2019). Of all the studies reviewed, 4.38% were focused on 3 species. Among these studies, three were on mammal, bird, and reptile-amphibian species(Albert et al., 2017; Meurant et al., 2018; Sahraoui et al., 2017), one was on insect and aquatic species and context(Ishiyama et al., 2014), and one was on context and bird and reptile-amphibian species(Xiu et al., 2017). There was also one study on five species, including plants, birds, reptiles and amphibians, mammals, and insects(Naicker et al., 2016).

Every year, researchers introduce new graph-based indexes for ecological research. For example, in 2017, 19 new indexes, and 2018, 13 new indexes were introduced to the field of ecological network analysis. This shows the dynamic nature of the application of graph theory in the field of ecology. Since the low usage frequency of some of these indexes is related to their novelty, it is still too soon to judge their effectiveness on this basis. Therefore, the usage frequency investigation should be repeated at a later date to see which indexes emerge as strong and popular options for use in ecological analyses compared to the years before (Period 2014 to 2019).

PC

PC has been used 52 times in 48 of the reviewed studies and has a usage frequency of approximately 30% in the literature. PC is the most popular index in this field, as researchers have used it incessantly over many years. This shows the effectiveness and functional validity of this index in connectivity analyses and its high acceptance among researchers in this field. PC has been used both individually and in combination with other indexes, which shows the flexibility of this index and its descriptive power when combined with other indexes. PC has been most commonly used in the ecological analysis of plants and mammals, and especially the latter. This shows that PC is more reliable for use in the analysis of connectivity in these fields. Of course, PC has been used in other areas as well and the results suggest that it can be used to analyze ecological networks of different varieties.

The PC index was used to analyze the ecological network in all categories of plants, birds, reptiles and amphibians, insects, aquatic animals and context. However, it has been used most in mammals and plants. This index is a leading indicator among graph theory indicators in the field of habitat network analysis. The high use and diversity of the studied species show its ability. However, it should be borne in mind that the PC index has a long history of ecological chip analysis, its low use in aquatic species with frequency(Appolloni et al., 2018), insects with a frequency of 2(Betbeder et al., 2017; Giannini et al., 2015), and context with a frequency of 2(Foltête et al., 2014; Liu et al., 2014), It will raise the question of whether it has capabilities in the field of aquatic species, insects and the field or not? Therefore, more caution or research is needed on the mentioned species to prove its capability.

IIC

The IIC index has been used in 30 studies and with 18.75% of the total 160 indices used in the studies, it has the second place in the use of graph theory indices in ecological network analysis. Although the IIC index has been used in all categories performed for ecological network analysis. The most use of this index is in the field of plants, so that out of 36 uses of this index in 16 cases has been used to analyze connections in plant fields. Therefore, the use of IIC index for analysis of connections in plant domains has more reliability and validity. This index has been used in other fields as well. It has been used as a mammalian analysis of connections with a frequency of 8. The use of the index in different contexts indicates its flexibility and application. However, the low use of the IIC index in the domains of amphibians and reptiles(Naicker et al., 2016), birds(Goulart et al., 2015; Naicker et al., 2016) and aquatic animals(Ishiyama et al., 2014; Ishiyama et al., 2015) birds raise the question of whether it can analyze the ecological network in these domains as well.

LCP

LCP has been used in 13 of the reviewed studies and has a usage frequency of 8.12%, which makes it the third most frequently used graph-based index in ecological analyses. This index has been used 19 times in various fields. Unlike the previous two indexes, LCP has been used alone in all the studies. This index has been used in all categories of analysis except the analysis of insect species. The interesting point regarding LCP, however, is its frequent use in the analysis of connectivity for reptile-amphibian species with frequency 4, which shows the suitability of this index rather than IIC for use in this particular field. In comparison to IIC and PC, LCP has a wider area of application.

Other Indexes

ECA has a usage frequency of 2.5% and has been used in 4 of the reviewed studies, of which three studies have been on animal species and one on plant species. LSP has been used 3 times in the studies on mammal, reptile-amphibian, bird, and plant species. NC has also been used 3 times, in two studies on plants and one study on animals. MGP, NL, AWF, F, and SP have each been used in two studies. For MGP and NL, both studies have been on plant species, for F and SP, the studies have been on mammals and context, and for AWF the studies have been on plant and mammal species. The remaining 47 have each been used in only one study. Among these indexes, SPT and EC have each been used in three areas, RNG, VIF, MSSN, and CI have each been used in two areas, and other indexes have been used in one area. The species for which graph-based indexes have been used least frequently are aquatic species with 5 instances and insect species with 6 instances, and the species for which these indexes have been used most frequently are mammal species and plant species with 58 and 53 instances, respectively.

Indexes Similarity and Correlation

The similarities of indexes and correlation between index could appear the cluster of related indexes. As Table 6 and 7 depicts, there is no considerable relationship between the indexes. While a variety of indexes is used, but no specific concentration is observed on a group of indexes. It means that although, some indexes such as PC, IIC and LCP have a relatively high frequency, but the collection of ecological networks is under evolving. Therefore, we face a collection of indexes which is applied in different domains. Consequently, no main core of indexes is shaped. Another reason is related to the different context that ecological networks are applying. The wide domain of use and indexes diversity lead to shape any core indexes.

Despite less statistical similarities, the PC, IIC and LCP have main used indexes. Moreover, the used indicators could be classified into three categories: first those indicators which is used lonely (frequency = 83). This group includes 72.81% of the studies that have used only one index; second, 20.17% of studies have used two indexes (frequency = 23); third, a combination of more than 2 indicators (frequency = 8). In the Last group, 3.51% used three indexes (Table 6). The highest number of indexes used in a study is five, which has occurred in only 1.75% of the studies.

As mentioned, the indexes most commonly used in the studies are PC and IIC with usage frequency of 29.81% and 18.63%, respectively. The results show that in 8.77% of the studies, PC has been used in combination with other indexes. For IIC, this figure is 7.02%. This shows the popularity of combining PC and IIC with other indexes. Considering the years in which these indexes have been used in combination with others, it can be concluded that they have not lost their analytical value over time.

Table 8
The composition of the index used

Combination of indicators	Frequency	Indicators
One indicator	83	PC, IIC, DNMS, ED, LCP, DF, SDM, SP, IM, MSSN, HI, CAT, GT, SRM, ECA, GD, KP, CT, MPG, RNG, MPG, PCM, DPC, MCA, BM, HG, GCC, MLT, VIF
Two indicators	23	PC-IIC, PC-ECA, IIC- IV, E-LSP, STRG-GED, EC-PC, LCD-RD, PC-BC, PC-EC, CI-LI, IIC-ECA, PC-C, SP-FBC, SPT-LSP, IIC-LSP
Three indicators	4	NSC-F-SHI, NL-NC-IIC, IIC-PC-NC, PC-KPR-KPF
Four indicators	2	ECA-PA-PC-TC, EB-NV-IIC-AWM
Five indicators	2	NL- NC- HI- AWF- IIC, F-AWF-PC-IP-OP-MCM

Dynamics of graph theory indicators Given the dynamic nature of graph theory-based analyses in the field of ecology, researchers introduce new indexes for this field every year. In this study, the 2014 figures were considered as baseline. Table 7 shows the number of graph-based indexes introduced in the field of ecology in each year since 2014. In 2018, for example, a total of 23 studies used 22 graph-based indexes, of which 13 were new. The year with the highest number of new indexes was 2017, in which 32% of the used indexes were novel. In 2019, only three new indexes were introduced.

Table 9
New indicators used in the field of ecology

Year	Frequency of researches	Total indicators	Frequency of new indicators	What are the new indicators?
2014	20	5	-	――――
2015	18	10	8	IV, LCP, DF, SDM, IM, MSSN, E, LSP
2016	21	15	11	HI, STRG, GED, CAT, EC, LCD, RD, GT, PA, TC, SP
2017	29	22	17	SRM, GD, NSC, F, SHI, NC, NL, AWF, BC, KP, CT, KPR, KPF, MPG, RNG, CI, LI
2018	23	22	13	C, FBC, IP, OP, MCM, PCM, DPC, MCA, BM, HG, SPT, GCC, MLT
2019	3	6	4	VIF, NV, AWM, EB
Frequency of Use of Graph-based Indexes for Different Ecosystems and Species				

In this regard, the results show that graph-based indexes have been used more frequently in terrestrial ecosystems. Naturally, this could be due to higher accessibility of terrestrial ecosystems, availability of data, ease of observation, and ease of access to target species in these ecosystems.

It was found that although a large portion of studies has been performed on only one species, graph theory is flexible enough to be used in the analysis of ecological connectivity and connections in multiple species. For example, in a 2016 study by Naicker et al., this approach was used to study five species.

The results also showed that most studies have been focused on animal species. Plant species and context are next in this ranking. Also, four of the studies have been general. These results demonstrate the wide applicability of graph theory in a wide variety of ecological network analyses. However, it should be noted that apparently this approach is mostly used for terrestrial plants and mammals. Nevertheless, given the flexibility of this approach, one can expect that it will be used more frequently and in a wider variety of applications. For example, in a 2019 study by Mestre in Iberia, context and landscape fragmentation were analyzed by considering roads and linear infrastructure as links and residential areas as nodes. In another example, Niculae et al. (2017) attempted to use a graph-based approach to investigate the spread of invasive species. This shows that graph theory can be used not only in ecological network analyses aimed at increasing connectivity but also in ecological network analyses with the purpose of decreasing connectivity or other aspects of ecological connections when necessary. Therefore, graph theory can be expected to find wider application in ecological research, including in the spread analysis of viruses and infectious diseases.

Future directions

In research, the use of graph theory in the field of ecological network connection focuses on ecological connections. Important issues that can be discussed in relation to the future of graph theory in ecological network analysis are geographical distribution and diversity in analysis approaches.

Given that the number of countries in which studies have been conducted is increasing every year. It is promising for researchers to use and familiarize themselves more with the application of graph theory in the field of ecological network analysis. The results showed that from 2014 to early 2019, the number of countries in which studies were conducted has increased. During this period, as shown in Fig. 4, 15 countries were added to the countries in which the studies were conducted. Continents of great ecological importance, such as South America with a frequency of 2 cases and Africa with a frequency of 2 cases, are very few in these new studies, while they can use the capacity of graph theory in ecological network analysis according to Problems in these continents that benefit greatly from the fragmentation or loss of ecological habitat. However, the results show that there are two points that new countries will join in the future. And the trend will be upward but not too fast and familiarity with this graph theory in ecological network analysis will have an upward trend with a low slope.

The diversity of the studied species is very high, but the point that is very important and should be considered is that the basis of graph theory is the analysis of the ecological network in its raw form, which can be used to both reduce and improve Ecological network used. So far, most studies have been done to protect or improve the ecological network of the species. While the high potential of chart theory can be used in areas that require ecological disconnection to study species that need to be disconnected, such as pest species, invasive

species, or diseases with Viral origin. Therefore, it is predicted that in the future, the use of Kraft theory in the field of reducing ecological network communications will increase due to its necessity and play a more prominent role in this field.

Conclusions

In this study, the past studies that have used graph theory in the analyses of ecological networks were reviewed. In general, it was found that the graph theory is flexible enough for the analysis of different ecological networks and has been extensively used in recent years to study and analyze ecological connections and connectivity in different ecosystems and a wide variety of species. For these reasons, graph theory is useful in the analysis of the ecological network of habitat networks. Therefore, in the future, this approach can be expected to be used more widely in the area of ecological network analysis.

One of the features of the use of graph theory in ecological network analyses is the continuous emergence of novel indexes, as every year researchers develop several new graph-based indexes for use in these analyses. Therefore, one can conclude that graph theory has enough flexibility to answer questions that may arise in the future in the field of ecological network analysis.

Although researchers are introducing novel graph-based indexes for ecological network analyses every year, the credibility of many of these indexes will be determined in time by whether they will be effectively used in future researches. But so far, PC, IIC, and LCP seem to be the most credible graph-based indexes for use in ecological network research.

There are many advantages to the use of graph theory in ecological network analysis as it has low information requirements and can be used in research on different species. Therefore, researchers need to direct more attention and effort to the development and adaptation of this theory for use in ecological network analyses. It is hoped and expected that researchers will make further use of this theory in the analyses of ecological networks, expand it for use on different aspects of connectivity in different species, and use it to develop more accurate and useful tools and indexes for these analyses.

Abbreviations

PC
Probability of Connectivity
IIC
Integral index of connectivity
DNMS
Dynamic network models
ED
Effective distance
ECA
Equivalent connected area
IV
Importance value
LCD
Least-cost distance
RD
Resistance distance
GT
Graph-theoretic approaches
SRM
Spatial-territorial reorganization model
AWF
Area-Weighted Flux
CT
Circuit theory
MPG
Minimal planar graph or Minimum planar graph
LI

Leaf Indicator
OP
Outflux Potential
HG
Harary graph
SPT
Spatial prioritization tool
MCM
Maximum clique analysis
VIF
Variance inflation factor
NV
Node value
PA
Size of a single patch
TC
Transboundary connectivity
DF
Dispersal flow
SDM
Species-distribution models
SP
Randomized Shortest Path
IM
Integrated metrics
MSSN
Multi-species spatial network
GD
Graph development index
NSC
Network Structural Connectivity index
F
Flow analyses
SHI
The Shimbel index
BC
Betweenness centrality
KPR
M-reach-closeness centrality
RNG
Relative neighbourhood graph algorithm
C
Connect
AWF
Area-Weighted Flux
BM
The bioenergy-based PANDORA model
GCC
Greatest connected component
PCM
Potential Connectivity Model
AWM

Area-Weighted Metric

E

Euclidean

LCP

Least-cost-path algorithm

HI

Harary index

STRG

Spatio-temporal relational graph

GED

Graph edit distance

CAT

Connectivity Analysis Toolkit

EC

Equivalent Connectivity

NC

Number of components

NL

Number of links

KP

KeyPlayer algorithm

KPF

Fragmentation centrality

CI

Cycle Indicator

FBC

current-Flow-based centrality

IP

The Influx Potential

MCA

Maximum clique analysis

LSP

Least-cost path

MLT

Metapopulation mean lifetime model

DPC

Relative values of habitat patches for connectivity

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

Funding

Authors' contributions

HD, RH, FL conceived and designed the research; RH, FL, performed the search and extracted data, HD, RH, analyzed the data; HD, RH, FL wrote and edited the manuscript; HD provided critical feedback and helped to shape the research.

Acknowledgements

Authors' information (optional)

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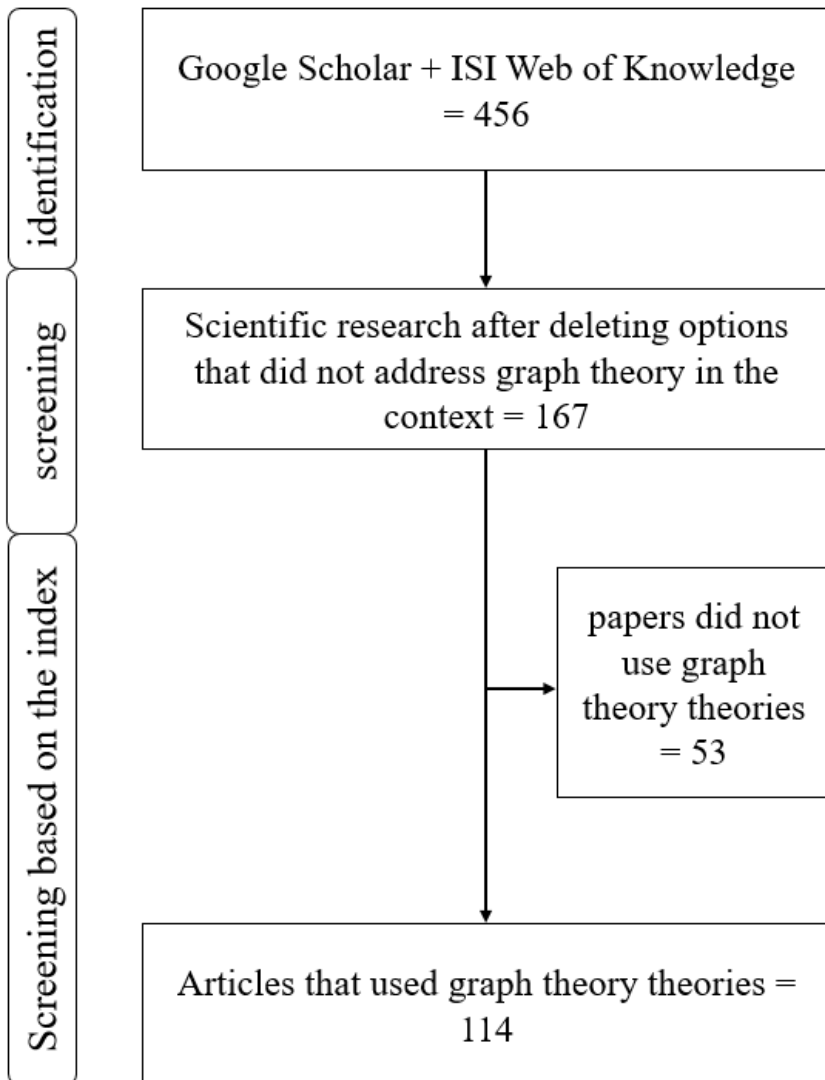
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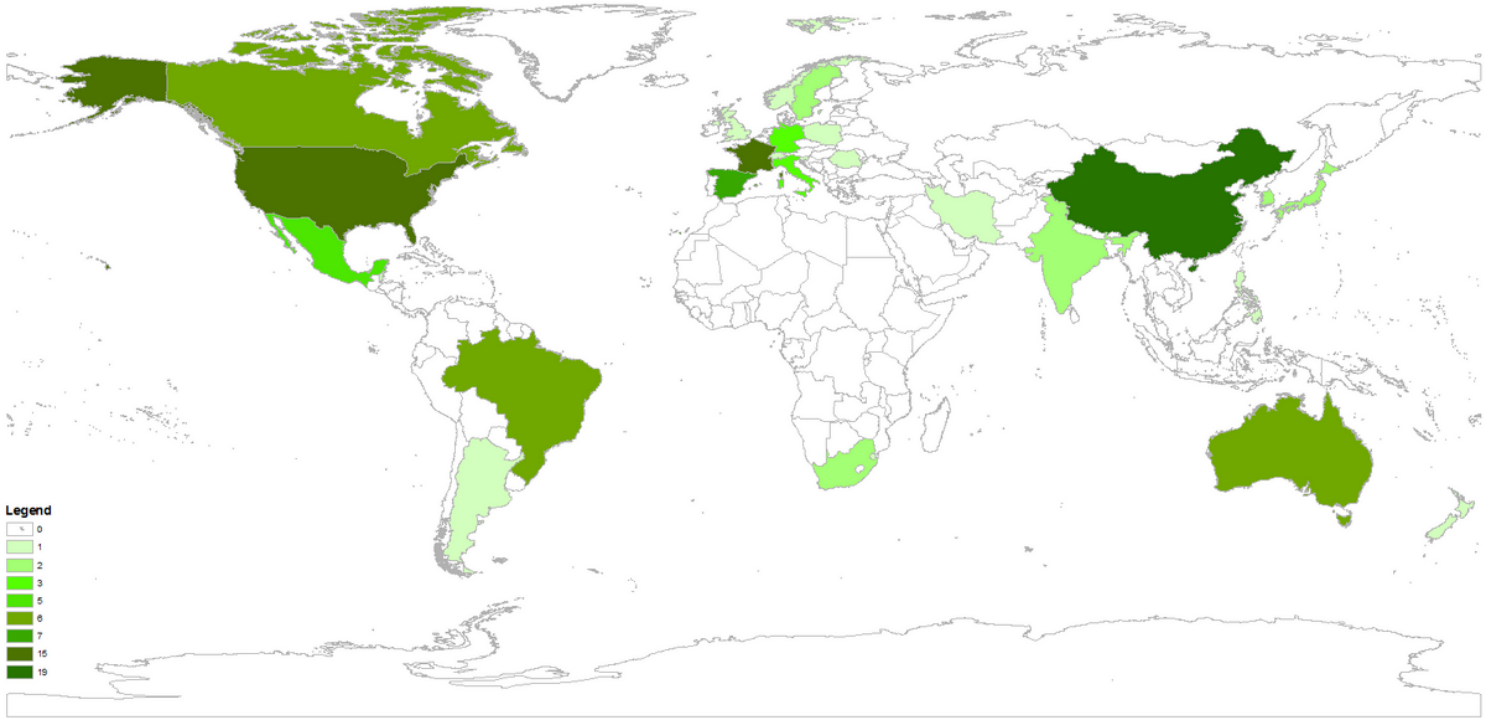

Figure 1

The process of selecting articles

Figure 2

Distribution of countries where research has been conducted. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
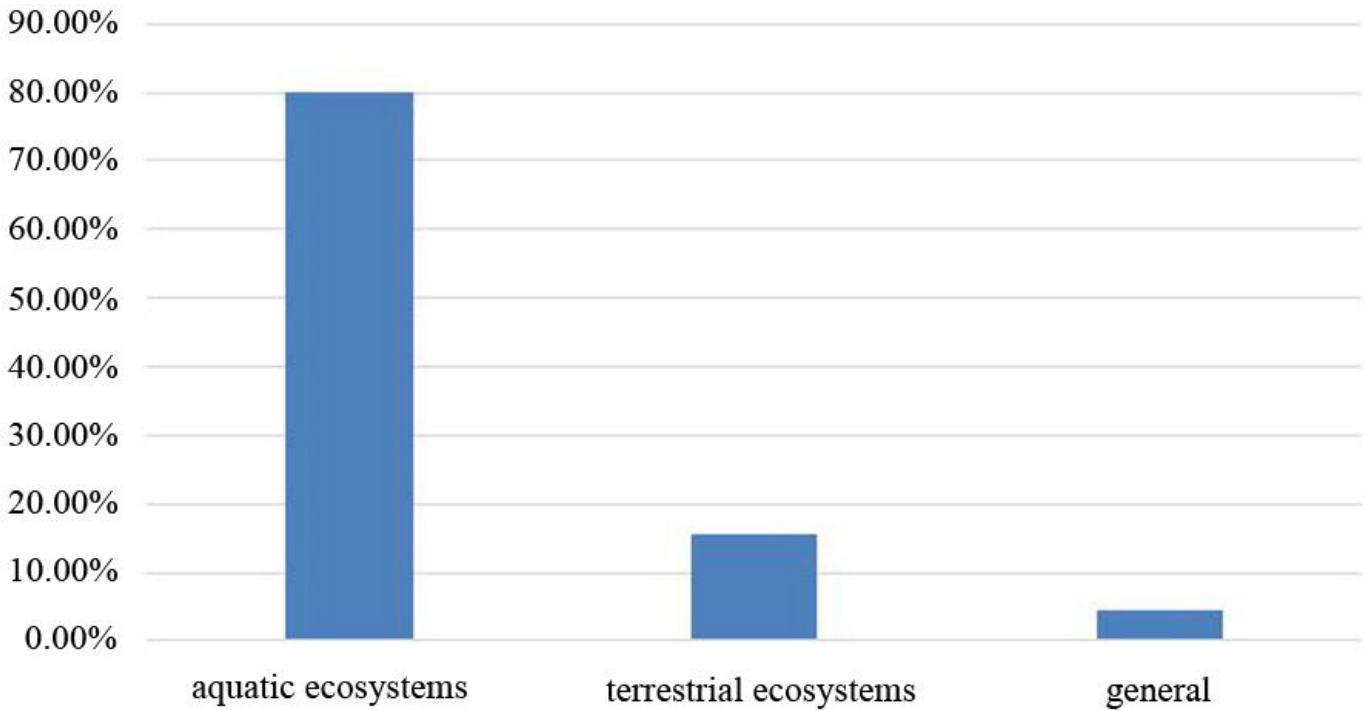

Figure 3

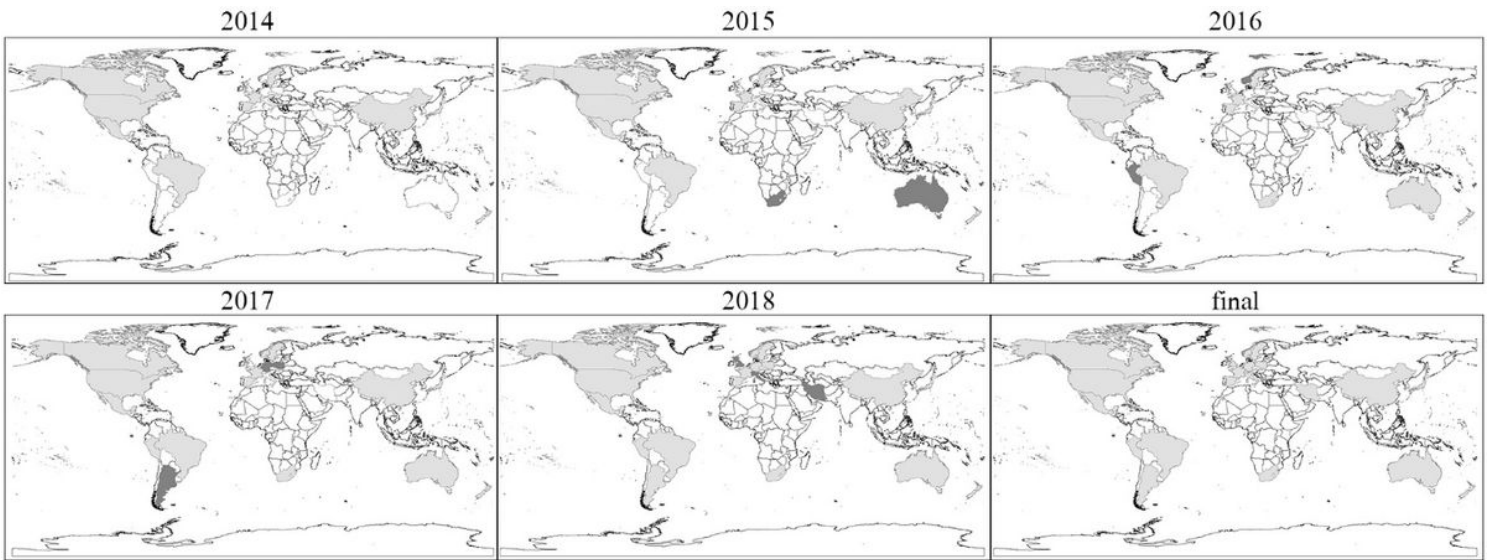Ecosystem composition of the use of graph theory in the field of ecology

Figure 4

The trend of adding countries to used graph theory in the ecological networks (2014-2019). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.