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What Geographers Research: An Analysis of Geography Topics, Clusters, and Trends Using a Keyword Network Analysis Approach and the 2000-2019 AAG Conference Presentations

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What Geographers Research: An Analysis of Geography Topics, Clusters, and Trends Using a Keyword Network Analysis Approach and the 2000-2019 AAG Conference Presentations

Abstract

The spectrum of geographic research topics is very broad, and several thousands of research projects are presented at AAG annual conferences. This research aims at analyzing geography research topics, clusters, and trends using conference presentation data. We analyzed the 2000-2019 AAG conference presentations with keyword network analysis methods. The most frequently used keywords during the 20-year span were GIS, followed by Remote Sensing, Climate Change, Urban, China, Education, Political Ecology, Migration, Gender, and Agriculture. Results showed that geographic research has focused on six major clusters during 2000-2019: GIS, Urban, Climate Change, Political Ecology, People, and Education. About 68.6 percent of keywords were about the GIS, People, and Urban issues. The GIS keyword showed very strong connections with Remote Sensing, Urban, Spatial, Education, Climate Change, and Health. Over the 2015-2019 period, big data analysis and artificial intelligence became popular as emerging fields. This research also shows that the keyword network analysis is an effective method to summarize research trends in geography using conference presentation data. To some fellow geographers, the findings in this research may also cast meaningful insights into what geography is and where it is heading.

Keywords

AAG Conference Papers, Geography Research Fields, Geography Research Trends, Keyword Network Analysis

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1. Introduction

Understanding what geographers research would help finding the identity of geography. Major themes or topics in the geography discipline have changed over time (Colby 1936; Hartshorne 1959; Zimmerer 2010). Considering the broad spectrum of geographical topics, identifying important topical clusters with an inductive bottom-up approach could be a steppingstone for understanding what current geography is and where it is heading. In addition, monitoring emerging topics and their tenure as geography's sub-domain may help geographers build robust academic programs, institutionally as well as nationally.

One way of finding what geographers research is to analyze their presentations at conferences. Among many geography conferences, the American Association of Geographers (AAG) annual conference is one of the largest events. Lately, several thousands of research papers have been presented at AAG annual conferences. Various topics, methodologies, and thoughts in geography are presented by professionals, graduate and undergraduate students, and practitioners. The AAG conference offers an excellent opportunity for geographers to learn about what fellow geographers research and to observe how research trends are changing. Without an automated way, it is, however, prohibitive to identify research trends in the flooding of thousands of presentations at a conference.

The keyword network analysis (KNA) approach provides an excellent toolset for summarizing voluminous research presentations. KNA is a sub-field of bibliometric analysis which uses keywords as objects, i.e., nodes. Bibliometric analysis has been used for researching author connections, citation graphs, keyword connections, geographic place connections, and research trends, to name a few (Batagelj and Cerinšek 2013; Cuccurullo, Aria, and Sarto 2016; Madani and Weber 2016; Miau and Yang 2018; Merediz-Sola and Bariviera 2019). KNA has been applied successfully to summarize various research fields. For example, Duvvuru, Kamarthi, and Sultornsanee (2012) analyzed research trends with the ten-year publications (1985-1994) of the European Journal of Operational Research. Chen et al. (2016) analyzed research trends of management science and engineering with 7304 funded project proposals in China during 2011-2015. Santonen and Conn (2016) applied KNA for summarizing research topics and their evolutions with the 1081 innovation management articles published during 2009-2014. Zhuang et al. (2013) also applied KNA for identifying research trends in remote sensing with 48754 publications in Science Citation Index and Social Science Citation Index during 1991-2010. Kho, Cho, and Cho (2013) identified research trend of technology management using KNA with 2611 articles published during 2002-2011. Kim and Jang (2017) analyzed 151 research articles for identifying research trends of life-long education for people with disabilities in Korea. Ji et al. (2018) analyzed research topics and trends in medical education with the 9379 articles published in PubMed during 1963-2015. Bielecka and Burek (2019) retrieved 2090 research papers from the Web of Science Core Collection and analyzed spatial data quality and uncertainty patterns and trends during 1990-2018. Melo and Queiroz (2019) analyzed geographic information systems (GIS) research papers published during 2007-2016. Lee et al. (2019) also analyzed GIS-specific research topics using AAG conference presentation papers published during 2000-2019.

We applied the KNA method to the AAG conference presentation papers to inductively analyze geography research topics, clusters, and trends. Specifically, our research objectives are, (1) identifying major keywords in geography that appeared during 2000-2019, (2) analyzing major clusters or themes in geography, (3) identifying persistent, transient, and emerging keywords during 2000-2019, (4) identifying annual trends of major keywords, and (5) analyzing connections among keywords.

2. Data and Methodology

2.1. Data

The AAG conference presentation datasets were collected with generous sharing and support by the AAG Headquarter Office in Washington, D.C. The 2018-2019 datasets were collected by crawling the AAG website (URL - http://www.aag.org/) using Python (v3.8.1). Most datasets, except web crawling, were in the portable document format (PDF) and they were converted to text files. The 2003 dataset was in the paper printout format thus it was digitized to PDF before converting to a text file. The text files were further processed in Python and R (v3.6.2) packages to retrieve keywords in each paper.

The AAG conference paper records contain various bibliographical information including title, authors, author affiliations, abstract, keywords, and pre-defined topical fields. Among them, keywords were used in this research because authors commonly choose keywords as the manifestation of their research topics, methods, or important findings (Whittaker 1989; Kim and Yu 2013). Keywords also provide important information to Internet search engines, where people frequently search research papers. In the following paragraphs and sections, keywords that were extracted from AAG conference papers will emphasized in Italics, and the Bahnschrift Condensed font type will be used for keyword network clusters.

The extracted keywords were pre-processed before analysis. Particularly, synonyms were unified, many plurals were changed to singular words, British English styles were replaced with American styles, and keywords except acronyms were reformatted into the title case. For example, Drone, Drones, and UAV were unified to UAS; Neighborhoods, Neighbourhood and Neighbourhoods were changed to Neighborhood; Lgbt, LGBT, and Lgbtq were unified to LGBTQ. About 160 preprocessing rules were developed to standardize keywords. Multi-word keywords were not split into single-word keywords after an experimental prototype test indicated that the interpretation of results from single-word keywords would be more cumbersome. The word Geography was removed for simplification, so that Physical Geography became Physical, as an example.

2.2. Multi-Word vs. Single-Word Keywords

One puzzle that we encountered early in our work was whether to use multi-word keywords or single-word keywords by splitting multi-word into individual entities. For example, Remote Sensing can be split into two keywords – Remote and Sensing. We found that each approach has advantages and disadvantages. Overall, the single-word keywords tend to generalize certain concepts more by ignoring detailed variants. For example, there were multiple keywords about labor such as Labor, Labor Flexibility, Labor Market, Labor Market Intermediaries, Labor Market Segmentation, Labor Markets, Labor Migration, Labor Mobility, Labor Movement, Labor Organizing, Labor Power, Labor Process, Labor Regulation, Labor Unions, Labor Regimes, and Labor Skilled. If multi-word keywords are used, the entire keywords except Labor will be ignored because of their low frequencies. However, when the multi-word keywords are decomposed into single-word keywords, at least the keyword Labor remains, and the total frequency of Labor increases by the amount of the Labor variants. One disadvantage of decomposing multi-word keywords is the difficulty of finding contextual meanings of single-word keywords. Even if it might be dependent on the interpreter's expertise, examples of keywords whose contextual meanings were difficult to infer are New, Cover, South, States, Data, Human, Theory, Based, Time, Science, Methods, Rights, Participation, Peoples, and Areas.

The number of keyword clusters were also affected when single-word keywords were used. The number of clusters was six when multi-word keywords were used, but it became seven when single-word keywords were clustered. In both multi-word and single-word analyses, we only kept keywords with frequencies of at least 400. This threshold was empirically set to provide a level of granularity that would allow a reduction in computational complexity and a more reasonable management of graph-based operations given our available resources. In addition, this threshold was also suitable for visualization purposes as it helped remove visual congestion of labels and symbols. The two most frequent keywords in each cluster of the single-word keyword network were: *Change* and *Climate*, *Development* and *China*, *Urban* and *Social*, *Political* and *Ecology*, *Services* and *Ecosystem*, *GIS* and *Spatial*, and finally, *United* and *States*. When compared with the multi-word keyword clusters, the single-word keyword network replaced the Education cluster with two new clusters whose top-two keywords were *Services* and *Ecosystem*, and *United* and *States*.

Figure 1 shows the keyword network developed from single-word keywords. A total of 175 keywords were identified of which frequencies are at least 400. The most frequent keyword was GIS, followed by Urban, Change, Climate, Land, Development, Political, Spatial, Sensing, Remote, Social, Ecology, and Environmental, in order. The eigenvector centrality values were much higher in the single-word keyword network. For example, the eigenvector centrality values of the top-10 most frequent keywords were Urban (1.00), GIS (0.97), Change (0.94), Development (0.89), Social (0.88), Land (0.88), Climate (0.86), Political (0.85), Spatial (0.85), and Ecology (0.83) in the single-word keyword network, while they were GIS (1.00), Urban (0.90), Climate Change (0.80), Political Ecology (0.71), Migration (0.71), Development (0.71), China (0.70), Gender (0.70), Tourism (0.66), and Sustainability (0.66) in the multi-word network. Interestingly, Urban was the most influential keyword in the single-word keyword network, while it was GIS in the multi-word network. The strongest edge connection was found between Climate and Change, Remote and Sensing, Land and Use, and United and States.

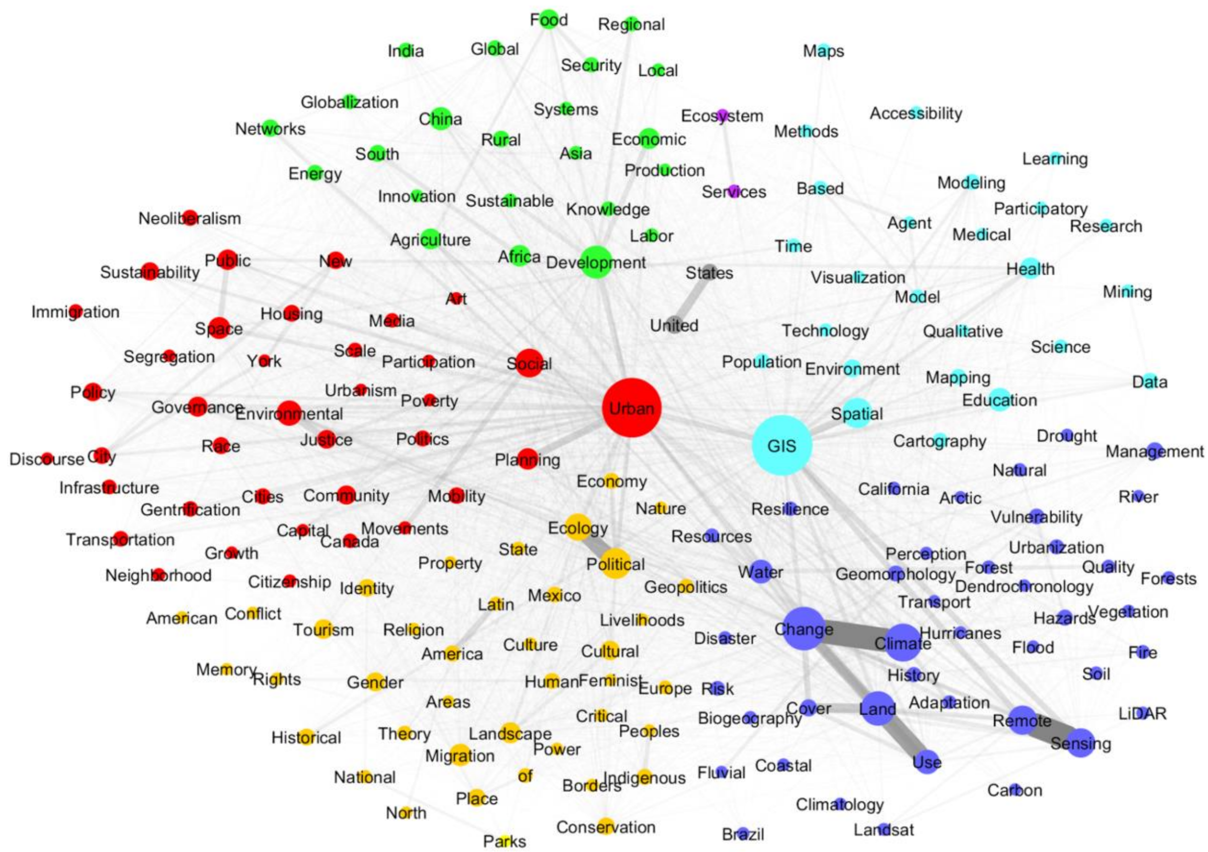

Figure 1 A keyword network constructed with single-word keywords

2.3. Preprocessing of Keywords

Another issue we encountered in working with keywords was to identify a satisfactory level of keyword preprocessing. We had to find a balanced position between two extremes – contextual accuracy, i.e., maximum preprocessing, and efficiency, i.e., minimum preprocessing. It would take a significant number of resources if all keywords were screened and modified manually. In our research, manually screening approximately 0.45 million keywords was practically impossible. On the other hand, implementing only minimal preprocessing might cause a reliability problem. In this research, we made a compromise at about 160 rules to preprocess keywords. Those rules cleaned up the raw datasets significantly; however, we later found room for more preprocessing rules to be developed. One example was the hierarchical structure of keywords. Some authors prefer using detailed variants, while others like to use more generalized keywords. The Labor variants described in the former section are a typical example of the keyword hierarchy problem. Down the road, a more systematic and even intelligent keyword preprocessing system needs to be developed to resolve various keyword preprocessing issues. Referencing keywords from glossaries or indices along with an intelligent preprocessing system could be an option too, even if we did not have enough time to implement such system in this research.

The 2000-2019 datasets were merged into one to make an overall summary for the twenty years. During the 20-year period, a total of 83,767 unique keywords were identified. They appeared 404,043 times in 95,122 papers. Among the unique keywords, 58,362 (69.7%) keywords appeared only once, and 9,888 (11.8%) keywords appeared only twice. For example, *Substate Nation*, *Imager*, *Subak*, *Subantarctic*, *Transpacific Partnership*, *Ecosystem Science*, *Collective Identity*, *Cognitosphere*, *Alfisols*, and *Albacore Tuna* appeared only once. The top 10 most frequently used keywords were *GIS* (7536, 7.9%), followed by *Remote Sensing* (3083, 3.2%), *Climate Change* (2899, 3.0%), *Urban* (2627, 2.8%), *China* (2140, 2.2%), *Education* (1723, 1.8%), *Political Ecology* (1722, 1.8%), *Migration* (1632, 1.7%), *Gender* (1463, 1.5%), and *Agriculture* (1376, 1.4%), where the numbers in parentheses indicate frequency and percent of papers having the keyword, respectively. Because of the large number of keywords, the one-time-appearing keywords were not used during keyword network construction and keywords clustering.

2.4. Research Methods

The 20-year dataset was analyzed in three different ways. The first was to combine the last 20-years (2000-2019) into one group, so that a grand summary could be made. The second was to divide the 2000-2019 dataset into four sub-groups (i.e., 2000-2004, 2005-2009, 2010-2014, and 2015-2019), so that general trends could be examined by reducing the effect of annual anomalies. The third was to use the annual data individually.

We analyzed keywords using multiple data science methods such as KNA, word cloud, clustering, and network graph visualization. The KNA method is an application of the traditional graph theory and network analysis techniques to article keywords (Pachayappan and Venkatesakumar 2018; Lee et al. 2020). Graph theory and network analysis use nodes and edges as network construction elements (Kwon and Cha 2016). Multiple research papers indicate KNA's effectiveness for analyzing research trends and summarizing voluminous research articles (Kho, Cho, and Cho 2013; Zhuang et al. 2013; Santonen and Conn 2016; Dotsika and Watkins 2017). In KNA, keywords become nodes, and co-occurrences of keywords in a paper form edges (Madani and Weber 2016). Each edge implies that a relationship exists between the nodes that are connected. Once a keyword network is constructed, its network structure and characteristics can be analyzed with diverse quantitative measures such as node frequency, node centrality, edge frequency, and clusters (Choi and Hwang 2014; Cuccurullo, Aria, and Sarto 2016; Aria and Cuccurullo 2017).

In general, a keyword's centrality value indicates how "central", or important, the keyword is relative to other keywords (Choi, Yi, and Lee 2011). Importance can be viewed from different angles and thus centrality can be defined in various ways that capture distinctive aspects of the network. For example, the degree centrality (DC) value of a keyword is simply calculated as the count of keywords that are directly connected to it (Lee and Su 2010). On the other hand, the eigenvector centrality value of a keyword indicates how influential that keyword is in the interaction or communication among other keywords (Madani and Weber 2016). The EC value is calculated from all possible communications among keywords in a network (Dotsika and Watkins 2017), not just the directly connected ones. The EC measures the node's importance as a function of the importance of its neighbors, such that more important connections will contribute more towards the node's EC value. In both cases, the higher the centrality value, the greater the importance of the node in the graph.

In our work, we used the keywords that the authors submitted for their articles as nodes in the network. An edge between two nodes was created to indicate that the two keywords occur together in an article. To build this initial keyword network, which is essentially an undirected graph, a co-occurrence matrix was first calculated with the Bibliometrix (Aria and Cuccurullo 2017) package in R. Second, an adjacency matrix was created by substituting the integer value one (denoting one co-occurrence) for a positive integer value denoting the frequency of co-occurrences for all articles in the dataset. The integer value one simply denotes that a connection exists between two keywords, whereas the frequency indicates the number of times this connection occurs in the dataset. Third, a graph model was constructed with the igraph (v1.2.4.1) package in R. Fourth, centrality values, particularly degree centrality and eigenvector centrality, were calculated from the graph model. Last, after exporting the network graph to a GraphML (Brandes et al. 2013) format file, the network graph was visualized with the Cytoscape (v3.7.2) software package.

3. Results

3.1. Analysis of 20-year Data: What Geographers Have Researched During 2000-2019

There were almost 100,000 papers presented during 2000-2019. As shown in Figure 2, the largest number of papers was presented at the 2017 conference, and it was very close to 7,000. The number of unique keywords increased as the number of papers increased. They show a very strong positive relationship. In 2019, about 12,000 unique keywords were used in articles. Figure 2 shows that the number of unique keywords in a year is slightly less than twice that of the number of papers presented.

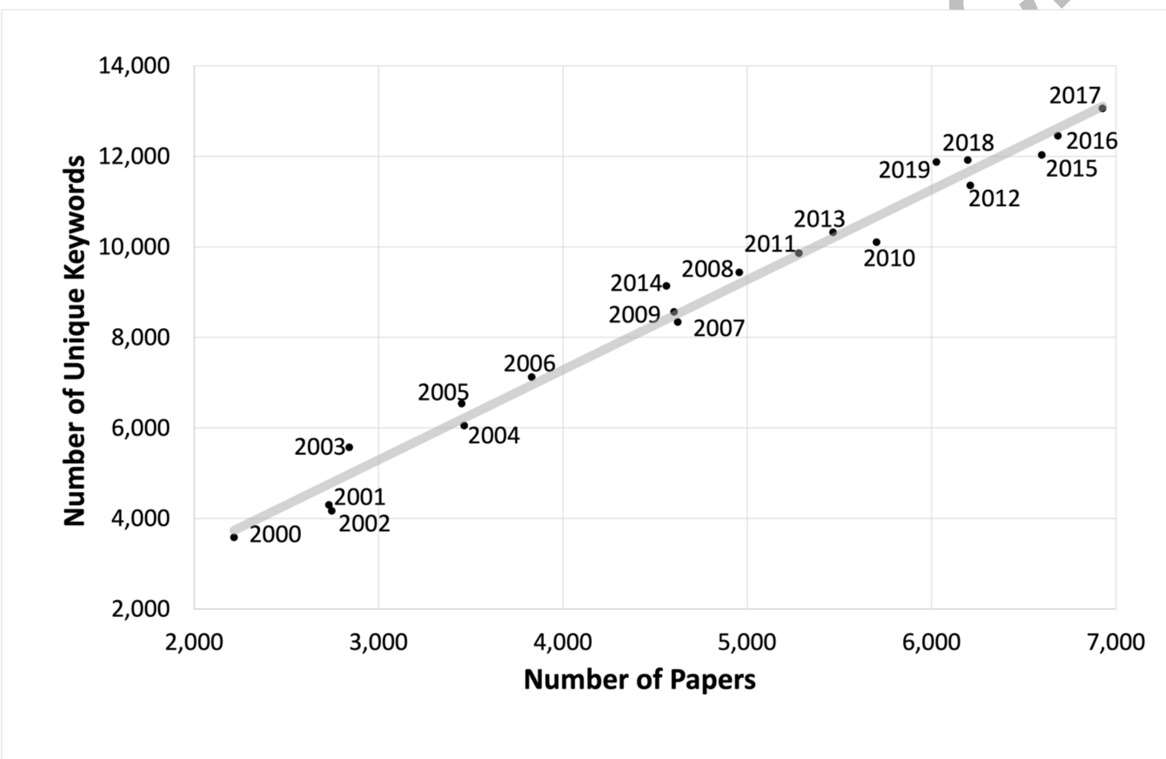

Figure 2 The relationship between the number of papers and the number of unique keywords presented at AAG conferences during 2000-2019

3.1.1. Keyword network

After building the keyword network, we filtered out low-frequency keywords for easier visualization, using the threshold value described in Section 2.2. There were 96 keywords of which frequencies were 400 or more. The 96 keywords appeared 85779 times (21.2 %) in total during 2000-2019. Figure 3 shows the final keyword network graph. The figure shows individual keyword frequencies as circle sizes, their connections as line topology and width, and cluster groups as circle colors. GIS and Remote Sensing show the thickest edge, which denotes the strongest connection. Strong connections to GIS also appear at Urban, Spatial, Education, Climate Change, and Health. This indicates that GIS is a very influential component in various geographical research fields.

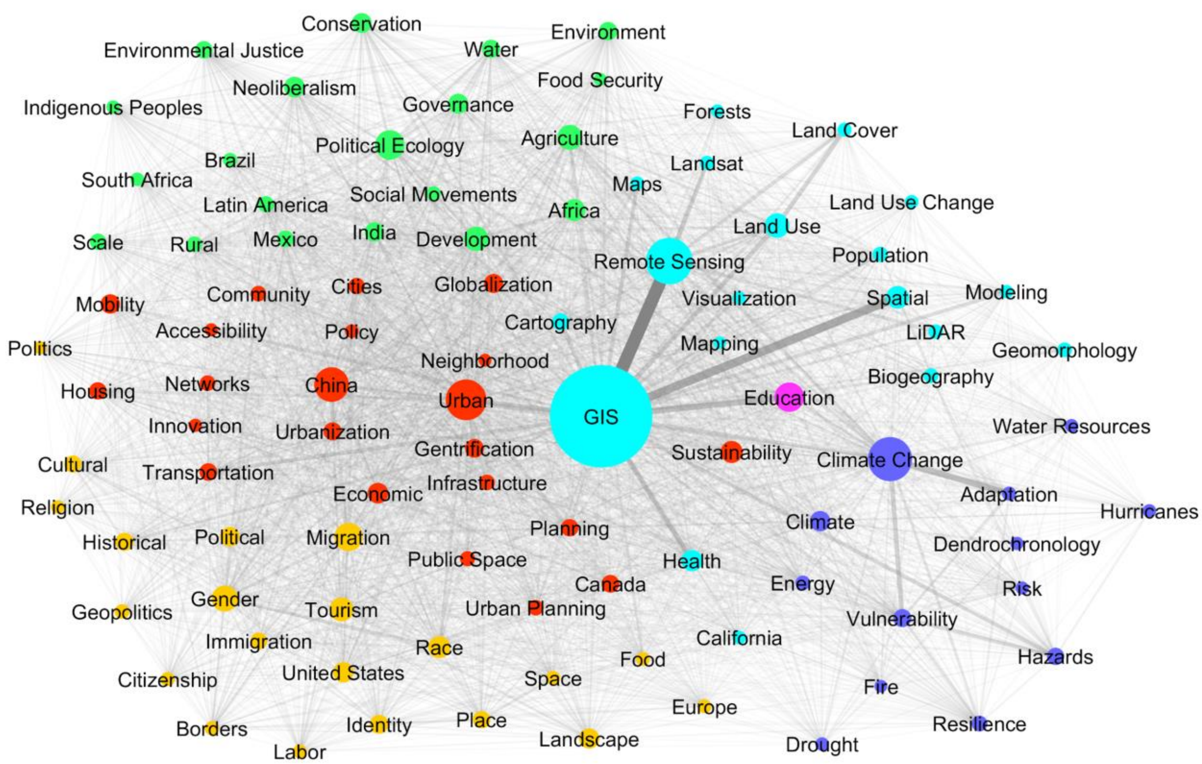

Figure 3 A keyword network developed with 2000-2019 AAG conference presentation papers

3.1.2. Clusters

It is interesting to see six clusters; and they seem to cast multiple, important insights about geography. Considering the members in each cluster, we called them as **GIS**, **Urban**, **Climate Change**, **Political Ecology**, **People**, and **Education** clusters.

- The **GIS** cluster includes geospatial technology keywords such as *GIS*, *remote sensing*, *LiDAR*, *mapping*, and *spatial modeling*. *Geomorphology*, *Biogeography*, and *Forests* also appear in the **GIS** cluster. Frequent analyses of health and medical datasets with GIS seem to be the reason why *Health* is in this cluster. Interestingly, California is the only geographic region frequently appearing in this cluster.

- The Climate Change cluster includes the keywords about climate, natural hazards, disaster planning, and energy. There is no geographic region appearing in this cluster, which is likely due to the pervasive global impact of climate change.
- The Urban cluster embraces various urban issues like infrastructure, urban planning and policy, cities, globalization, sustainability, and urban community. Overall, many post-urbanization keywords appear frequently in this cluster. Interestingly, China and Canada are two geographic regions that are included in this cluster.
- The People cluster clinches various geographical aspects of human issues. People migrate, work, travel, play, eat, and worship. People also have different historical, political, and ethnic identities. *Migration* is the most frequent keyword in this cluster. Interestingly, Europe and United States are two geographic regions that appear frequently in this cluster.
- The Political Ecology cluster covers natural environmental issues. Keywords about environment, conservation, water, agriculture, and food appear along with political perspectives such as justice, neoliberalism, governance, development, and social movement. Multiple developing countries and regions appear in this cluster, such as Mexico, Brazil, India, Africa, and Latin America.
- In the Education cluster, *Education* is the only keyword that is included in the top 96 keywords. More keywords in the Education cluster, but not included in the top 96, are, for example, *Higher Education*, *Public Engagement*, *Pedagogy*, *Online*, *STEM*, *Physical*, *Study Abroad*, *Fieldwork*, *Professional Development*, *Teaching*, *K-12 Education*, *Undergraduate Research*, *Spatial Thinking*, and *Active Learning*.

Table 1 shows the percentage of the sum of keyword frequencies, the sum of eigenvector centrality values, and the sum of degree centrality values in each cluster. For example, 23.5 percent in the upper left cell indicates that 23.5 percent of total keywords are the GIS cluster keywords. Table 1 also tells that the Urban and People cluster keywords appear as frequently as the GIS cluster keywords, which indicates that the three clusters have been major geographic research themes over the last twenty years. Political Ecology and Climate Change clusters also take significant parts of geographical research. The Education cluster uniquely positions in its own research realm, which seems to imply the importance of geography education in undergraduate liberal study. The high EC and DC values of the Urban and People clusters indicate that their keywords are more diversely connected to other keywords. This implies that the Urban and People clusters cover a wider spectrum of topical sub-fields. The EC values also indicate that the **GIS** and **Political Ecology** cluster keywords have less diverse connections than the **Urban** and **People** cluster keywords.

Table 1 The frequencies of the keywords in six clusters, and their influences in the keyword network measured with eigenvector centrality (EC) and degree centrality (DC).

	Clusters						
	GIS	**Urban**	**Political Ecology**	**People**	**Climate Change**	**Education**	**Others**
Frequency	23.5%	22.4%	17.0%	22.7%	12.2%	2.0%	0.3%
EC Sum	66.44	86.96	66.36	95.29	38.42	5.91	0.75
DC Sum	86372	97568	72440	102378	47447	6855	1446

3.1.3. Frequency vs. Centrality

Figure 4 shows a scatterplot between frequency and centrality. We have marked the keywords that tend to drift from the apparent expected pattern, which is the curved cluster of points stretching vertically along the y-axis. The marked outliers located over and under this curve exhibit interesting features. As shown by Figure 4, human geography keywords (e.g., development, policy) tend to have higher eigenvector centrality values than expected, while Remote Sensing and keywords pertaining to physical geography, like Geomorphology, Biogeography and Climate, have lower eigenvector centrality values. This appears to be due to the broader connection of human geographic topics than the remote sensing and physical topics. In other words, remote sensing and physical geography topics seem to be more cohesive and clustered than human geography topics.

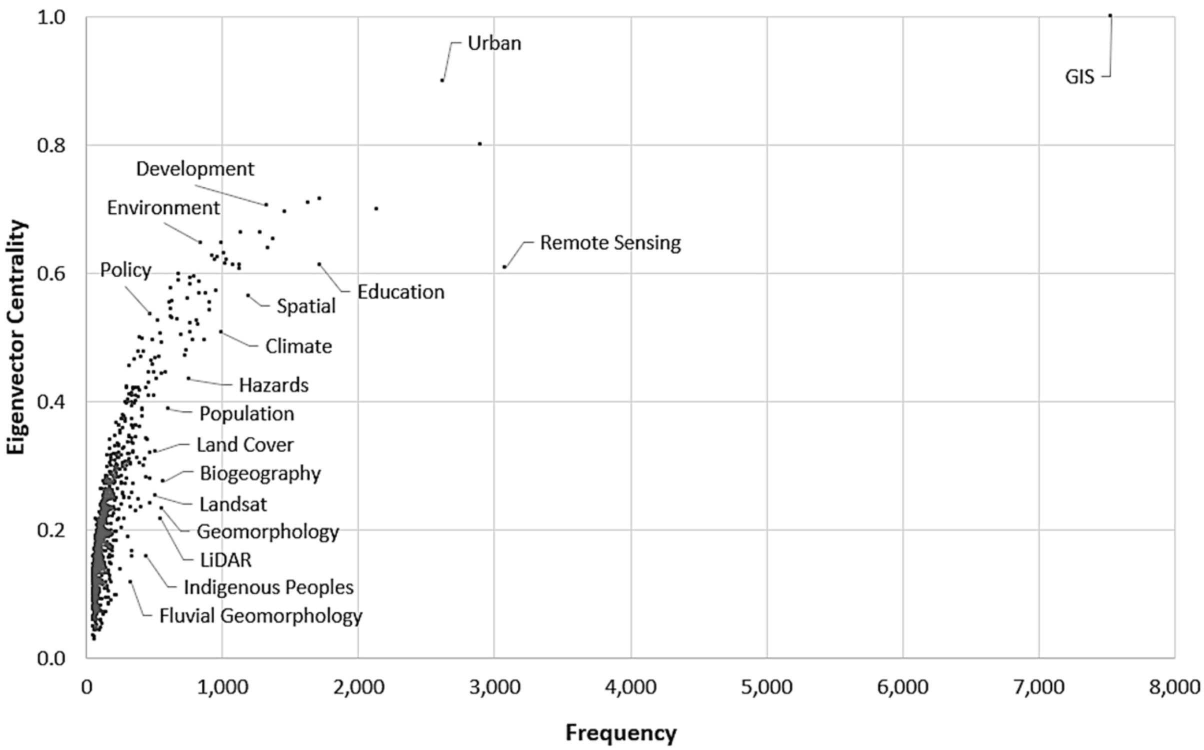

Figure 4 A scatterplot of frequency vs. eigenvector centrality

3.2. Analysis of 5-year merged Data: Trends of Geography Research Topics

3.2.1. Keywords Appearance

The annual data files from 2000 to 2019 were merged into four 5-year datasets in order to reduce annual anomalies and to examine how geography research topics have changed every 5-years, i.e. 2000-2004, 2005-2009, 2010-2014, and 2015-2019. When the top-100 frequent keywords were extracted from each merged dataset, there were 149 unique keywords found from the four merged datasets. As shown in

Table 2, 61 (41%) keywords appeared consistently in all four datasets. 39 (26%) keywords appeared only once in four datasets. Among the 39 keywords, many cultural and political topics made top-100 during 2000-2014 but failed to stay competitive during 2015-2019. Interestingly, it shows that data science and intelligent technology keywords such as *Big Data*, *Machine Learning*, and *Smart City* made top-100 lately.

Table 2 Appearance of keywords in four merged datasets.

Appearance	Keywords
In All Four Datasets (61 keywords, 41%)	GIS, Remote Sensing, Globalization, Gender, Education, Urban, Political Ecology, Land Use, Tourism, China, Migration, Climate Change, United States, Agriculture, Identity, Landscape, Development, Political, Economic, Environment, Mexico, Historical, Scale, Cartography, Internet, Africa, Race, Latin America, Cultural, Spatial, Hazards, Visualization, Biogeography, Climate, Planning, India, Place, Immigration, Population, Conservation, Climatology, Transportation, Sustainable Development, Religion, Public Space, Citizenship, Women, Medical, Europe, Canada, South Africa, Geomorphology, Nationalism, California, Fire, Community, Housing, Fluvial Geomorphology, New York City, Transnationalism, Land Use Change
In Three Datasets (19 keywords, 13%)	Environmental Justice, Economic Development, Water Resources, Russia, Land Cover Change, Sustainability, Vulnerability, Landscape Ecology, Urban Sprawl, Urbanization, Networks, Neoliberalism, Indigenous Peoples, Landsat, Japan, Dendrochronology, Drought, Representation, Space
In Two Datasets (30 keywords, 20%)	Regional Development, Ethnicity, Brazil, Wetlands, Governance, History, Social Movements, Nature, Social Capital, Water, Precipitation, Caribbean, Hurricanes, Rural, Soil, Innovation, Cities, Pennsylvania, Land Cover, Health, Gentrification, Geopolitics, Mobility, Modeling, Maps, Policy, LiDAR, Culture, Forests, Neighborhood
Only During 2000-2004	Poverty, Food, Cultural Landscape, Urban Planning, Arctic, Discourse, Borders, Resilience, Adaptation, Energy, Temporal, Politics, Risk, Infrastructure
Only During 2005-2009	Culture, Cultural Landscape
Only During 2010-2014	Food Security, Political Economy, Youth, Art, Labor, Mapping
Only During 2015-2019	Big Data, Social Media, UAS, Accessibility, Financialization, Refugees, Affect, Ecosystem Services, Anthropocene, Indigenous, Machine Learning, Displacement, Disaster, Smart City, Urban Agriculture, Water Quality, Inequality

3.2.2. Clusters

From each 5-year dataset, the top-100 keywords were selected, and their cluster memberships were examined. Table 3 lists the most frequent keyword in each cluster. There were 12, 7, 5 and 7 clusters for the 2000-2004, 2005-2009, 2010-2014, and 2015-2019 datasets, respectively. The number of clusters indicates that more topical fields in geography were competitive during 2000-2004. Since

2005, clusters have converged to 6±1 sub-fields in geography. As shown in Table 3, the 6±1 sub-fields match significantly with the six clusters that were identified from the 20-year merged dataset (i.e., **GIS**, **Urban**, **Climate Change**, **Political Ecology**, **People**, and **Education** clusters).

Table 3 The most frequent keyword in each cluster.

Period			
2000-2004	**2005-2009**	**2010-2014**	**2015-2019**
12 clusters:	7 clusters:	5 clusters:	7 clusters:
1. GIS	1. GIS	1. GIS	1. GIS
2. Gender	2. Urban	2. Urban	2. Urban
3. Climate Change	3. Climate Change	3. Climate Change	3. Climate Change
4. Migration	4. Migration	4. Migration	4. Tourism
5. Political Ecology	5. Political Ecology	5. China	5. Political Ecology
6. Globalization	6. China		6. China
7. Rural	7. Fluvial Geomorphology		7. Urban Agriculture
8. Russia			
9. Africa			
10. Biogeography			
11. Geomorphology			
12. Education			

3.2.3. Keywords Clouds

Word clouds were created in R to visualize a trend of frequent keywords and their frequencies. Figure 5 shows word clouds from the four datasets. *GIS*, *Remote Sensing* and *Urban* show consistently frequent appearances. *Globalization* and *Gender* issues were strong during 2000-2004. *Neoliberalism* strongly popped up during 2005-2009. *Climate Change*, *Political Ecology*, and *China* have become popular since 2010. In the figure, different word sizes indicate their frequencies. They were not normalized by the total number of papers in each period; therefore, larger keywords appear more frequently during 2015-2019 because more papers were presented during that period.

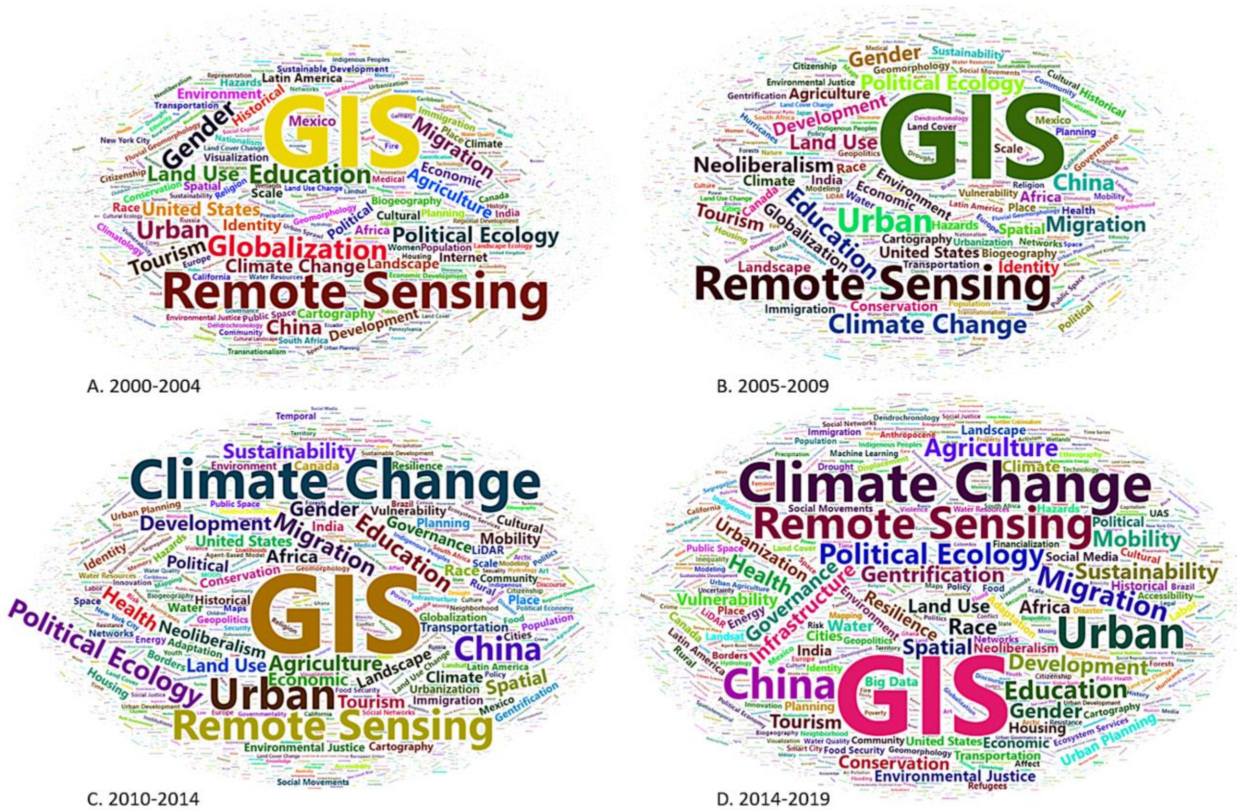

Figure 5 Word clouds of four five-year merged datasets

3.3. Analysis of Annual Trends: Most Frequent Keywords within the Six Clusters

We picked five most frequent keywords from each cluster of the 2000-2019 merged dataset. A total of 30 keywords were selected as listed in Figure 6. To examine their annual trends, data cells were conditionally formatted with a red-green color scale. In the conditional 2-color formatting method, the median value of the dataset is colored with the middle color between two colors, and colors get stronger as values deviate more from the median. The medians of frequency and EC values were 58 and 0.27, respectively. The conditional color formatting also shows subtle changes among reddish or greenish tones.

Figure 6 shows significant increases in frequencies of most keywords during the last 2-3 years. However, decreases are also observed in the keywords such as *Spatial*, *Urban*, *Mobility*, *Neoliberalism*, and *Field Work*. In terms of the eigenvector centrality, steady increases of influence are observed in *Remote Sensing*, *Health*, *Agriculture*, *Migration*, *Gender*, *Resilience*, and *Education*.

Keywords by Clusters	Year																			
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GIS	159	140	178	222	290	373	380	427	438	427	481	452	475	380	388	552	474	512	402	386
Remote Sensing	86	86	82	102	144	125	134	176	188	183	213	163	169	158	133	197	175	193	178	198
Land Use	26	43	47	46	49	58	74	82	67	71	98	72	72	67	61	91	77	71	69	95
Spatial	9	15	26	25	38	43	44	48	52	59	83	57	87	82	71	101	97	107	83	68
Health	5	8	13	6	19	20	27	40	51	45	70	79	81	92	73	83	94	103	80	95
Urban	50	29	36	55	79	58	116	124	90	177	178	162	216	197	122	189	204	212	179	154
China	27	47	46	34	51	58	60	80	85	110	120	118	155	134	121	177	193	203	159	162
Sustainability	7	10	16	14	18	14	27	40	62	50	77	63	94	88	87	83	125	86	87	87
Economic	36	16	14	35	35	15	50	63	33	73	79	68	82	72	48	63	61	58	65	60
Mobility	1	4	5	15	7	12	17	34	34	36	53	52	73	69	51	107	115	94	73	77
Political Ecology	30	42	46	38	55	66	73	84	77	62	115	103	108	113	100	121	162	110	110	107
Agriculture	27	27	28	36	52	40	39	63	55	63	97	75	93	82	73	90	104	111	106	115
Development	21	32	25	33	31	45	50	74	64	82	72	66	101	90	80	125	112	91	56	78
Africa	25	26	19	28	25	37	50	48	51	69	86	55	88	75	61	82	81	77	80	63
Neoliberalism	5	8	6	16	27	43	67	91	88	76	72	49	87	80	43	58	73	49	56	36
Migration	41	41	29	44	42	57	68	79	88	73	87	70	117	107	87	123	137	120	123	99
Gender	35	64	54	48	60	61	61	79	83	78	88	87	80	80	62	87	84	105	89	78
Tourism	28	42	43	50	44	60	69	65	55	71	74	69	85	65	60	68	85	86	72	91
Race	20	18	27	29	28	35	44	51	54	47	60	61	77	59	56	86	99	112	97	68
United States	41	40	21	34	48	43	55	52	57	64	81	60	53	66	42	49	55	68	42	40
Climate Change	31	26	35	40	52	59	60	88	110	139	240	235	208	199	209	223	235	266	235	209
Climate	11	13	23	22	34	46	43	39	62	57	74	60	67	48	63	66	58	88	73	54
Vulnerability	4	9	12	14	25	21	33	27	41	45	45	57	44	41	59	67	63	85	87	48
Hazards	18	16	20	22	31	29	38	49	56	39	48	47	42	25	42	47	40	40	71	39
Resilience	0	0	0	1	3	3	4	8	14	19	41	38	35	44	57	74	83	71	73	72
Education	54	37	52	50	63	77	80	94	94	89	121	85	111	83	79	119	92	119	100	124
Higher Education	1	3	4	5	3	8	11	9	12	6	12	9	12	11	14	20	24	29	20	19
Pedagogy	3	5	0	2	3	2	10	10	8	7	8	14	17	21	11	12	13	11	20	12
Physical	3	2	1	7	10	3	5	3	3	5	12	3	12	17	5	21	10	19	12	15
Fieldwork	3	7	5	2	5	4	11	11	10	11	15	4	9	10	8	13	10	12	6	3

A. Frequency

Keywords by Clusters	Year																			
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GIS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Remote Sensing	0.48	0.66	0.41	0.43	0.38	0.34	0.38	0.47	0.44	0.45	0.48	0.34	0.40	0.42	0.42	0.38	0.42	0.40	0.51	0.52
Land Use	0.20	0.41	0.30	0.33	0.27	0.23	0.29	0.37	0.29	0.37	0.45	0.28	0.35	0.34	0.30	0.32	0.37	0.30	0.38	0.46
Spatial	0.12	0.15	0.17	0.13	0.15	0.19	0.16	0.14	0.19	0.25	0.31	0.20	0.32	0.42	0.35	0.34	0.33	0.32	0.34	0.29
Health	0.10	0.08	0.09	0.02	0.13	0.09	0.15	0.25	0.25	0.26	0.35	0.30	0.37	0.42	0.37	0.36	0.38	0.40	0.43	0.41
Urban	0.38	0.31	0.15	0.32	0.44	0.26	0.49	0.54	0.39	0.70	0.67	0.63	0.72	0.83	0.56	0.66	0.77	0.77	0.78	0.70
China	0.15	0.41	0.21	0.16	0.19	0.19	0.25	0.27	0.29	0.34	0.40	0.36	0.48	0.54	0.41	0.44	0.51	0.47	0.51	0.48
Sustainability	0.04	0.06	0.04	0.09	0.10	0.07	0.12	0.24	0.31	0.25	0.37	0.25	0.44	0.46	0.38	0.30	0.48	0.36	0.47	0.42
Economic	0.21	0.14	0.16	0.22	0.20	0.09	0.22	0.31	0.13	0.35	0.38	0.28	0.35	0.42	0.26	0.22	0.30	0.28	0.25	0.33
Mobility	0.01	0.01	0.01	0.09	0.08	0.06	0.06	0.20	0.16	0.20	0.29	0.25	0.36	0.48	0.35	0.41	0.41	0.40	0.39	0.37
Political Ecology	0.22	0.43	0.21	0.24	0.31	0.25	0.33	0.41	0.35	0.30	0.45	0.38	0.49	0.60	0.44	0.45	0.63	0.43	0.53	0.50
Agriculture	0.20	0.43	0.20	0.27	0.26	0.21	0.20	0.37	0.30	0.35	0.42	0.29	0.44	0.45	0.35	0.33	0.42	0.45	0.53	0.54
Development	0.11	0.29	0.19	0.27	0.18	0.25	0.26	0.40	0.34	0.40	0.34	0.30	0.49	0.57	0.46	0.48	0.55	0.49	0.44	0.49
Africa	0.19	0.27	0.13	0.19	0.18	0.16	0.25	0.24	0.26	0.33	0.39	0.26	0.44	0.44	0.35	0.35	0.36	0.34	0.43	0.37
Neoliberalism	0.02	0.07	0.03	0.11	0.13	0.17	0.24	0.35	0.31	0.39	0.32	0.25	0.43	0.42	0.20	0.26	0.37	0.28	0.33	0.29
Migration	0.17	0.34	0.13	0.25	0.21	0.18	0.25	0.36	0.33	0.35	0.40	0.33	0.50	0.52	0.40	0.42	0.55	0.45	0.55	0.54
Gender	0.22	0.50	0.23	0.31	0.30	0.23	0.23	0.35	0.32	0.38	0.42	0.36	0.44	0.44	0.31	0.37	0.39	0.41	0.51	0.49
Tourism	0.13	0.25	0.18	0.23	0.22	0.19	0.23	0.31	0.24	0.36	0.35	0.28	0.39	0.33	0.25	0.27	0.36	0.35	0.36	0.43
Race	0.16	0.13	0.13	0.14	0.22	0.14	0.22	0.25	0.24	0.28	0.26	0.27	0.39	0.34	0.24	0.39	0.47	0.46	0.47	0.37
United States	0.25	0.28	0.16	0.20	0.26	0.15	0.28	0.30	0.28	0.35	0.42	0.28	0.28	0.40	0.24	0.21	0.31	0.32	0.22	0.27
Climate Change	0.09	0.19	0.11	0.11	0.15	0.17	0.21	0.30	0.37	0.50	0.71	0.65	0.59	0.65	0.67	0.60	0.69	0.66	0.80	0.75
Climate	0.09	0.13	0.04	0.10	0.09	0.12	0.17	0.17	0.25	0.23	0.27	0.21	0.20	0.26	0.36	0.25	0.26	0.30	0.35	0.31
Vulnerability	0.01	0.13	0.05	0.12	0.06	0.09	0.17	0.16	0.20	0.21	0.30	0.28	0.24	0.28	0.34	0.28	0.31	0.32	0.42	0.29
Hazards	0.14	0.14	0.15	0.14	0.14	0.14	0.15	0.22	0.20	0.20	0.25	0.22	0.17	0.17	0.25	0.18	0.18	0.19	0.35	0.19
Resilience	0.00	0.00	0.00	0.02	0.00	0.01	0.02	0.07	0.12	0.14	0.23	0.17	0.18	0.30	0.31	0.28	0.39	0.32	0.43	0.43
Education	0.22	0.25	0.20	0.15	0.18	0.14	0.25	0.26	0.25	0.25	0.37	0.25	0.35	0.27	0.22	0.34	0.30	0.34	0.38	0.43
Higher Education	0.01	0.02	0.03	0.04	0.02	0.04	0.06	0.06	0.05	0.04	0.05	0.04	0.03	0.04	0.07	0.10	0.09	0.13	0.09	0.10
Pedagogy	0.02	0.03	0.00	0.01	0.04	0.03	0.05	0.07	0.01	0.05	0.03	0.05	0.10	0.11	0.07	0.06	0.06	0.04	0.09	0.06
Physical	0.02	0.01	0.06	0.04	0.05	0.01	0.02	0.01	0.01	0.01	0.03	0.01	0.05	0.10	0.01	0.09	0.06	0.06	0.10	0.07
Fieldwork	0.07	0.02	0.02	0.01	0.04	0.00	0.04	0.06	0.04	0.05	0.08	0.01	0.03	0.07	0.03	0.09	0.03	0.07	0.06	0.00

B. Eigenvector Centrality

Figure 6 The changes annual changes in the frequency (A) and eigenvector centrality (B) values of the top-five most frequent keywords in the six major clusters. Data cells are conditionally formatted with a red-green color scale, where red indicates a low value and green indicates a high value. The median value is shown in white, and colors get stronger as values deviate from the median. The medians of frequency and eigenvector centrality values were 54 and 0.26, respectively.

4. Discussion

4.1. AAG Specialty Groups (SGs)

The AAG Specialty Groups are voluntary associations of AAG members who share interest in regions and topics. The statistics of SGs may also help understand what geographers are interested in and cast insights about the validity of our keyword analysis results. As of May 7, 2020, there are 68 SGs identified from AAG's website (http://www.aag.org/cs/membership/specialty_groups), and their names and member counts are summarized in Table 4. When the SGs are sorted by the member counts, the top-nine largest SGs are mostly about human geography and geographical methodology subjects. The next four SGs, i.e., the 10th through 13th are about physical and environmental topics. Some SGs like Climate, China, Geography Education, and Geographies of Food and Agriculture show less members than expected when considering that they are included in the 2000-2019 top-ten keywords list. The difference may be attributed partially to the facts that the SGs represent only the year of 2020 and that SG members change annually. Table 4 also shows concentrated coalitions in Urban, GIS, Political Ecology, Climate and Education SGs, while the People-related SGs are rather dispersed. The coalition pattern matches well with the 2000-2019 keyword network clusters. As shown in Table 1, the People cluster shows the largest values in frequency, sum of eigenvector centrality, and sum of degree centrality, which indicates a diversely decentralized coalition.

Table 4. AAG Specialty Groups and Their Members (May 7, 2020)

Name	Members	Name	Members
Urban Geography	1090	Digital Geographies	218
Geographic Information Science and Systems	1030	Geomorphology	218
Cultural and Political Ecology	757	Ethics, Justice, and Human Rights	216
Spatial Analysis and Modeling	657	Population	210
Political Geography	563	Landscape	209
Cultural Geography	547	Coastal and Marine	186
Economic Geography	522	Recreation, Tourism, and Sport	161
Remote Sensing	519	Mountain Geography	148
Socialist and Critical Geography	519	Queer and Trans Geographies	141
Water Resources	446	Latinx Geographies	139
Climate	434	Ethnic Geography	136
Hazards, Risks, and Disasters	429	Geography of Wine, Beer, and Spirits	134
Human Dimensions of Global Change	411	Paleoenvironmental Change	123
Development Geography	402	Animal Geography	121
Geographies of Food and Agriculture	396	Cyberinfrastructure	117
Energy and Environment	383	Legal Geography	115
Health and Medical Geography	379	Business Geography	114
Feminist Geographies	360	Middle East	114
Cartography	335	Military Geography	107
Applied Geography	333	Caribbean Specialty Group	103
Regional Development and Planning	325	Media and Communication	101
Latin America	316	Study of the American South	101
Geography Education	298	European	98
Asian Geography	293	Eurasian	91
Africa	283	Polar Geography	86
Biogeography	280	Disability	84
Transportation Geography	278	Cryosphere	81
China	273	History of Geography	81
Black Geographies	270	Critical Geographies of Education	80
Qualitative Research	268	Geography of Religions and Belief Systems	76
Environmental Perception & Behavioral Geography	254	Canadian Studies	70
Rural Geography	253	Bible Geography	61
Indigenous Peoples	237	Film-making and Screening Specialty Group	56
Historical Geography	230	Protected Areas	27

4.2. Dichotomy or Trichotomy in Geography

The six major clusters described in the results cast multiple implications to the current geography practices. As an example, it makes us question the tradition of segmenting geography into two or three subfields. Dichotomously, geography is frequently divided into human geography and physical geography (e.g. Arbogast 2014, and Berglee 2017). Trichotomously, geospatial technologies are generally added to the dichotomous branches. We may easily find "Human Geography" and "Physical Geography" courses in high school or undergraduate liberal study curriculums. Also common is to call our colleagues with reference to the three categories like "Human Geographer", "Physical Geographer" or "GISer." The six clusters found in this research challenge the dichotomy or trichotomy in geography. In a narrow perspective, the People cluster directly handles the characteristics of human beings; the Climate Change cluster is strongly associated with the physical characteristics of the Earth; and the GIS cluster carries most geographic methodologies and techniques. Other clusters such as Urban, Political Ecology, and Education are rather cross-cutting multiple subfields. Hartshorne (1959, p.8) states that "… geography is what geographers have made it, and in large part it is likely to change that character but slowly." Considering what geographers have made over the last twenty years and its dynamically changing nature, the traditional segmentation of geography subfields seems too simplistic to incorporate the wide spectrum of geography. The six clusters identified in this research – GIS, Urban, Climate Change, Political Ecology, People and Education, can make strong candidates that may supplement the traditional identification of geography subfields.

5. Conclusions

AAG conferences have been the most influential events for geographic research presentations in the United States since AAG was founded in 1904. It is not unusual to see several thousands of research papers be presented at AAG's annual conferences in recent years. Analyzing the AAG conference presentation papers can give us an insight about the past, present, and future of geographic research. We analyzed the 2000-2019 AAG conference papers in this research. To identify major geography topics, their temporal trends, and connections, we analyzed the keywords in each paper with the keyword network analysis technique. Results showed multiple interesting points, listed below.

First, the number of unique keywords has increased linearly as the number of presentation papers increases. In 2017, unique keywords reached the maximum of 13,054 from 6,928 papers. The most frequently used keywords during 2000-2019 were *GIS*, *Remote Sensing*, *Climate Change*, *Urban*, *China*, *Education*, *Political Ecology*, *Migration*, *Gender*, and *Agriculture*. About 7.9 percent of all papers included *GIS* as their keywords. Second, when the presentations were analyzed, six unique topical clusters were identified and they were **GIS**, **Urban**, **Climate Change**, **Political Ecology**, **People**, and **Education**. Third, the keywords in the **GIS**, **Urban**, and **People** clusters, took 68.6 percent of total keywords. They formed three major geography research fields. The research in

Urban and **People** clusters carried more diverse sub-fields. The **GIS** and **Political Ecology** clusters showed less diversity. Fourth, *GIS* and *Remote Sensing* keywords showed the strongest relationship, followed by *GIS* and *Urban*, *GIS* and *Spatial*, *GIS* and *Education*, *GIS* and *Climate Change*, and *GIS* and *Health*. The keyword network showed that GIS has been the central part of geographic research since 2000. Fifth, about 41 percent of keywords appeared consistently in the top-100 keyword lists during 2000-2019. Some cultural geography keywords were briefly popular during 2005-2009, and some economic geography keywords gained attention during 2010-2014. During 2015-2019, some keywords in the big data and artificial intelligence became popular as an emerging field. Sixth, when annual trends were analyzed with the top-five keywords in each cluster, most keywords showed increasing trends in frequencies during the last 2-3 years. However, the *Spatial*, *Urban*, *Mobility*, *Neoliberalism* and *Field Work* keywords showed slight frequency decreases. Several keywords also showed their increasing influence in relation to other keywords, and examples are *Remote Sensing*, *Health*, *Agriculture*, *Migration*, *Gender*, *Resilience*, and *Education*. Seventh, this research also found that multi-word keywords were better in identifying the keywords' contextual meanings and in representing the relationships among keywords. Last, analyzing AAG conference papers using keyword network analysis methods revealed a great potential to summarize what geographers have been researching. Hopefully, the clusters identified in this research may also help geographers build robust academic programs, institutionally as well as nationally.

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