Themes and Trends in Global Maritime Journals Using Keyword Network Analysis

Se-Eun Jhang * · Ho-Min Park ** · Yaochen Deng *** · Sunghwa Lee ****

ABSTRACT

This study identifies research themes and trends of international journal data in global maritime affairs, fisheries, marine and transport policy, and logistics over the last 20 years from 2000 to 2020 using keyword network analysis through degree centrality. This study pays special attention to six different types of patterns through the Delta-C algorithm. First, we discuss highly remarkable research themes that are shared throughout all the three periods defined as Type A. Second, we focus on interest-increased, interest-decreased, and newly emerging research themes shown in the most recent period (the third period) from Type B to Type F. Finally, we show the networks of researchers and the distribution and network visualization of research nations. This study shows two new findings. First, in Type A representing consistently shared themes, the main research themes change from *growth* and *fishery management* in fisheries and *sustainability* and *governance* in maritime sectors in the 2000s; to *growth* and *aquaculture* in fisheries and *accessibility, China* and *sustainability* in maritime sectors in the early 2010s; and to *aquaculture* and *growth* in fisheries and *accessibility, climate change,* and *China* in maritime sectors in the late 2010s. Second, in Type F as new trends, the top 10 keywords in newly issues illustrate that issues surrounding *climate change* and *Green House Gas emission* attract more attention in the literature, the subjects of *machine learning* and *artificial Intelligence (AI)* become popular in accordance with the development of internet of things (IoT) in the late 2010s, and *Belt-Road initiative* demonstrates the enlargement of China`s economic potential in the 2010s.

Keywords: international maritime journals, trend analysis, keyword network analysis, degree centrality, Delta-C, algorithm, data, network of researchers

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1. Introduction

Network analysis [1] has been used to scientifically analyze various features to model diverse systems of the real world being represented as a link of connected relations between nodes, while the identity of a person or a thing is represented as a node. When we set this identity as a keyword (designated by the authors), keyword networks can show various relation properties of keywords so that we could reveal creative phenomena derived from such relation properties. For trend analysis, network analysis has been used in various fields, such as healthcare, administration, private security, tourism research, circular economy, e-learning, maritime economics, and offshore industry trends (Benkendorff, 2009; Lee and Kang, 2011; Jang, Kang, and Lee, 2012; Lee, 2012; Kho, Cho, and Cho, 2013; Ryu and Hyun, 2013, Choi and Kang, 2014; Jhang and Lee, 2014; Jhang, Lee, Lee, and Kim, 2015; Jhang and Lee, 2016; Bai, Li, and Liu, 2020; Khitous, Strozzi, Urbinati, and Alberti, 2020).

In particular, Jhang and Lee (2016) examined themes and trends in maritime economics and logistics by analyzing author keywords of international journals. They invented the Delta-Centrality (Delta-C) algorithm to identify the differences in centrality by five-year periods: this algorithm revealed interest-increased and interest-decreased research themes. In line with the keyword network analysis conducted by Jhang and Lee (2016), this study extends this Delta-C idea to investigate some interesting patterns of remarkable themes in a particular period and prominent trends of such themes in research fields of global maritime affairs and fisheries over time by using network analysis. The purpose of this study is to identify research themes and trends in global maritime affairs, fisheries, marine and transport policy, and logistics during the last 20 years from 2000 to 2020 using keyword network analysis through degree centrality in Netminer 4.4.

This study is organized as follows. Section 2 displays the previous research about trend analysis using keyword network analysis and author network analysis. Section 3 shows data and methodology of degree centrality and Delta-C algorithm used in this study. Section 4 discusses several patterns to show trends of keywords over time by examining the distribution of shared keywords in three different periods by using the Delta-C algorithm, resulting in six different types of patterns. Here, we discuss highly remarkable research themes that are shared throughout all the three periods as Type A. We also focus on interest-increased, interest-decreased, and newly emerging research themes in the most recent period (the third period) from Type B to Type E through the Delta-C algorithm. Furthermore, we show the networks of researchers and the distribution

1 Network analysis can be used because frequency of author keywords is subject to Zipf's law and degree distribution of keyword nodes also follows power law, according to Jhang and Lee (2014, 2016).

of research nations that deal with the most recent trending themes and new themes emerging in the third period in the global maritime fields. Section 5 summarizes this paper and provides some suggestions for future research.

2. Previous Studies

2.1 Network Analysis and trend analysis

For network analysis used in the field of Sociology, Lee and Kang (2011) examined two-way mode data, such as articles and keywords, journals and keywords, and journals and authors. Articles from 20 academic journals in the Korean Journal Citation Index from 2004 to 2020 were collected. By analyzing degree centrality and betweenness centrality, they revealed what journals retained high centrality.

For trend analysis using keyword network analysis, Choi and Kang (2014) explored the research trends shown in the Korean Educational Technology by examining 645 articles in the Journal of Educational Technology for three time periods: 1985-1994, 1995-2004, and 2005-2013. Keywords that displayed a high degree centrality were analyzed by utilizing Netdraw of UCINET. The analysis indicated that keywords associated with 'structuralism' have steadily increased and that social media-related keywords have emerged in recent years. They argued that network analysis is a useful tool to predict future changes in Educational Technology. Jhang et al. (2015) explored research themes and trends of the offshore industry by analyzing author keywords. A total of 800 articles – 200 articles per period – were selected for the analysis. Both shared keywords and newly occurring keywords were examined; they revealed that betweenness centrality indicates the degree of significance in the case of new keywords. Jhang and Lee (2016) also examined themes and trends in maritime economics and logistics by analyzing keywords from 303 articles in international journals from 2000 to 2014. They invented the Delta-C algorithm to identify the differences in centrality by five-year periods. They argued that degree centrality reveals research themes whereas betweenness centrality discloses newly emerging themes in each period.

More recently, Khitous et al. (2020) identified themes and emerging research trends in circular economy (CE) by utilizing citation network analysis (based on references), keywords co-occurrence network (based on keywords), global citations score, and burst detection of keywords, based on references and keywords systematic literature network analysis. They revealed evidence of eight main trends of CE research that have been dominated by environment and engineering scholars. Bai et al. (2020) studied themes and trends in e-learning research by analyzing keywords collected from 7214 articles published in 10 journals over two decades by dividing into two time periods (1999-2008 and 2009-2018). Knowledge constructions were visualized by employing a clustering method, a social network analysis, and a strategic diagram; popular topics, core topics and bridge topics were presented.

Based on Jhang and Lee (2016), this study further develops the Delta-C application to be able to identify themes and trends as distinguishable types according to increasing and/or decreasing interest as well as newly emerging themes in a specific period and shared themes in all the periods. This Delta-C extended application allows us a new way to closely investigate various trends of research.

2.2 Co-author network analysis

McCarty, Jawitz, Hopkins, and Goldman (2013) examined the co-author network in order to identify collaborative behaviors that maximize scientific impact of a focal author. The scientific impact was represented by the h-index (Hirsch, 2005) that shows the scientific achievement of individual authors by combining the work and the Impact Factor. They randomly selected 238 authors across all disciplines from the Web of Science and scrutinized their h-index and also their co-authors' h-index as well. They found that the highest h-index can be attained when publishing with as many co-authors as possible and with co-authors who already have high h-index at the time of publication.

Liu, Bollen, Nelson, and Sompel (2015) presented a structure of scientific collaborations by using betweenness centrality and closeness scores to examine the digital library research community. Co-authorship links signified previous engagement in scholarly collaboration and the analysis showed how they work together toward design-based research.

Li, Kramer, Gordon, and Agogino (2018) identified cross-disciplinary collaboration patterns in the human-centred design for the development academic community. They selected 78 papers by 247 authors from 2004 to 2014. Important metrics for this study included "density, clustering coefficient, network diameter, largest connected component, betweeness centrality, closeness centrality, and authors who are 'cut-points' "(p. 7). Although most authors published a small number of papers and they were part of a well-connected sub-community, the lack of a closely connected core indicated that there is no eminent leading community of researchers that bridge separate communities.

Most recently, Hu, Govindjee, Tan, Xia, Dai, and Guo (2019) analyzed the co-author network and the co-cited reference network in chlorophyll fluorescence research by scientometric data-driven analysis. They collected metadata information, such as names of authors, institutions, journals, countries, citations, and cited references by using the Core Collection database of the Web of Science in order to reveal the structure of the scientific collaboration community and research trends. As McCarty et al. (2013) reported, they found that the number of co-authors plays a significant role in deciding activeness of the author and that the UK, Sweden, France, Australia, and the USA are top high-citation-per paper countries. A knowledge map was provided in four-time periods from 1991 to 2018, which demonstrated that different authors were active in different time periods.

Over a decade, studies on co-author network analysis have been done in various disciplines. No research, however, has been pursued in the field of maritime affairs and fisheries. The present study provides a valued addition to co-author network research to interesting and prominent themes in a specific period.

3. Data and Methodology

3.1 Data

For the purpose of this study, we selected 15 international maritime journals and extracted 26,359 articles of the journals listed in the Web of Science by entering key words such as *maritime, fishery, marine environment, port, shipping, shipbuilding, etc.* into the search bar in the periods of 2000 to 2020, as seen in Table 1 below. These journals were confirmed by maritime and marine specialists who are working at Korea Maritime Institute (KMI)[2].

Table 1. Basic information about research data

No	Titles of international journals used in this research	Number of articles	Total number of token (frequency)	Total number of lemmatized keywords	Ratio of top seven shared keywords pertaining to top 50% coverage	
1	Aquaculture	11,326	59,815	18,433	6/7	0.857
2	Marine Policy	3,424	17,586	7,430	7/7	1
3	Transportation Research Part B-Methodological	1,986	9,499	5,548	1/7	0.142
4	Transportation Research Part E-Logistics and Transportation Review	1,786	8,375	5,054	3/7	0.428
5	Journal of Transport Geography	1,658	8,268	4,503	4/7	0.571
6	Transport Policy	1,538	7,425	4,486	4/7	0.571
7	American Journal of Agricultural Economics	1,456	7,686	4,301	5/7	0.714
8	Ocean & Coastal Management	1,147	5,835	3,675	5/7	0.714
9	Maritime Policy & Management	358	2,360	1,379	1/7	0.142

2 We would like to thank Dr. Yong-An Park, who has been working at KMI for his survey.

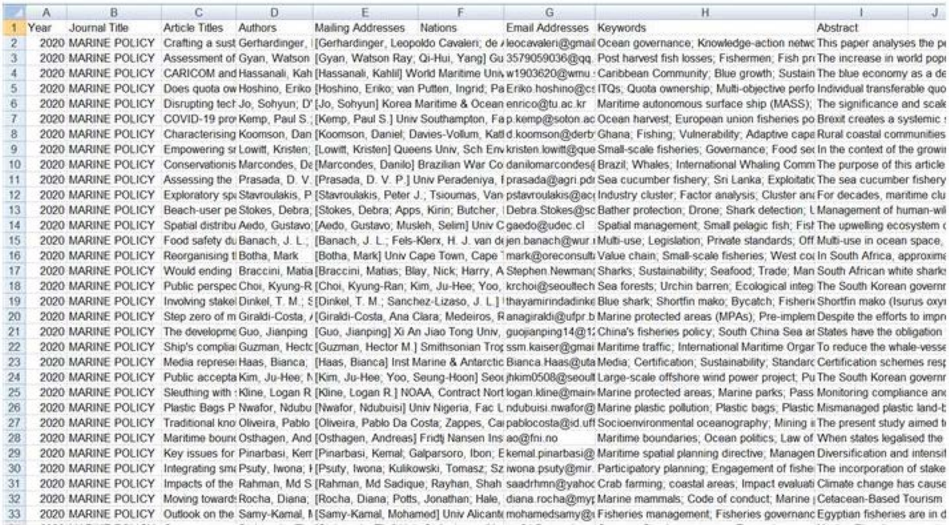
No	Titles of international journals used in this research	Number of articles	Total number of token (frequency)	Total number of lemmatized keywords	Ratio of top seven shared keywords pertaining to top 50% coverage	
10	International Journal of Logistics Management	440	2,312	1,156	3/7	0.428
11	International Journal of Shipping and Transport Logistics	336	2,003	1,461	3/7	0.428
12	Marine Resource Economics	306	1,498	1,035	5/7	0.714
13	Maritime Economics & Logistics	310	1,540	1,111	3/7	0.428
14	Aquaculture Economics & Management	202	959	659	4/7	0.571
15	Maritime Business Review	86	370	338	2/7	0.285
	Total	26,359	135,531	60,569		

As shown in Table 1, the full data-set contains 26,359 articles that include 135,531 author keywords and 60,569 lemmatized keywords.[3] Here, we have a question, "which journals have very coherent and consistent themes to global maritime affairs and fisheries throughout the last 20 years?" To pursue the answer to this question, we have considered seven shared keywords such as *aquaculture, Atlantic salmon, governance, growth, marine protected area, sustainability,* and *transport* that occur within the top 30 keywords when sorted by high degree centrality in each period[4] among 76 shared keywords[5] co-occurring within the top 200 in each period of the last 20 years. Of 15 international journals, just five journals highlighted in gray — *Marine Policy, Aquaculture, American Journal of Agricultural Economics, Ocean & Coastal Management,* and *Marine Resource Economics* — seem to deal with long-standing consistent maritime and fisheries related themes in the last 20 years. This heuristic approach is based on the high ratio of these top seven shared keywords pertaining to top 50% coverage since the ratio of all of these five journals is higher than 0.7, whereas that of other ten journals is lower than 0.6. Later, we will discuss this pattern of the coherent and consistent themes during the 20 years.

In this study, we divide the 20 years from 2000 to 2020 into three periods; the first period is the ten years from 2000 through 2009, the second period is five years from 2010 to 2014, and the third period is the most recent period of five years from 2015 to 2020. In the data-collecting stage, we saved the data in Excel files by classifying into the order of year, journal title, article titles, authors, mailing addresses, nations, email addresses, keywords, and abstract, as seen in Figure 1 below.

3 The reason why lemmatized keywords should be less is that the number of author keywords can be counted as frequency of type or lemma and the number of lemmatized keywords is counted as frequency of lemma in the definition of words. For example, author keywords. *fishery* and *fisheries* are different words as type but they are the same word as lemma (*fishery*), i.e., a word listed in the dictionary.
4 See Table 5 of 4.1.2 for the top 30 keywords sorted by high degree centrality in each period.
5 See a list of 76 shared keywords in Appendix

Figure 1. A screen shot of a data-collection sample for *Marine Policy*



Next, we made a list of keywords used in an individual journal per period in order to obtain information for synchronic comparison with other journals and diachronic comparison of other periods for remarkable themes and trends, as seen in Figure 2.

Figure 2. A screen shot of a list of keywords per journal in the third period (2015-2020)

As illustrated in Figure 2, the number of keywords per thousand is needed to be compared with the frequency of keywords of journals due to different numbers of articles in even the same period. For example, let us take a keyword of *aquaculture* appearing in the five journals as an example, it occurs 47 times in *Marine Policy (MP)*, 282 times in *Aquaculture*, 3 times in *American Journal of Agricultural Economics (AJAE)*, 21 times in *Ocean & Coastal Management (OCM)*, and 9 times in *Marine Resource Economics (MRE)*. The order of ranking based on the frequency is as follows: *Aquaculture* (282), *MP* (47), *OCM* (21), *MRE* (9), and *AJAE* (3). However the order of ranking based on the normalized number of keywords per thousand differs as *MRE* is jumped to first place from fourth place, as follows: *MRE* (13.93), *Aquaculture* (12.87), *MP* (6.49), *OCM* (3.69), and *AJAE* (1.29).

Finally, the research data divided into three periods can be summarized as seen in Table 2 below.

Table 2. Periodic information

	P1 (2000–2009)	P2 (2010–2014)	P3 (2015–2020)	Total
Number of articles	7,445	6,376	12,538	26,359
Number of author keywords as type	37,554	32,442	65,535	135,531
Number of author keywords as lemma	15,878	16,439	29,826	62,143[6]
Type and Lemma Ratio	0.4233	0.5067	0.4551	0.4617

Although the first period is 10 years and the second and third periods are five years respectively, the third period produced about 1.5 time more articles than the first period.[7] However, token and lemma ratio of the third period (0.4551) is as almost the same as that of the first period (0.4233). Considering type and lemma ratios of three periods, we assume that each period has a similar scope for the study of lemma keywords.

3.2 Methodology

3.2.1 Degree Centrality

Degree centrality is defined as the number of links incident upon a node (i.e., the number of ties that a node has) according to Freeman (1978/1979). The higher the degree, the more central the node is. Degree is a simple centrality measure that counts how many neighbors a node has. The formula of degree centrality is illustrated in (1).

6 Lemma number of author keywords was 60,569. However, it is natural that this number differs as the number of lemmas of each period may overlap with that of each journal.

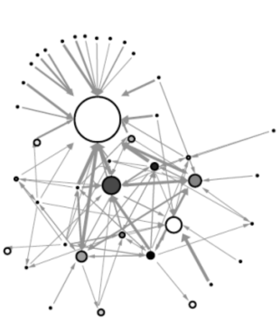
7 This reason for the first period containing far fewer articles than the third period can be understood due to the journal's late registration year in the Web of Science and the first issue's late publications since some of the journals published their first issues in 2005 (*Transport Policy*) and in 2009 (*Marine Policy, International Journal of Shipping and Transport Logistics, Maritime Economics & Logistics*).

$$C_D = \frac{\sum_{i=1}^{g}\left[\overset{\text{maximum value in the network}}{\boxed{C_D(n^*)}} - C_D(i)\right]}{[(N-1)(N-2)]} \tag{1}$$

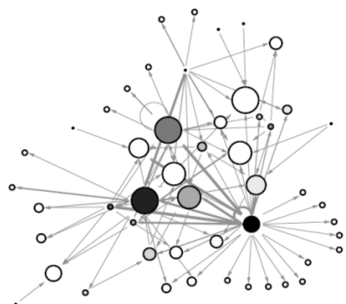
where n = number of points
$C_x(P_i)$ = one of the point centralities defined above
$C_x(P^*)$ = largest value of $C_x(P_i)$ for any point in the network

(1) is Freeman's general formula for centralization (can use other metrics, e.g., gini coefficient or standard deviation). Let us take two examples of financial trading networks: high centalization in (2a) and low centralization in (2b).

(2a) high centralization: one node trading with many others



(2b) low centralization: trades are more evenly distributed



In Netminer 4.4, degree centrality is calculated through the main menu of Analyze >> Neighbor >> Degree. For undirected networks, this study does not need two measures of degree (in-degree and out-degree) because there is no direction between a node of keywords and a node of articles in this study. In order to visualize networks, we need to set up a threshold of minimum frequency of 10-times occurrences so that we have a total of 1,149 keywords.

3.3.2 Delta-C

Although degree centrality is a good measure of the total connections a node has, it does not show difference between quantity and quality. That is, degree centrality does not necessarily indicate the importance of a node in connecting others or how central it is to the main group. So this study utilizes Delta-C in order to examine research trends by identifying the differences of degree centrality in specific periods. Delta-C is an algorithm that was initially proposed by Jhang and Lee (2016), in which C is the abbreviation of Centrality. The formula of the Delta-C is illustrated in (3).

$$\Delta\ D(C) = \frac{E(c) - O(c)^{8}}{N} \quad (3)$$

In (3), E (c) refers to the period of the most recent year or years, O (c) refers to the period of the past year or years, and N denotes the sum of the total centrality. A plus value represents higher degree centrality of the recent years, whereas a minus value represents higher degree centrality of the past.

Table 3. Types of keywords categorized by Delta-C value of periods

TYPE	P1 (2000-2009)	P2 (2010-2014)	P3 (2015-2020)	Delta-C
A	Presence of DC	Presence of DC	Presence of DC	*[9]
B	No Occurrence of Keywords	Presence of DC	Higher DC than P2	P3 − P2 = Plus value
C	No Occurrence of Keywords	Presence of DC	Lower DC than P2	P3 − P2 = Minus value
D	Presence of DC	No Occurrence of Keywords	Higher DC than P1	P3 − P1 = Plus value
E	Presence of DC	No Occurrence of Keywords	Lower DC than P1	P3 − P1 = Minus value
F	No Occurrence of Keywords	No Occurrence of Keywords	Newly introduced keywords	N/A

According to the Delta-C (DC) algorithm and degree centrality, more than six types of trends can be logically drawn. In this study, however, we present six type trends illustrated in Table 3, which will be examined in detail one by one in Section 4. Six types of trends are selected by focusing on the presence of keywords occurring in P3.

As seen in Table 3 keywords in Type A occur throughout three time periods. This type of research seems to represent most popular and frequently explored fields. Type B represents a research trend that shows the following patterns in each period: No keywords appear in P1; a certain degree centrality exists in P2; degree centrality of P3 is higher than that of P2; and Delta-C value is positive. Type B thus explains the keywords that started to appear since 2010 and keep appearing more frequently in the recent years. Type C shows a trend that is similar to Type B other than the P3 status, of which degree centrality is lower than that of P2, and Delta-C has negative value. Type C keywords started to appear in P2 but the usage has decreased during the recent years. Types D and E are interesting in that they occurred in P1 but disappeared in P2, and then they reappear in P3. Depending on the Delta-C value, whether it has plus or minus value, Type D and Type E are categorized respectively. Last but not least, Type F shows a research trend in which new keywords occur in the recent years.

8 There are typos in Jhang and Lee (2016): E and O in the formula are misplaced and should be switched as in (3).
9 Delta-C value can be calculated, but no Delta-C was presented because we consider shared property to be significant here.

4. Results and Discussion

4.1 Six types of trends

This subsection discusses several patterns to show trends of keywords over time by examining the distribution of shared keywords in three different periods by using the Delta-C algorithm resulting in six different types of patterns. Before discussing six types of trends, first let us display three different whole networks.

4.1.1 One-mode keyword networks of three periods

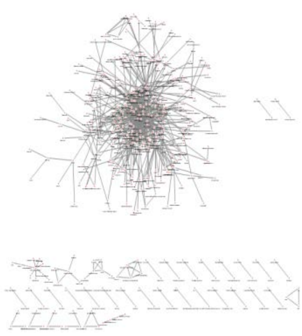
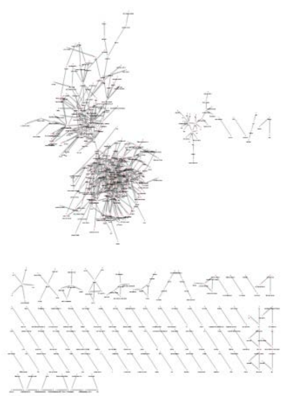
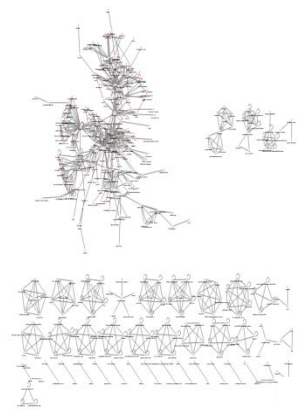
Each of the three periods has by using 227 keywords in P1, 285 keywords in P2, and 149 keywords in P3 — enough to run degree centrality in Netminer 4.4. The keywords used to draw networks of degree centrality are shown in Table 4.

Table 4. Keyword information for drawing networks of degree centrality in three periods

P1 (2000–2009)	In–Degree Centrality	Out–Degree Centrality
1. growth	0.336283186	0.336283186
2. Atlantic salmon	0.075221239	0.075221239
...	...	...
226. sea cucumber	0.004424779	0.004424779
227. phytase	0.004424779	0.004424779
P2 (2010–2014)		
1. growth	0.154929577	0.154929577
2. marine protected area	0.049295775	0.049295775
...	...	...
284. coral reef	0.003521127	0.003521127
285. arctic	0.003521127	0.003521127
P3 (2015–2020)		
1. management	0.074324324	0.074324324
2. shipping	0.067567568	0.067567568
...	...	...
148. sea level rise	0.006756757	0.006756757
149. complex system	0.006756757	0.006756757

Now let us draw one-mode keyword networks of P1, P2 and P3, using the above keywords, are seen in Figure 3 below.

Figure 3. One-mode keyword networks of three periods

P1 (2000-2009)	P2 (2010-2014)	P3 (2015-2020)
		

As seen in Figure 3, each period has one giant clump. Interestingly enough, the second period features two giant clumps, where the node *fishery* connects with the node of *aquaculture* in the other giant clump. Especially, the third period has the most cliques. The following subsections are mainly concerned with one giant clump composed of interesting nodes.

4.1.2 Type A as consistently shared themes

First of all, let us discuss highly remarkable research themes that are shared throughout all the three periods as Type A. As a heuristic approach to answering a question raised in Table 1 (“which journals have very coherent and consistent themes to global maritime affairs and fisheries throughout the last 20 years?”), we provided seven shared keywords such as *aquaculture, Atlantic salmon, governance, growth, marine protected area, sustainability,* and *transport*. They occur within the top 30 keywords when sorted by high degree centrality in each of the three periods, as seen in Table 5 below, of 76 shared keywords that co-occur within the top 200 keywords that the Delta-C values have in each period of the last 20 years.

Table 5. Top 30 keywords sorted by high degree centrality in each period

P1 (2000–2009)	P2 (2010–2014)	P3 (2015–2020)
growth*	accessibility	aquaculture*
fishery management	growth*	growth*
aquaculture*	transport*	management
co management	China	accessibility
fishery	shipping	climate change
Atlantic salmon*	travel behavior	fishery
temperature	aquaculture*	China
shrimp	sustainability*	growth performance
rainbow trout	GI	sustainability
fatty acid	commuting	governance*
survival	mobility	marine protected area*
larva	cycling	conservation
marine protected area*	port	fishery management
reproduction	liner shipping	shipping
fish	governance*	public transport
lipid	mode choice	port
sustainability*	container shipping	fish
digestibility	climate change	built environment
nutrition	travel behaviour	policy
governance*	walking	Atlantic salmon*
protein	transport logistics	liner shipping
salmon	container terminal	gene expression
participation	high speed rail	impact
salmo salar	airport	land use
transport*	Atlantic salmon*	mobility
tilapia	public transport	container terminal
stress	logistics	transport*
feeding	supply chain	rainbow trout
microsatellites	time geography	competition
penaeus monodon	marine protected area*	Europe

As seen in Table 5 above, keywords with an asterisk* are shared throughout the three periods within the top 30 keywords sorted by high degree centrality of each period. These keywords are seven consistently occurring themes throughout three periods.

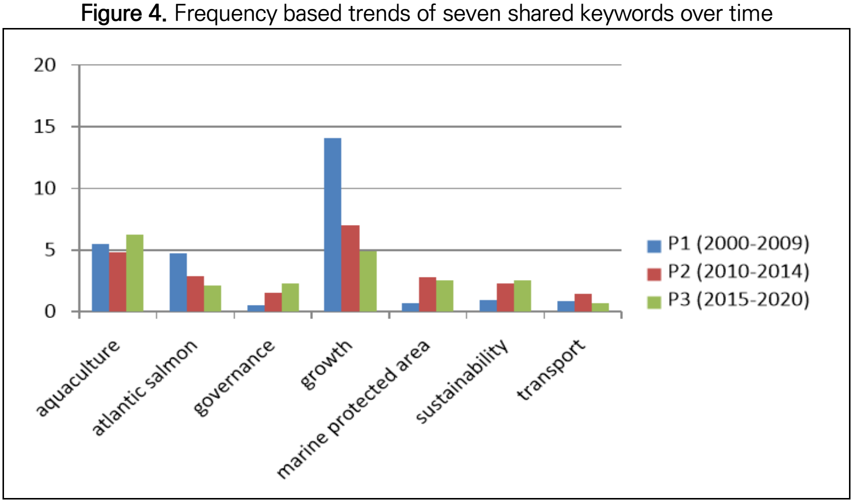
Before looking at the trends through degree centrality, let us consider the frequency of these seven shared keywords throughout three periods in order to compare the result of frequency based trend analysis with that of degree centrality based analysis. Occurrence frequency of these seven shared keywords in each period is illustrated in Table 6 below.

Table 6. Occurrence frequency of shared keywords in each period

Shared keywords	P1 (2000-2009)		P2 (2010-2014)		P3 (2015-2020)	
	Freq.	Normalized Freq.	Freq.	Normalized Freq.	Freq.	Normalized Freq.
aquaculture	206	5.485	156	4.808	410	6.256
Atlantic salmon	178	4.739	93	2.866	140	2.136
governance	20	0.532	50	1.541	150	2.288
growth	528	14.059	227	6.997	319	4.867
marine protected area	27	0.718	90	2.774	166	2.532
sustainability	36	0.958	73	2.250	169	2.578
transport	33	0.878	47	1.448	45	0.686

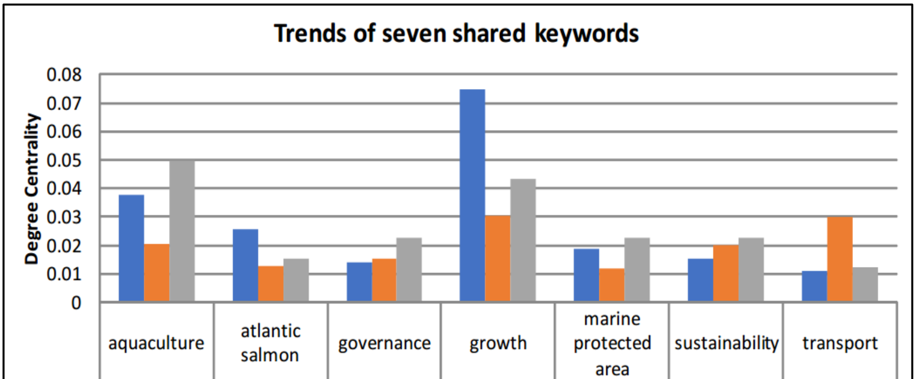
As seen in Table 6, frequency-based analysis indicates that blue-colored keywords show the most occurrences in each period in alphabetic order. However, what about the gray-colored keyword, *marine protected area*? Even though it is assumed that the more frequently used keywords are more important, is it correct that a theme of *marine protected area* is more prominent in P3 (166) than P2 (90)? When the different frequency of use of the target word in different periods is compared, normalization should be necessary. The most straightforward approach is to make a comparison of normalized frequency. Based on the normalized frequency of per 1,000 words, P2 (2.774) is greater than P3 (2.532). Hence it is correct that a theme of *marine protected area* is more prominent in P2 than P3, as seen in Figure 4 below.

Figure 4. Frequency based trends of seven shared keywords over time



Now let us take a close look at how these themes change over time using degree centrality, as shown in Figure 5 below.

Figure 5. Degree centrality based trends of seven shared keywords over time



	aquaculture	atlantic salmon	governance	growth	marine protected area	sustainability	transport
P1	0.037590773	0.025843657	0.013882956	0.074967962	0.018795387	0.01516446	0.010892781
P2	0.020503677	0.012703365	0.015154892	0.030309784	0.012034767	0.019835079	0.030086918
P3	0.049639372	0.015485787	0.022698345	0.04327535	0.022486211	0.022698345	0.012303776

Since these seven keywords occur in three periods, it seems that they are consistent as they continuously appear to be themes of interest throughout the last 20 years. As seen in Figure 5, *governance* and *sustainability* are two themes which show a steady, minor increase from P1 to P3. Others do not show this trend. Interestingly enough, a theme of *aquaculture* is extremely prominent in the most recent period of P3, compared with other themes. Comparing Figure 4 with Figure 5, the trends of all the target keywords are not the same since trend patterns of at least three keywords of *atlantic salmon*, *growth*, and *marine protected area* are different.

Thus we assume that these seven shared keywords (i.e., *aquaculture, Atlantic salmon, governance, growth, marine protected area, sustainability,* and *transport)* are long-standing consistent maritime and fisheries related themes throughout the last 20 years. It is also interpreted that research themes of Type A as consistently shared themes changed from *growth* and *fishery management* in fisheries and *sustainability* and *governance* in maritime sectors in the 2000s; to *growth* and *aquaculture* in fisheries and *accessibility, China* and *sustainability* in maritime sectors in the early 2010s; and to *aquaculture* and *growth* in fisheries and *accessibility, climate change,* and *China* in maritime sectors in the late 2010s.

4.1.3 Type B as highly interest-increased themes

Now, let us focus on interest-increased, interest-decreased, and newly emerging research themes in the most recent period of P3 through the Delta-C algorithm. In this subsection, we consider Type B as highly interest-increased themes from P2 to P3 with no occurrence in P1. In other words, Type B is a pattern of no occurrence in P1 and more important themes in P3 than in P2. This difference between interest-increased themes between the two periods can be captured by the Delta-C algorithm. The top 10 keywords belonging to Type B are illustrated in Table 7 below.

Table 7. Top 10 keywords belonging to Type B

Keywords (2015–2020)	Degree Centrality	Freq.	Normalized Freq.[10]	Delta-C against P2 (2010~2014)	Delta C against P1 (2000~2009)
1. ecosystem service	0.009546033	80	1.220	0.001180780	no occurrence
2. big data	0.006151888	27	0.411	0.001007571	no occurrence
3. public transit	0.008061095	32	0.488	0.000826014	no occurrence
4. mixed integer linear programming	0.004242681	26	0.396	0.000697701	no occurrence
5. inland port	0.004879084	11	0.167	0.000691785	no occurrence
6. maritime	0.004242681	21	0.320	0.000656749	no occurrence
7. buyer supplier relationship	0.004242681	20	0.305	0.000656749	no occurrence
8. maritime transport	0.009970301	33	0.503	0.000644456	no occurrence
9. customer satisfaction	0.005939754	16	0.244	0.000640972	no occurrence
10. transit	0.004879084	15	0.228	0.000568928	no occurrence

As seen in Table 7, degree centrality value of a theme, *maritime transport* (0.00997001) is a little higher than that of another theme, *ecosystem service* (0.009546033) in P3. Nonetheless, the latter is ranked the first because the Delta-C of the latter (*ecosystem service* (0.00118078)) has much bigger plus difference between degree centrality value of P1 and P2 than that of the former (*maritime transport* (0.000644456)).

10 Throughout this study, all the normalized frequency means frequent number per thousand keywords

4.1.4 Type C as extremely interest-decreased themes

In this subsection, we consider Type C as extremely interest-decreased themes from P2 to P3 with no occurrence in P1. In other words, Type C is a pattern of no occurrence in P1 and less important themes in P3 than in P2. The top 10 keywords belonging to Type C are illustrated in Table 8 below.

Table 8. Top 10 keywords belonging to Type C

Keywords (2015-2020)	Degree Centrality	Freq.	Normalized Freq.	Delta-C against P2(2010~2014)	Delta C against P1 (2000~2009)
1. high speed rail	0.004879084	48	0.732	-0.00151964	no occurrence
2. Finland	0.00106067	2	0.030	-0.001197477	no occurrence
3. Hong Kong	0.000424268	7	0.106	-0.001150609	no occurrence
4. supply chain security	0.002121341	4	0.061	-0.000838767	no occurrence
5. hub	0.000212134	4	0.061	-0.000821018	no occurrence
6. fuzzy logic	0.000212134	4	0.061	-0.000780066	no occurrence
7. corridor	0.000424268	5	0.076	-0.000741086	no occurrence
8. black sea	0.000212134	5	0.076	-0.000739114	no occurrence
9. punctuality	0.000212134	2	0.030	-0.000739114	no occurrence
10. port security	0.001484938	3	0.045	-0.000709994	no occurrence

As seen in Table 8, the degree centrality value of a theme, *high speed rail* (0.004879084) is the highest in a group of Type C in P3. Nonetheless, this theme is ranked the first in the group of interest-decreased themes because the Delta-C of this keyword (*high speed rail* (-0.00151964)) has the bigger difference between degree centrality value of P2 and P3 than other keywords.

4.1.5 Type D as retro trends with interest-increased themes

In this subsection, we consider Type D as interest-increased themes of P3 being higher than P1 with no occurrence in P2. In other words, Type D is a pattern of no occurrence in P2 and a discontinuous series of more important themes in P3 than in P1. This means that there were some preferred themes in P1 and these themes unexpectedly disappeared in P2 but they re-appeared in P3 with interest-increased themes higher than P1.This type seems to be understood as retro trends because there are no occurrences in P2 between P1 and P3. The top 10 keywords belonging to Type D are illustrated in Table 9 below.

Table 9. Top 10 keywords belonging to Type D

Keywords (2015–2020)	Degree Centrality	Freq.	Normalized Freq.	Delta-C against P1 (2000–2009)	Delta C against P2 (2010–2014)
1. impact	0.013364446	68	1.037	0.002416511	no occurrence
2. maritime logistics	0.005939754	20	0.305	0.000934461	no occurrence
3. shipping market	0.005091218	7	0.106	0.00077854	no occurrence
4. Malaysia	0.003818413	15	0.228	0.000583905	no occurrence
5. marine	0.003182011	29	0.442	0.000545457	no occurrence
6. stochastic frontier analysis	0.003394145	12	0.183	0.000505944	no occurrence
7. bulk shipping	0.003394145	9	0.137	0.000466698	no occurrence
8. fuzzy set theory	0.003394145	4	0.061	0.000466698	no occurrence
9. dynamic model	0.003182011	5	0.076	0.000427717	no occurrence
10. Kenya	0.003394145	16	0.244	0.000427451	no occurrence

As seen in Table 9, the top 10 keywords are sorted by the high plus value of Delta-C against P1. The difference between Type B and Type D lies in a discontinuous series of some themes as retro trends. For example, a theme, *impact*, has comparatively high degree centrality value in P1 but it does not occur in P2 but re-appears in P3 with a degree centrality value (0.013364446) higher than *transport* (0.012303776) as shown in Figure 5 for Type A.

4.1.6 Type E as retro trends with interest-decreased themes

In this subsection, we consider Type E as extremely interest-decreased themes of P3 being lower than P1 with no occurrence in P2. In other words, Type E is a pattern of no occurrence in P2 and a discontinuous series of less important themes in P3 than in P1. This means that there were some preferred themes in P1 and these themes unexpectedly disappeared in P2 but they re-appeared with interest-decreased themes lower than P1. The top 10 keywords belonging to Type E are illustrated in Table 10 below.

Table 10. Top 10 keywords belonging to Type E

Keywords (2015–2020)	Degree Centrality	Freq.	Normalized Freq.	Delta-C against P1 (2000–2009)	Delta-C against P2 (2010–2014)
1. pollution	0.001060670	16	0.244	−0.001100240	no occurrence
2. coastal management	0.003818413	61	0.930	−0.001025210	no occurrence
3. law sea	0.001060670	10	0.152	−0.001021746	no occurrence
4. legitimacy	0.000848536	13	0.198	−0.001021480	no occurrence
5. oxytetracycline	0.000848536	8	0.122	−0.000825246	no occurrence
6. globalisation	0.000212134	3	0.045	−0.000785200	no occurrence
7. fishing effort	0.000424268	13	0.198	−0.000746220	no occurrence
8. decommissioning	0.000212134	4	0.061	−0.000706707	no occurrence
9. exclusive economic zone	0.000848536	8	0.122	−0.000629013	no occurrence
10. texture	0.000636402	8	0.122	−0.000628746	no occurrence

As seen in Table 10, the degree centrality value of a theme, *pollution* (0.001060670) is not the highest in P3 and this theme is ranked the first in a group of interest-decreased themes because the Delta-C of this keyword (*pollution* (-0.001100240)) has the bigger difference between degree centrality value of P1 and P3 than other keywords.

4.1.7 Type F as new trends

Last but not least, let us consider newly emerging research themes in the most recent period of P3 through the Delta-C algorithm. It is interesting to extract new themes which do not occur in P1 and P2 but do occur in P3 when we use the Delta-C algorithm against P1 and P2. New themes introduced to P3 can be sorted by the high degree centrality value, as seen in Table 11 below.

Table 11. Top 10 keywords belonging to Type F

Keywords (2015–2020)	Degree Centrality	Freq .	Normalized Freq.	Delta-C against P2 (2010–2014)	Delta-C against P1 (2000–2009)
1. literature review	0.009970301	45	0.686	no occurrence	no occurrence
2. sea level rise	0.006151888	54	0.823	no occurrence	no occurrence
3. lipid metabolism	0.005727620	45	0.686	no occurrence	no occurrence
4. machine learning	0.005727620	20	0.305	no occurrence	no occurrence
5. GHG emission	0.005303352	13	0.198	no occurrence	no occurrence
6. Belt Road Initiative	0.005091218	28	0.427	no occurrence	no occurrence
7. demand elasticity	0.005091218	4	0.061	no occurrence	no occurrence
8. comanagement	0.004242681	23	0.350	no occurrence	no occurrence
9. AI	0.004030547	11	0.167	no occurrence	no occurrence
10. random forest	0.004030547	8	0.122	no occurrence	no occurrence

As seen in Table 11, the frequency of keywords is not directly related to how much some keywords are important, since the frequency of *sea level rise* is the greatest in this group of Type E, but its degree centrality value is not the highest. Furthermore, the frequency of *machine learning* (20) and *GHG emission* (13) is less than *Belt Road Initiative* (28) and *co-management* (23) but the former's degree centrality values (0.005727620 and 0.005303352) are greater values than the latter's (0.005091218 and 0.004242681) respectively.

It can be interpreted that these top 10 keywords having emerged as new issues of concern illustrate that the issues of *sea level rise* and *Green House Gas emission* attract more attention in the literature, the subjects of *machine learning* and *artificial Intelligence (AI)* become popular in accordance with the development of internet of things (IoT) in the late 2010s, and *Belt Road Initiative* demonstrates the enlargement of China's economic potential in the 2010s.

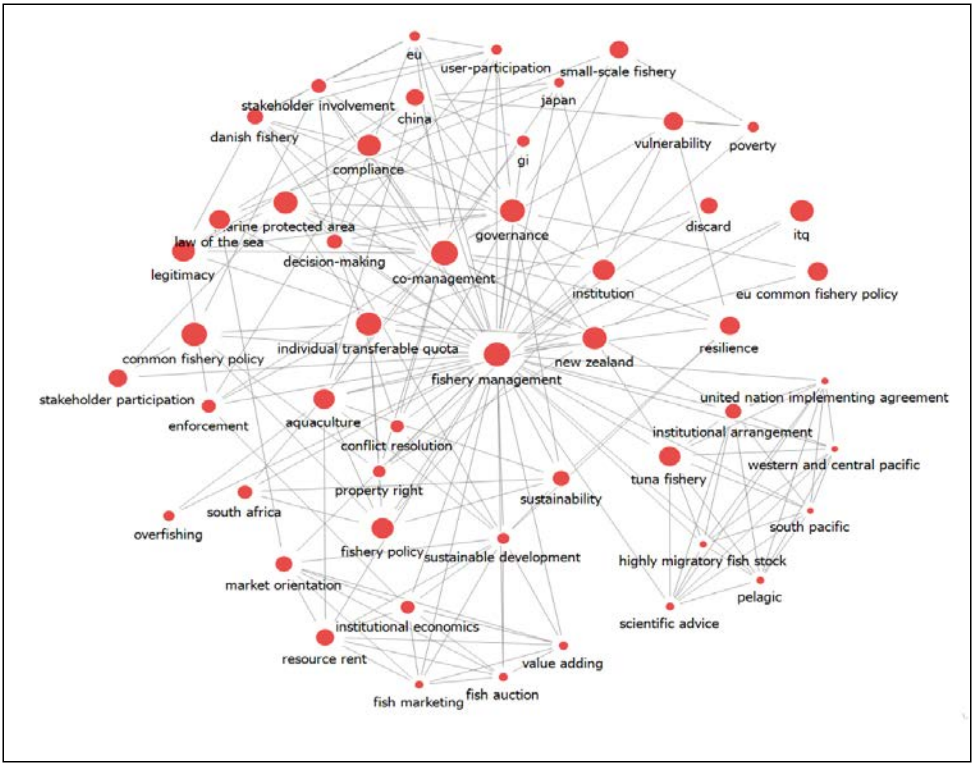
4.2 Networks of three periods

This subsection discusses an interesting theme occurring in each period and several interesting themes belonging to interesting types of trends using keyword network visualization.

4.2.1 Prominent themes in each period

Let us take the first example, *fishery management* ranking second in P1. Its degree centrality visualization is as follows:

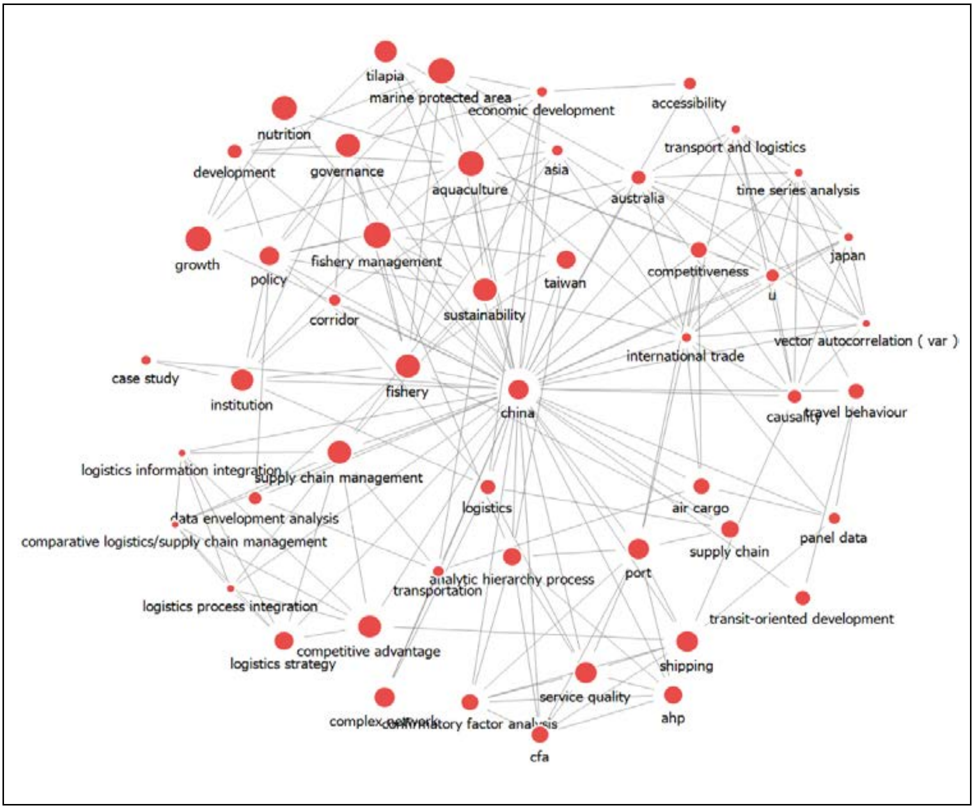
Figure 6. Degree centrality visualization of *fishery management* ranking second in P1



In Figure 6, a center node, *fishery management* directly connects many important nodes such as *governance*, *aquaculture*, *sustainability* and *co-management* co-occurring within the top 20 as well as nations such as China, New Zealand, South Africa, and EU.

Let us take a second degree centrality visualization example, China, ranking fourth in P2, as seen in Figure 7.

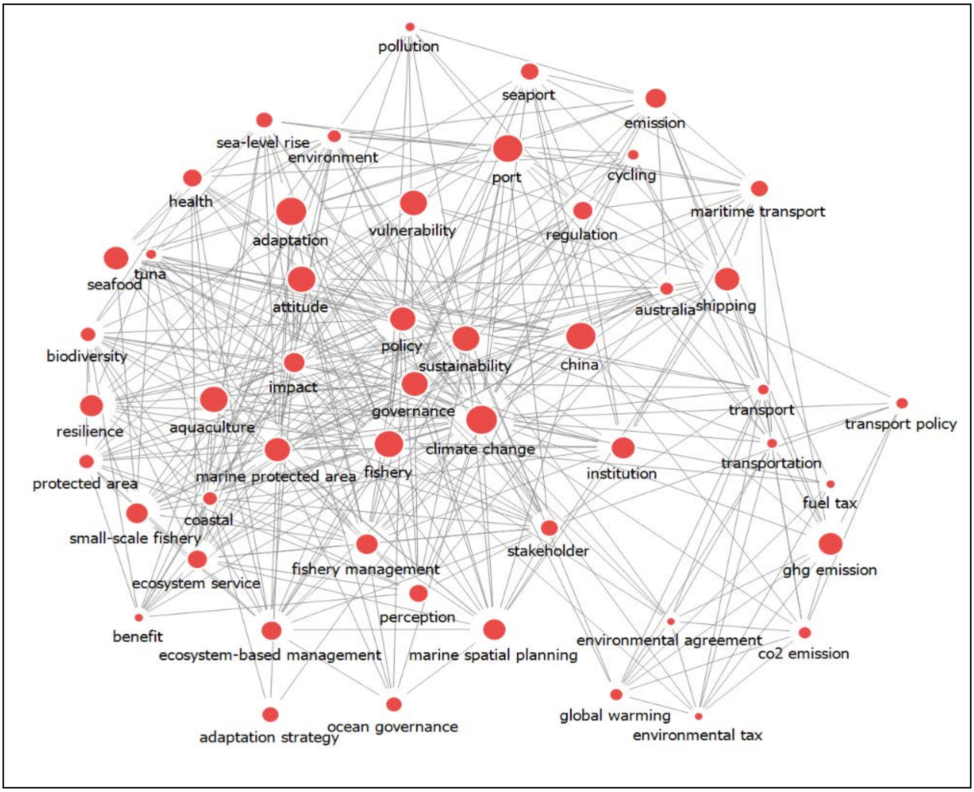
Figure 7. Degree centrality visualization of *China* ranking fourth in P2



In Figure 7, China as a center node directly connects important themes co-occurring within top 20 (i.e., *growth*, *shipping*, *travel behavior, aquaculture, sustainability, and governance*, 'environment matters' of *greenhouse gas* (*GHG*), *emission reduction*, and *emission trading scheme* and 'analysis methods' such as *supply chain management*, *analytic hierarchy process*, *data envelopment analysis*, and *time series analysis* as well as nations and regions, such as Taiwan, Australia, Asia and Japan.

Let us take a third degree centrality visualization example, *climate change*, ranking fifth in P3, as seen in Figure 8.

Figure 8. Degree centrality visualization of *climate change* ranking fifth in P3

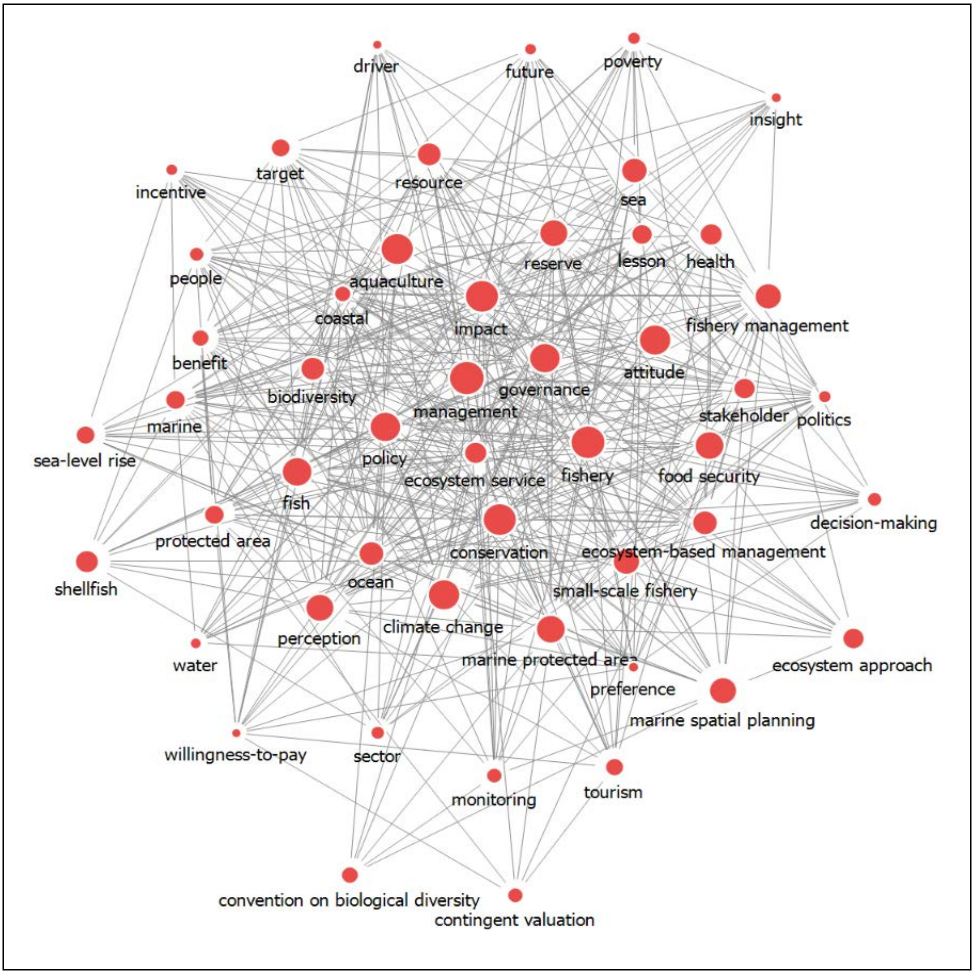


In Figure 8, *climate change* directly connects important themes such as *aquaculture, sustainability, marine protected area, fishery, fishery management, shipping, fish, port, impact*, etc. occurring within the Top 30 in P3.

4.2.2 Prominent themes in type patterns

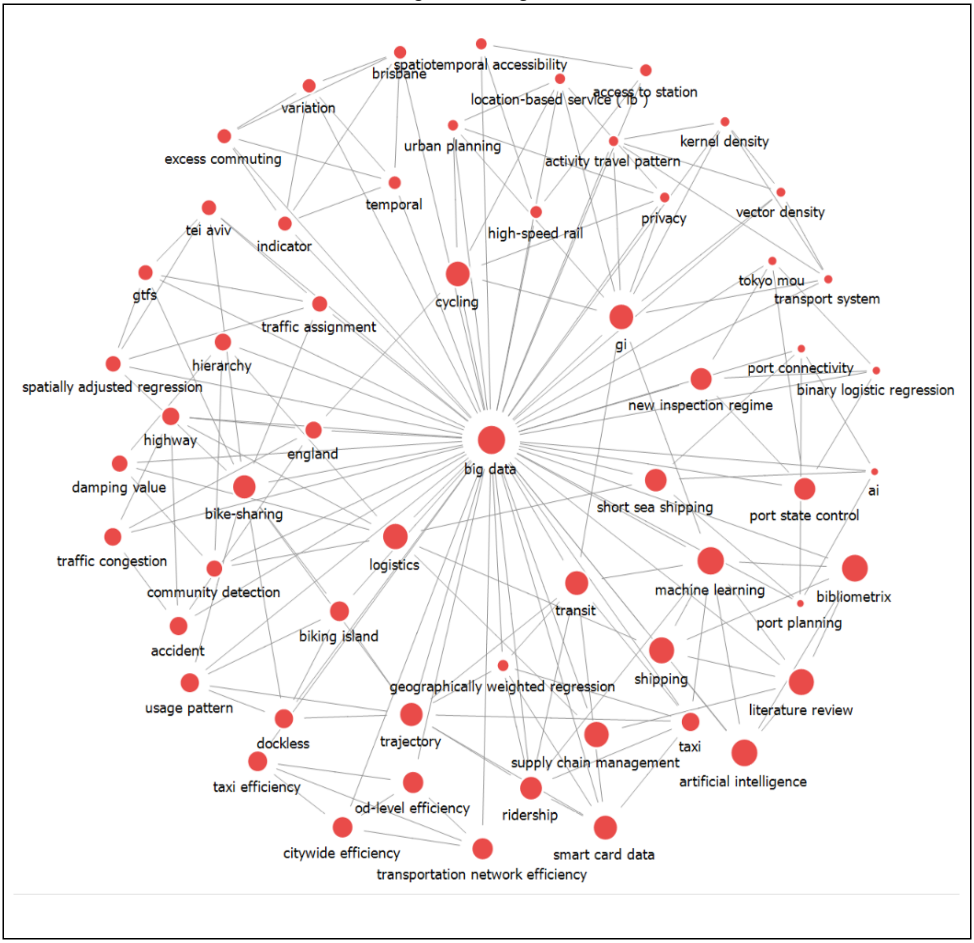
In the previous section, we have discussed three interesting themes belonging to Type A. To save space, this subsection is limited to discussion of several interesting themes belonging to Type B and Type F in the most recent period. Now, let us take two themes ranking first (*ecosystem service*) and second (*big data*) in Type B.

Figure 9. *ecosystem service*



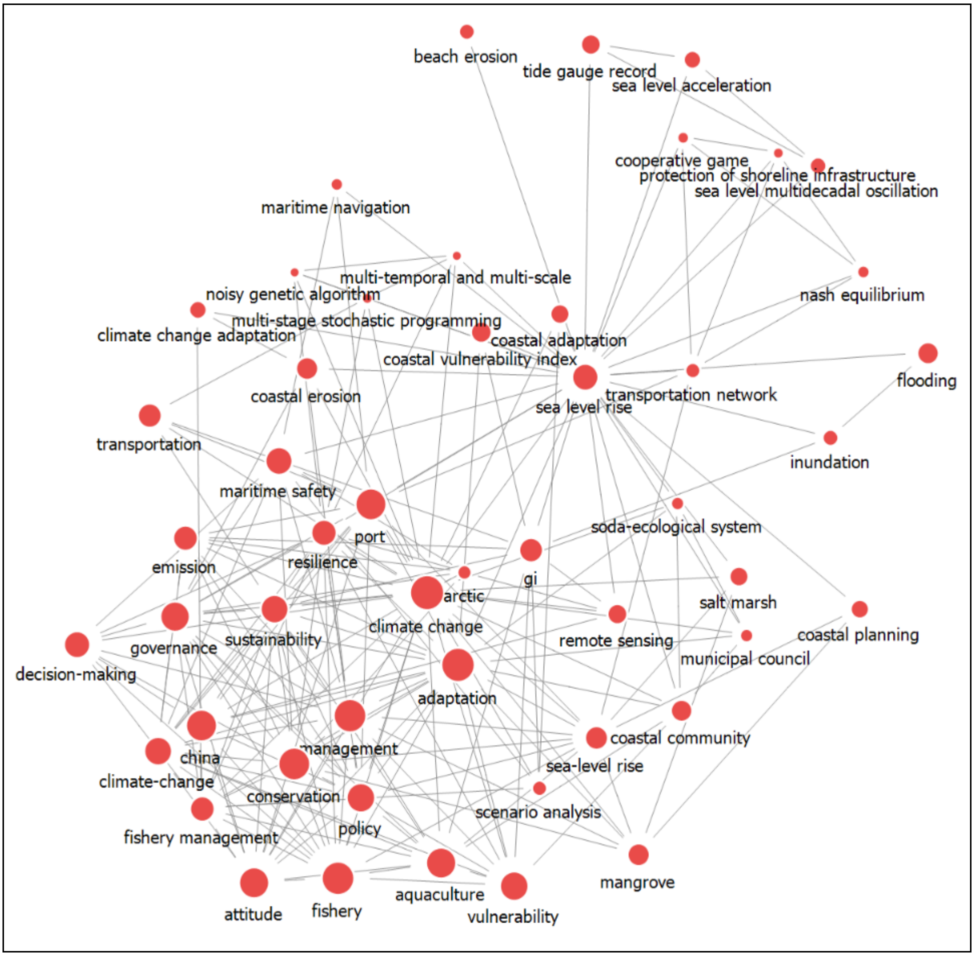
As seen in Figure 9 and Figure 10, *ecosystem service* ranking first has more nodes than *big data* ranking second. The former connects a nation such as Kenya as well as regional areas such as *Gulf Mexico*, *Baltic Sea*, *marine protected area*, and *wetland*, whereas the latter connects a nation such as England and new trends of Type F such as *machine learning*, *artificial intelligence*, *general transit feed specification (GTFS)*, *decision making*, etc.

Figure 10. *big data*



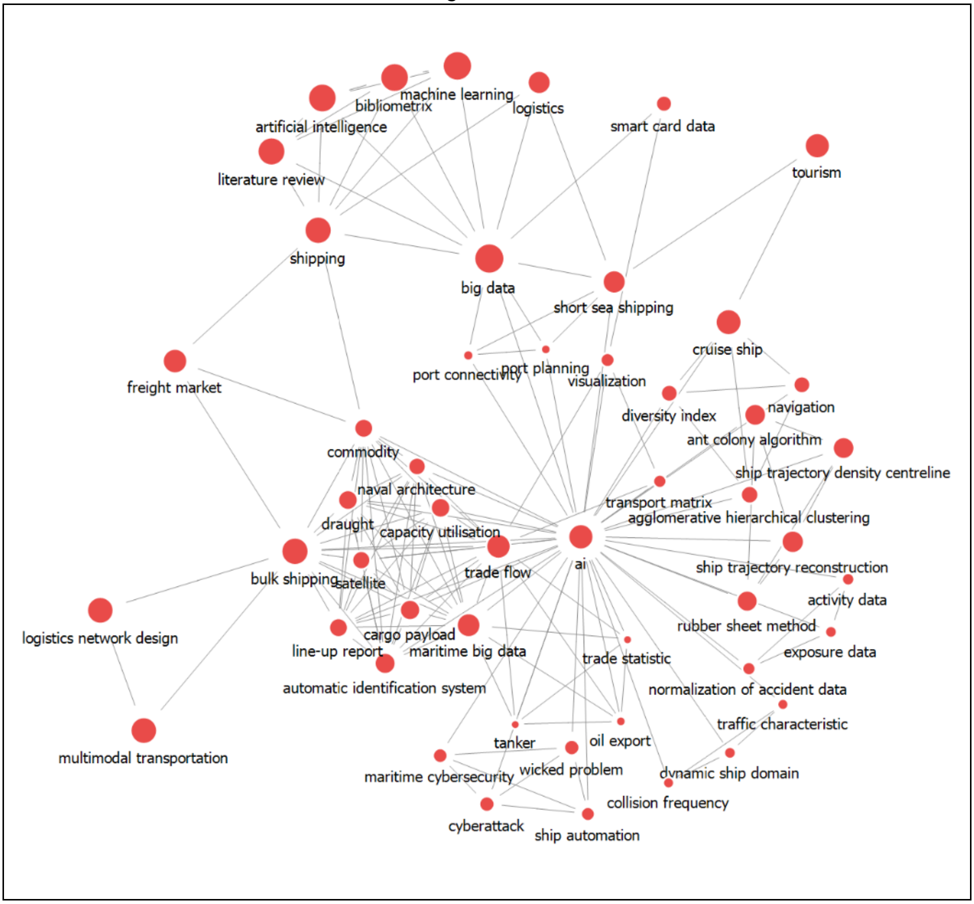
Next, let us take two themes newly introduced to the most recent period: *sea level rise* ranking second and *AI* ranking ninth.

Figure 11. *sea level rise*



As seen in Figure 11, *sea level rise* is associated with 'climate' such as *climate change* and *climate change adaption*, 'erosion' such as *beach erosion* and *coastal erosion*, 'maritime services' such as *maritime safety, port, Global Initiative* (*GI*), and *maritime navigation*, and 'coastal problems' with *coastal adaption, coastal flooding, coastal planning, coastal management, coastal community, coastal wetland, coastal vulnerability index, etc*. As seen in Figure 12, *AI* is mainly associated with 'maritime navigation affairs' such as *navigation, automatic identification system, draught, bulk shipping, maritime big data*, etc. and 'shipbuilding' such as *cruise ship, ship trajectory reconstruction, ship trajectory density centerline, rubber sheet method*, etc.

Figure 12. *AI*



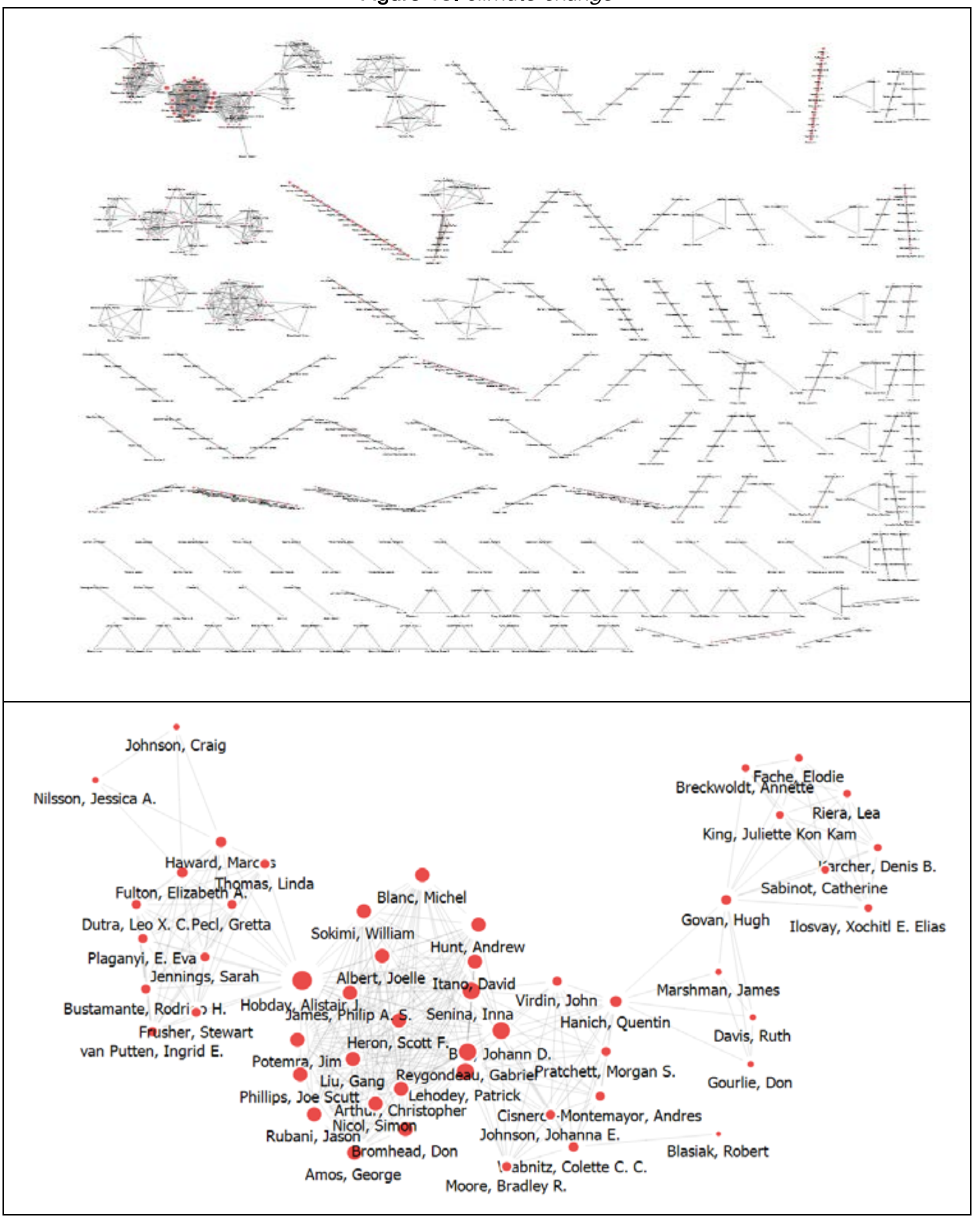
4.3 Networks of researchers and distribution of research nations

This subsection discusses networks of researchers and the distribution of research nations dealing with the most recent trending themes and new themes emerging in the third period in the global maritime fields.

4.3.1 Networks of researchers

First, let us focus on one theme in Type A, *climate change*, one theme in Type B, *big data*, and two new themes in Type F about *machine learning* and AI for networks of researchers

Figure 13. *climate change*



As seen in the upper of Figure 13, there are two giant clumps, six small clumps, numerous stings and cliques for co-authors networks of *climate change*. The below of Figure 13 enlarges the largest giant clump. This network visualization can be captured by the following edge list as seen in Table 12 below.

Table 12. Edge list for co-authors networks of *climate change*

climate change			
	Author1	Author2	Frequency
1	Bailey, David Mark	Potts, Tavis	2
2	Bell, Johann D.	Lehodey, Patrick	2
3	Bell, Johann D.	Reygondeau, Gabriel	2
4	Bell, Johann D.	Senina, Inna	2
5	Cheung, William W. L.	Sumaila, U. Rashid	2
6	de Rubens, Gerardo Zarazua	Kester, Johannes	2
7	de Rubens, Gerardo Zarazua	Sovacool, Benjamin K.	2
	...	...	
1274	Zigler, Sarah Bess Jones	Pinsky, Malin L.	1
1275	Zigler, Sarah Bess Jones	Provost, Mikaela M.	1
1276	Zigler, Sarah Bess Jones	St Martin, Kevin	1

On the other hand, as seen in Figure 14 below, there are no giant and small clumps but three stings and 14 cliques for co-authors networks of *big data*. This network visualization can be captured by the following edge list as seen in Table 13 below.

Figure 14. *big data*

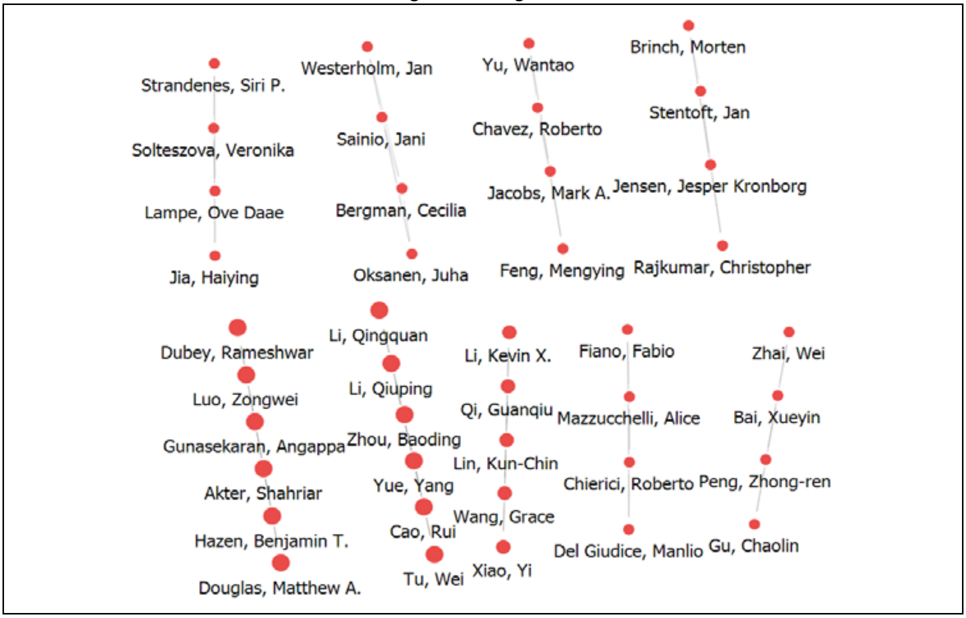
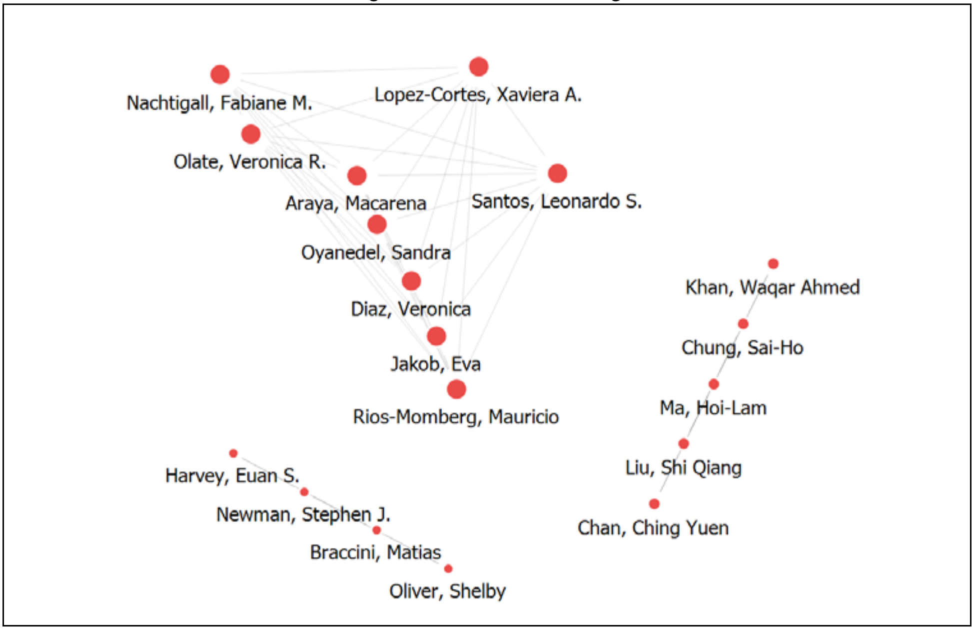


Table 13. Edge list for co-authors networks of *big data*

big data			
	Author 1	Author 2	Frequency
1	Akter, Shahriar	Hazen, Benjamin T.	1
2	Akter, Shahriar	Douglas, Matthew A.	1
3	Bai, Xueyin	Peng, Zhong-ren	1
4	Bai, Xueyin	Gu, Chaolin	1
5	Beckers, Joris	Vanhoof, Maarten	1
6	Beckers, Joris	Verhetsel, Ann	1
7	Bergman, Cecilia	Sainio, Jani	1
8	Bergman, Cecilia	Westerholm, Jan	1
	...	...	
95	Zhou, Baoding	Li, Qiuping	1
96	Zhou, Baoding	Li, Qingquan	1
97	Zhou, Jiangping	Murphy, Enda	1

Next, let us consider two new themes discussed in Type F for networks of researchers: *machine learning* and *AI*.

Figure 15. *machine learning*



As seen in Figure 15, co-authors networks of *machine learning* have one small clump, four stings and ten cliques. This network visualization can be captured by the following edge list as seen in Table 14 below.

Table 14. Edge list for co-authors networks of *machine learning*

	machine learning		
	Author 1	Author 2	Frequency
1	Araya, Macarena	Oyanedel, Sandra	1
2	Araya, Macarena	Diaz, Veronica	1
3	Araya, Macarena	Jakob, Eva	1
4	Araya, Macarena	Rios-Momberg, Mauricio	1
5	Araya, Macarena	Santos, Leonardo S.	1
6	Braccini, Matias	Newman, Stephen J.	1
7	Braccini, Matias	Harvey, Euan S.	1
8	Christodoulou, Aris	Christidis, Panayotis	1

	machine learning		
	Author 1	Author 2	Frequency
9	Chung, Sai-Ho	Ma, Hoi-Lam	1
10	Chung, Sai-Ho	Liu, Shi Qiang	1
11	Chung, Sai-Ho	Chan, Ching Yuen	1
	...	...	
78	Zhou, Xiaolu	Wang, Mingshu	1
79	Zhou, Xiaolu	Li, Dongying	1

On the other hand, as seen in Figure 16, co-authors networks of *AI* have are two small clumps, two stings and four cliques This network visualization can be captured by the following edge list as seen in Table 15 below.

Figure 16. *AI*

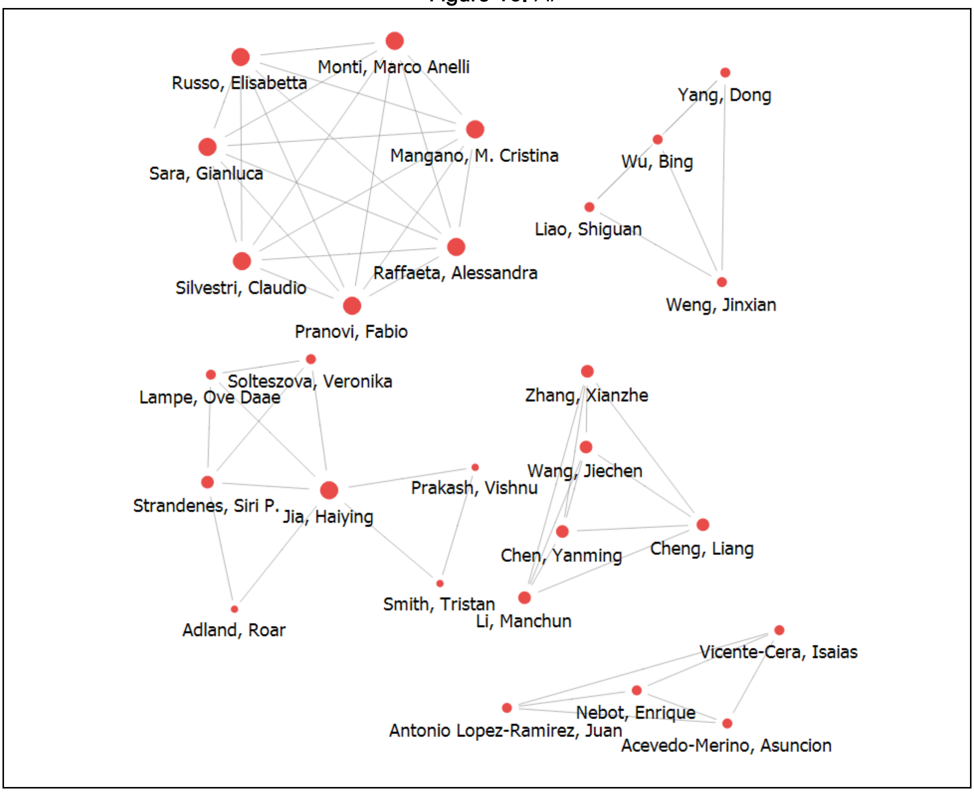


Table 15. Edge list for co-authors networks of *AI*

	AI		
	Author 1	Author 2	Frequency
1	Jia, Haiying	Strandenes, Siri P.	3
2	Jia, Haiying	Lampe, Ove Daae	2
3	Jia, Haiying	Solteszova, Veronika	2
4	Lampe, Ove Daae	Solteszova, Veronika	2
5	Lampe, Ove Daae	Strandenes, Siri P.	2
6	Solteszova, Veronika	Strandenes, Siri P.	2
7	Zhang, Xianzhe	Wang, Jiechen	1
8	Zhang, Xianzhe	Chen, Yanming	1
9	Zhang, Xianzhe	Li, Manchun	1
10	Zhang, Xianzhe	Cheng, Liang	1
	...	...	...
57	Sara, Gianluca	Silvestri, Claudio	1
58	Sara, Gianluca	Pranovi, Fabio	1
59	Silvestri, Claudio	Pranovi, Fabio	1

4.3.2 Distribution and network visualization of research nations

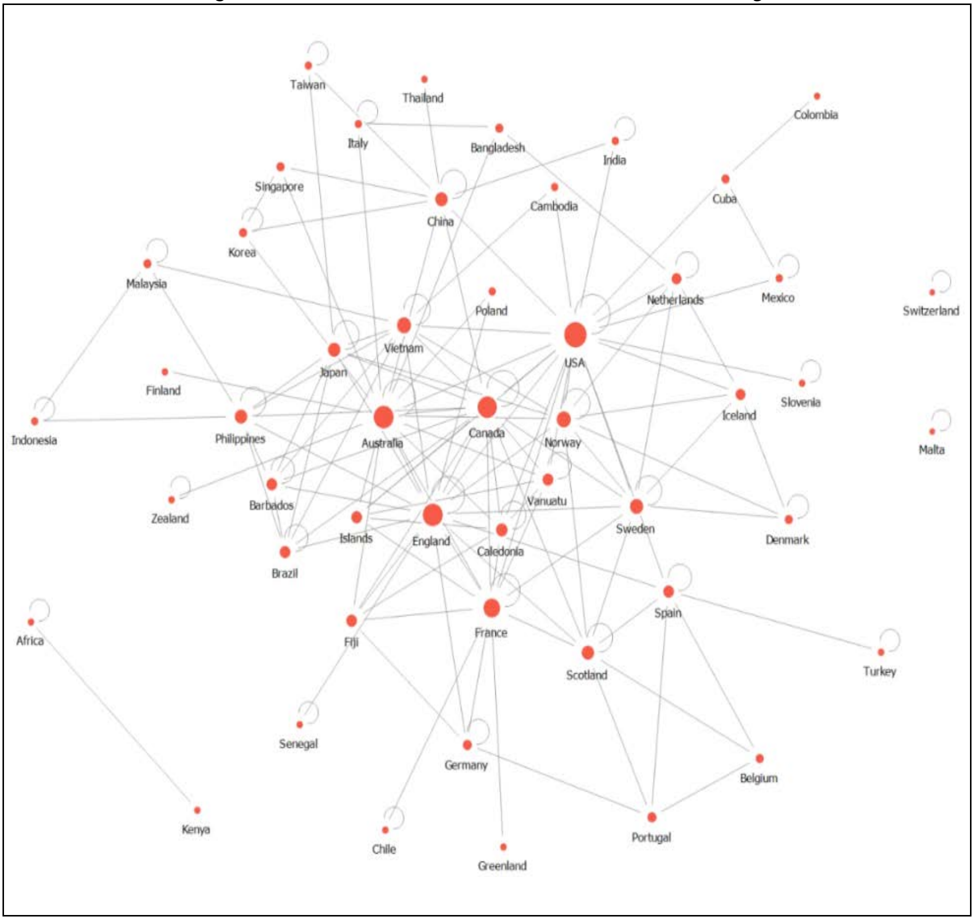
In line with the same data discussed in the previous subsection, let us also discuss the distribution and network visualization of research nations dealing with the most recent trending themes and new themes emerging in the third period in the global maritime fields. First, let us focus on one theme in Type A, *climate change*, one theme in Type B, *big data*, and two new themes in Type F about *machine learning* and *AI* for distribution and network visualization of research nations.

Let us discuss the distribution and network visualization of research nations about *climate change*. There are many nations having done research on this theme, as seen in Table 16.

Table 16. Edge list for research nations of *climate change*

	Nation1	Nation2	Frequency
1	USA	USA	250
2	Australia	Australia	246
3	England	England	68
4	Zealand	Zealand	66
5	France	France	60
6	Canada	Canada	59
7	China	China	35
8	Caledonia	Australia	31
9	Spain	Spain	27
10	Japan	Japan	25
...	...	...	...
213	Greenland	France	1

Figure 17. Networks for research nations of *climate change*



Based on the edge list of Table 16, the network visualization can be drawn as shown in Figure 17.

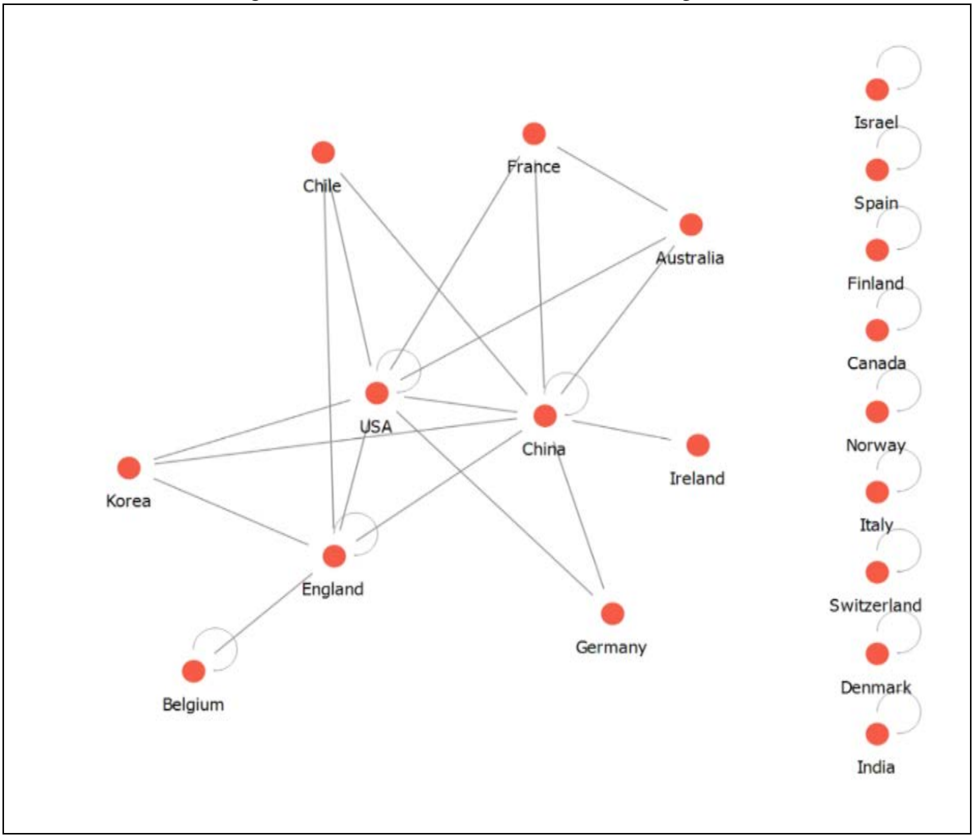
As seen in Figure 16, there is one giant clump and one string of Africa and Kenya as well as two isolated nations such as Switzerland and Malta. In one giant clump, four nations such as the USA, Australia, Canada, and England have many nodes and they are more powerful than others in the theme of *climate change*. The next powerful nations may include France, Scotland, Sweden, Vietnam, Norway, Sweden, Vanuatu, Spain, Japan, the Philippines, Brazil, etc.

Let us discuss the distribution and network visualization of research nations about *big data*. Based on the edge list of Table 17 below, the network visualization can be drawn as shown in Figure 18.

Table 17. Edge list for research nations of *big data*

	Nation 1	Nation 2	Frequency
1	China	China	16
2	USA	USA	6
3	Finland	Finland	6
4	Norway	Norway	6
5	Italy	Italy	6
6	Denmark	Denmark	6
7	USA	China	5
8	China	USA	5
9	Israel	Israel	3
10	Spain	Spain	3
...	...	...	
35	USA	Australia	1
36	Switzerland	Switzerland	1
37	India	India	1

Figure 18. Networks for research nations of *big data*



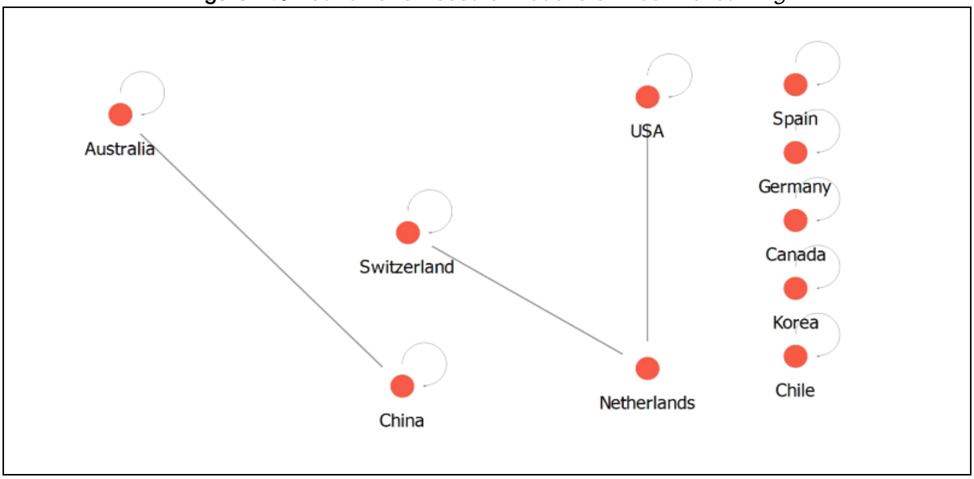
There are one small clump and nine isolated nations in networks for research nations of *big data.* In the small clump, China has eight links with the USA, Korea, England, Germany, Ireland, Australia, France and Chile, whereas the USA has seven links with China, Korea, England, Germany, Australia, France, and Chile and England has five links with the USA, China, Korea, Belgium, and Chile. Interestingly, Korea has three links with China, the USA and England.

Let us discuss the distribution and network visualization of research nations about *machine learning and AI.* Based on the edge list of Table 18 below, the network visualization can be drawn as shown in Figure 19.

Table 18. Edge list for research nations of *machine learning*

Nation1	Nation2	Frequency
Chile	Chile	36
China	China	11
USA	USA	10
Australia	Australia	6
Germany	Germany	4
Canada	Canada	3
China	Australia	2
Spain	Spain	1
USA	Netherlands	1
Netherlands	USA	1
Switzerland	Netherlands	1
Switzerland	Switzerland	1
Netherlands	Switzerland	1
Korea	Korea	1

Figure 19. Networks for research nations of *machine learning*



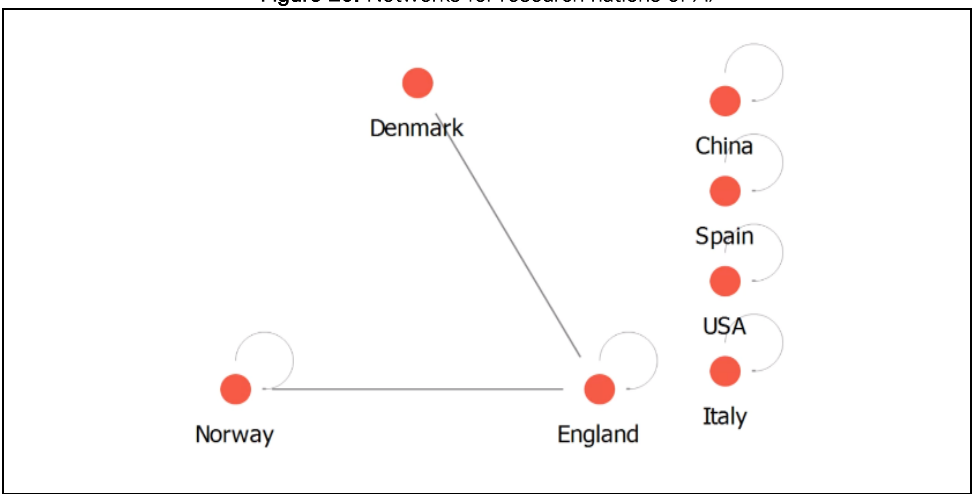
As seen in Table 18 and Figure 19, there is one clique and one string of Australia and China as well as five isolated nations such as Spain, Germany, Canada, Korea and Chile. The Netherlands has linking nodes of two nations such as Switzerland and the USA as a clique. Maritime-related research nations of *machine learning* are somewhat restrictive since there are 10 nations such as the USA, Chile, Australia, Germany, Canada, China, Spain, the Netherlands, Switzerland, and Korea.

On the other hand, as seen in Table 19 and Figure 20, maritime-related research nations of *AI* are very restrictive since there are seven nations: Italy, Norway, China, Spain, the USA, England, and Denmark. Only England links with two nations: Norway and Denmark. Other nations are isolated.

Table 19. Edge list for research nations of *AI*

Nation 1	Nation 2	Frequency
Italy	Italy	21
Norway	Norway	16
China	China	13
Spain	Spain	6
USA	USA	3
Norway	England	2
England	England	1
Denmark	England	1

Figure 20. Networks for research nations of *AI*



As seen in Figure 20 for network visualization of research nations of *AI*, England has two linking nations such as Denmark and Norway as a clique and there are five isolated nations such as China, Spain, the USA, and Italy.

5. Conclusion

This study has identified research themes and trends in global maritime affairs, fisheries, marine and transport policy, and logistics over the last 20 years from 2000 to 2020 using keyword network analysis through degree centrality. We investigated 31,606 articles of 15 international maritime journals listed in the Web of Science. We used the Delta-C algorithm to discover several patterns indicating trends of keywords over time by examining the distribution of shared keywords in three different periods (P1: 2000 to 2009, P2: 2010 to 2014, P3: 2015 to 2020).

We have paid special attention to six different types of patterns through the Delta-C algorithm. First, we discussed highly remarkable shared research themes (i.e., seven shared keywords such as *aquaculture, Atlantic salmon, governance, growth, marine protected area, sustainability,* and *transport)* throughout the three periods as Type A. Second, we focused on interest-increased, interest-decreased, and newly emerging research themes shown in the third period (P3) from Type B to Type E. As for Type B to Type E, we discussed the top 10 themes of each type. Finally, we showed the networks of researchers and the distribution and network visualization of research nations that deal with the most recent trending themes such as *climate change* in Type A, *big data* in Type B, and *machine learning* and *AI* in Type F about new themes emerging in the third period in the global maritime fields. This study showed two new findings. First, in Type A, representing consistently shared themes, the main research themes changed from *growth* and *fishery management* in fisheries and *sustainability* and *governance* in maritime sectors in the 2000s; to *growth* and *aquaculture* in fisheries and *accessibility, China* and *sustainability* in maritime sectors in the early 2010s; and to *aquaculture* and *growth* in fisheries and *accessibility, climate change,* and *China* in maritime sectors in the late 2010s. Second, in Type F as new trends, the top 10 keywords illustrated that the issues of *sea level rise* and *Green House Gas emission* attract more attention in the literature. It can also be interpreted that the subjects of *machine learning* and *artificial Intelligence (AI)* become popular in accordance with the development of internet of things (IoT) in the late 2010s and *Belt Road Initiative* demonstrates the enlargement of China's economic potential in the 2010s.

The findings of this study lead us to some suggestions for future research. First of all, the Delta-C algorithm used in this study is very helpful to identify new themes emerging in a designated period. Second, this algorithm is also able to show the trend of how much a theme of interest has been increased or decreased in a designated period. Last but not least, keyword network analysis through degree centrality used in this study is extremely helpful to list valuable information of researchers and research nations that deal with the most recent trending themes. However, this study has also a data limitation. We realize that 15 international maritime related journals are not enough to inform us of all the trends and important themes in the maritime fields during the last 20 years. In a future study, we need far more maritime related journals included in order to offer more accurate and significant trends and themes in global maritime journals.

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Appendix

Type A: a list of 76 shared keywords throughout all the three periods in alphabetical order (cf. Seven shaded keywords are discussed in this paper.)

No	Shared Keywords	Degree Centrality	Frequency	Frequency Per Thousand	Periods
1	abalone	0.007689022	61	1.624328	P1
	abalone	0.002897259	24	0.739782	P2
	abalone	0.002545609	28	0.427253	P3
2	amino acid	0.006193934	39	1.038505	P1
	amino acid	0.002228661	25	0.770606	P2
	amino acid	0.002757743	37	0.564584	P3
3	aquaculture	0.037590773	206	5.485434	P1
	aquaculture	0.020503677	156	4.808581	P2
	aquaculture	0.049639372	410	6.256199	P3
4	atlantic salmon	0.025843657	178	4.739841	P1
	atlantic salmon	0.012703365	93	2.866654	P2
	atlantic salmon	0.015485787	140	2.136263	P3
5	body composition	0.005766766	32	0.852106	P1
	body composition	0.001782928	19	0.585661	P2
	body composition	0.001484938	29	0.442512	P3
6	china	0.008970525	31	0.825478	P1
	china	0.025406731	61	1.880279	P2
	china	0.025243954	137	2.090486	P3
7	co management	0.027552328	44	1.171646	P1
	co management	0.003788723	31	0.955551	P2
	co management	0.003818413	40	0.610361	P3
8	common carp	0.004698847	38	1.011876	P1
	common carp	0.000445732	15	0.462364	P2
	common carp	0.001272804	26	0.396735	P3
9	competition	0.004485263	28	0.745593	P1
	competition	0.008691776	22	0.678133	P2
	competition	0.011667374	57	0.869764	P3
10	cortisol	0.008329774	55	1.464558	P1
	cortisol	0.003120125	31	0.955551	P2
	cortisol	0.003606279	40	0.610361	P3
11	crassostrea gigas	0.009184109	70	1.863983	P1
	crassostrea gigas	0.005125919	37	1.140497	P2
	crassostrea gigas	0.006364022	48	0.732433	P3
12	cryopreservation	0.003203759	39	1.038505	P1
	cryopreservation	0.000891464	16	0.493188	P2
	cryopreservation	0.003818413	29	0.442512	P3
13	data envelopment analysis	0.00598035	21	0.559195	P1
	data envelopment analysis	0.010028973	22	0.678133	P2
	data envelopment analysis	0.009758167	52	0.793469	P3
14	diet	0.008329774	66	1.757469	P1
	diet	0.000668598	17	0.524012	P2
	diet	0.002545609	30	0.457771	P3
15	digestibility	0.014737292	90	2.396549	P1
	digestibility	0.003788723	37	1.140497	P2
	digestibility	0.006576156	46	0.701915	P3
16	digestive enzyme	0.005766766	29	0.772221	P1
	digestive enzyme	0.003788723	35	1.078848	P2
	digestive enzyme	0.007212558	58	0.885023	P3
17	disease	0.001495088	23	0.612451	P1
	disease	0.001560062	18	0.554836	P2
	disease	0.001697073	27	0.411994	P3

No	Shared Keywords	Degree Centrality	Frequency	Frequency Per Thousand	Periods
18	disease resistance	0.00598035	37	0.985248	P1
	disease resistance	0.004234455	25	0.770606	P2
	disease resistance	0.008909631	68	1.037613	P3
19	efficiency	0.004271679	21	0.559195	P1
	efficiency	0.010028973	30	0.924727	P2
	efficiency	0.004454815	38	0.579843	P3
20	environment	0.00598035	21	0.559195	P1
	environment	0.008023178	23	0.708958	P2
	environment	0.00572762	33	0.503548	P3
	fatty acid	0.02007689	119	3.16877	P1
21	fatty acid	0.006685982	59	1.81863	P2
	fatty acid	0.008909631	77	1.174945	P3
22	fish	0.016018795	108	2.875859	P1
	fish	0.003120125	38	1.171321	P2
	fish	0.016334323	128	1.953155	P3
23	fishery	0.026484408	52	1.384673	P1
	fishery	0.011143303	93	2.866654	P2
	fishery	0.026516759	200	3.051804	P3
	fishery management	0.051900897	105	2.795974	P1
24	fishery management	0.011143303	94	2.897479	P2
	fishery management	0.021213407	159	2.426184	P3
	gene expression	0.00106792	21	0.559195	P1
25	gene expression	0.004903053	44	1.356267	P2
	gene expression	0.013788714	114	1.739528	P3
26	genetic correlation	0.004912431	24	0.63908	P1
	genetic correlation	0.00111433	17	0.524012	P2
	genetic correlation	0.004879084	40	0.610361	P3
27	governance	0.013882956	20	0.532566	P1
	governance	0.015154892	50	1.541212	P2
	governance	0.022698345	150	2.288853	P3
28	growth	0.074967962	528	14.05975	P1
	growth	0.030309784	227	6.997103	P2
	growth	0.04327535	319	4.867628	P3
29	growth performance	0.005126015	44	1.171646	P1
	growth performance	0.008023178	59	1.81863	P2
	growth performance	0.024819686	200	3.051804	P3
30	heritability	0.009184109	61	1.624328	P1
	heritability	0.00624025	37	1.140497	P2
	heritability	0.010182435	88	1.342794	P3
	histology	0.00811619	40	1.065133	P1
31	histology	0.002005795	21	0.647309	P2
	histology	0.00466695	36	0.549325	P3
32	histopathology	0.001708672	28	0.745593	P1
	histopathology	0.001560062	21	0.647309	P2
	histopathology	0.003394145	38	0.579843	P3
33	larva	0.018795387	121	3.222027	P1
	larva	0.006685982	44	1.356267	P2
	larva	0.005303352	40	0.610361	P3
	lipid	0.01516446	87	2.316664	P1
34	lipid	0.002005795	24	0.739782	P2
	lipid	0.003182011	27	0.411994	P3
	litopenaeus vannamei	0.008329774	75	1.997124	P1
35	litopenaeus vannamei	0.00624025	66	2.0344	P2
	litopenaeus vannamei	0.010182435	98	1.495384	P3
36	macrobrachium rosenbergii	0.006621102	42	1.11839	P1
	macrobrachium rosenbergii	0.001337196	21	0.647309	P2
	macrobrachium rosenbergii	0.002333475	27	0.411994	P3
37	management	0.009184109	28	0.745593	P1
	management	0.004680187	26	0.80143	P2
	management	0.037123462	218	3.326467	P3
38	marine protected area	0.018795387	27	0.718965	P1
	marine protected area	0.012034767	90	2.774182	P2

No	Shared Keywords	Degree Centrality	Frequency	Frequency Per Thousand	Periods
	marine protected area	0.022486211	166	2.532998	P3
39	microsatellite	0.007475438	41	1.091761	P1
	microsatellites	0.009611277	57	1.517814	P1
	microsatellites	0.000891464	16	0.493188	P2
40	mortality	0.005126015	40	1.065133	P1
	mortality	0.001337196	17	0.524012	P2
	mortality	0.002545609	30	0.457771	P3
	network	0.005766766	20	0.532566	P1
41	network	0.009137508	22	0.678133	P2
	network	0.006576156	35	0.534066	P3
42	nutrition	0.014523708	110	2.929115	P1
	nutrition	0.004903053	43	1.325442	P2
	nutrition	0.009970301	69	1.052873	P3
43	optimization	0.004698847	28	0.745593	P1
	optimization	0.005794517	23	0.708958	P2
	optimization	0.002969877	49	0.747692	P3
	oreochromis niloticus	0.006621102	51	1.358044	P1
44	oreochromis niloticus	0.001560062	20	0.616485	P2
	oreochromis niloticus	0.004454815	68	1.037613	P3
	oyster	0.007475438	48	1.278159	P1
45	oyster	0.002228661	23	0.708958	P2
	oyster	0.003818413	39	0.595102	P3
46	penaeus monodon	0.009397693	82	2.183522	P1
	penaeus monodon	0.004457321	42	1.294618	P2
	penaeus monodon	0.002333475	27	0.411994	P3
47	probiotic	0.005339598	48	1.278159	P1
	probiotic	0.005125919	37	1.140497	P2
	probiotic	0.00572762	48	0.732433	P3
48	productivity	0.001708672	20	0.532566	P1
	productivity	0.003565857	26	0.80143	P2
	productivity	0.002757743	26	0.396735	P3
49	public transport	0.007261854	20	0.532566	P1
	public transport	0.012257633	51	1.572036	P2
	public transport	0.017607128	103	1.571679	P3
50	quality	0.003844511	32	0.852106	P1
	quality	0.000668598	18	0.554836	P2
	quality	0.002333475	28	0.427253	P3
	rainbow trout	0.02114481	156	4.154018	P1
51	rainbow trout	0.008691776	74	2.280994	P2
	rainbow trout	0.011667374	104	1.586938	P3
52	regulation	0.005339598	29	0.772221	P1
	regulation	0.00735458	28	0.863079	P2
	regulation	0.005091218	45	0.686656	P3
53	reproduction	0.016445963	117	3.115514	P1
	reproduction	0.004457321	35	1.078848	P2
	reproduction	0.005515486	48	0.732433	P3
	risk	0.005553182	19	0.505938	P1
54	risk	0.001782928	17	0.524012	P2
	risk	0.003606279	46	0.701915	P3
	risk assessment	0.005515486	30	0.457771	P3
55	risk management	0.003342991	15	0.462364	P2
	risk management	0.002757743	35	0.534066	P3
56	salinity	0.008756941	85	2.263407	P1
	salinity	0.001782928	23	0.708958	P2
	salinity	0.001909207	40	0.610361	P3
57	salmo salar	0.010892781	76	2.023752	P1
	salmo salar	0.002674393	28	0.863079	P2
	salmo salar	0.003818413	31	0.47303	P3
58	salmon	0.012174284	60	1.597699	P1
	salmon	0.002674393	29	0.893903	P2
	salmon	0.003394145	47	0.717174	P3
59	selective breeding	0.003203759	28	0.745593	P1

No	Shared Keywords	Degree Centrality	Frequency	Frequency Per Thousand	Periods
	selective breeding	0.002897259	24	0.739782	P2
	selective breeding	0.002545609	32	0.488289	P3
60	shrimp	0.022426314	147	3.914363	P1
	shrimp	0.007577446	61	1.880279	P2
	shrimp	0.003818413	55	0.839246	P3
	simulation	0.001708672	25	0.665708	P1
61	simulation	0.011811901	35	1.078848	P2
	simulation	0.002757743	42	0.640879	P3
62	soybean meal	0.003630927	29	0.772221	P1
	soybean meal	0.001782928	18	0.554836	P2
	soybean meal	0.004242681	29	0.442512	P3
63	stocking density	0.006621102	52	1.384673	P1
	stocking density	0.002451527	21	0.647309	P2
	stocking density	0.001697073	35	0.534066	P3
	stress	0.009824861	83	2.210151	P1
64	stress	0.002674393	29	0.893903	P2
	stress	0.007212558	69	1.052873	P3
	supply chain	0.000640752	22	0.585823	P1
65	supply chain	0.012257633	27	0.832254	P2
	supply chain	0.008697497	64	0.976577	P3
66	supply chain management	0.008756941	43	1.145018	P1
	supply chain management	0.007800312	62	1.911103	P2
	supply chain management	0.010394569	89	1.358053	P3
67	survival	0.019008971	149	3.96762	P1
	survival	0.004011589	49	1.510388	P2
	survival	0.005515486	56	0.854505	P3
68	sustainability	0.01516446	36	0.95862	P1
	sustainability	0.019835079	73	2.25017	P2
	sustainability	0.022698345	169	2.578775	P3
69	temperature	0.025202905	174	4.633328	P1
	temperature	0.009137508	75	2.311818	P2
	temperature	0.004879084	61	0.9308	P3
70	tilapia	0.010252029	89	2.369921	P1
	tilapia	0.002674393	32	0.986376	P2
	tilapia	0.005303352	66	1.007095	P3
	transport	0.010892781	33	0.878735	P1
71	transport	0.030086918	47	1.448739	P2
	transport	0.012303776	45	0.686656	P3
	turbot	0.004485263	42	1.11839	P1
72	turbot	0.003120125	25	0.770606	P2
	turbot	0.002333475	35	0.534066	P3
73	uncertainty	0.002990175	24	0.63908	P1
	uncertainty	0.002897259	33	1.0172	P2
	uncertainty	0.00572762	66	1.007095	P3
	water quality	0.004912431	49	1.304788	P1
74	water quality	0.000445732	21	0.647309	P2
	water quality	0.004242681	60	0.915541	P3
	welfare	0.003417343	29	0.772221	P1
75	welfare	0.004680187	36	1.109673	P2
	welfare	0.002969877	37	0.564584	P3
	willingness pay	0.002776591	19	0.505938	P1
76	willingness pay	0.001782928	21	0.647309	P2
	willingness pay	0.002333475	42	0.640879	P3