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Review Article

A Decade of Artificial Intelligence (AI) and Geography: Bibliometric Insights with AI-Powered Analysis

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Abstract: In the last decade, there has been a significant increase in the number of geography studies utilizing artificial intelligence (AI) applications and algorithms. Despite this increase, what is known about related studies is limited. The study aims to reveal the current state, trends, themes, and collaborations of the studies carried out in the interaction of AI and geography in the last decade and to highlight the prospects of AI within geography. Accordingly, the study is based on the bibliometric data of geography studies that have AI applications and algorithms. In the analysis of the data, basic analyses were first conducted covering titles, abstracts, keywords, and so on. Topic modelling was performed using the BERTopic to identify the research themes. Additionally, natural language processing (NLP) tasks were utilized to enhance the efficiency of the analysis. Between 2015 and 2024, productivity in the interaction of geography and AI has shown a significant increase, with 124 different countries contributing to this productivity. This reflects a growing global interest in the field. With increasing interest and productivity, it has been concluded that the methodologies, data, and focal topics have evolved and diversified, while the number of collaborations has also increased. The role of AI in geography is expected to become even more prominent in the future, thanks to its advanced data processing capacity, real-time analysis capabilities, and complex spatial modelling skills. However, soon, some specific approaches and issues (ethical and technical) regarding the interaction between geography and artificial intelligence are noteworthy.

Keywords: Artificial Intelligence (AI); Geography; GeoAI; Bibliometric Insights; AI-powered Analysis

Highlights:

- AI and geography research expanded globally, with 124 countries contributing.
- AI has evolved and diversified geography research methods, data, and focal topics.
- The role of AI in geography is expected to become more prominent.
- Ethical and technical issues in geography-AI interaction require urgent attention.

1. Introduction

Defined from various perspectives, artificial intelligence is generally described as the science of developing systems capable of thinking, learning, and making rational decisions (Russell & Norvig, 2016). Research and efforts aimed at developing intelligent models and machines capable of performing these tasks constitute the main goal of artificial intelligence (Nilsson, 2010). Whitby (2012:16) characterized this objective as "one of the most difficult and arguably one of the most exciting endeavours that humanity has ever undertaken." Historically, four distinct approaches have been used to define artificial intelligence: thinking humanly, thinking rationally, acting humanly, and acting rationally (Russell & Norvig, 2016). Despite the existence of multiple definitions, the absence of a universally agreed-upon definition has contributed to the expansion of research and applications in this field (Stone et al., 2016).

Over the last decade (2015–2024), significant advancements have been made in artificial intelligence, including generative artificial intelligence, large language models (LLMs), machine learning (ML), deep learning (DL), and natural language processing (NLP). With this, access and engagement with artificial intelligence technologies have also substantially increased. Metrics from leading scientific databases such as Web of Science (WoS) and Scopus reveal that advances in artificial intelligence have been generating interest in different disciplines, and the advances have permeated into academic research.

Considering the last decade, there has been a growing effort to integrate artificial intelligence applications into geographical research. According to WoS data, the number of geography studies utilizing artificial intelligence applications and algorithms has increased significantly since 2015. The alignment between AI's innovative, adaptive solutions and geography's evolving methodological needs has expanded the integration of AI tools, thereby facilitating the diversification of research topics, methodological transformations, and new interdisciplinary collaborations. Despite these developments, little is known about the current state of studies on the interaction between artificial intelligence and geography in recent years. Limited studies have examined the focal points and trends of these studies—whether they are concerned with the environment, humans, methodology, or something else. Similarly, there is a lack of information regarding collaborations and connections in this field, and the scientific mapping of the research remains insufficient. To address these gaps, this study aims to analyse the current status, trends, themes, and collaborative networks (including authors, institutions, and countries) of studies on the interaction of artificial intelligence and geography over the past decade. Utilizing WoS data and AI-powered analytical methods, this study seeks to answer the following research questions:

Q1. How have geography studies incorporating artificial intelligence algorithms and techniques evolved over the last decade?

Q2. What are the methodological trends and developments in studies?

Q3. Who are the most influential authors, journals, institutions, and countries in this interaction?

Q4. What are the main research themes, and where is further research needed?

Reflecting the growing interest in AI applications in geography, several review studies have been conducted examining trends in this intersection. For instance, Lavallin and Downs (2021) discussed the status of machine learning in geography, Jiang et al. (2022) examined the use of artificial intelligence in geohazard research, Wang et al. (2024) analysed artificial intelligence applications in quantitative human geography, and Cheng et al. (2024) investigated the interaction between cartography and neural networks. Existing studies tend to focus on more specialized subfields of geographical practices. These pioneering studies provide valuable insights into more specialized sub-areas of the field. However, a holistic examination of the role of AI in geography, including its overall intellectual structure and thematic evolution, remains limited.

Providing a general analysis of the use of artificial intelligence in geography studies over a specific period, this study contributes to the field in two main ways: (1) it outlines the current status, focal points, collaborations, and trends at the interaction of artificial intelligence and geography, and (2) it offers a comprehensive framework for understanding the role of artificial intelligence in geography.

The study is structured as follows: Section 2 provides a historical overview of the development of the interaction of artificial intelligence and geography; Section 3 outlines the data and methodology used in this study; Section 4 presents the findings from both basic and advanced analyses; and Section 5 offers conclusions and discusses future directions.

2. Artificial Intelligence and Geography

The origins of artificial intelligence research can be traced back to the post-World War II era and the pioneering work of Alan Turing (McCarthy, 2007). Turing stated that machines could possess problem-solving abilities, language-processing capabilities, and the capacity to learn (Turing, 1950). The field was formally conceptualized as "artificial intelligence" during the Dartmouth Workshop in 1956, marking a significant turning point and catalysing further research in the domain (Franklin, 2014; Say, 2021). Since then, artificial intelligence has attracted significant interest and has often been influenced by ambitious, sometimes utopian, visions. However, the field has also experienced periods of stagnation, known as "AI winters", during which technical limitations and unmet expectations hindered progress (Duan et al., 2019).

Although financial and academic support declined during the AI winters, leading to a slowdown, research never completely ceased (Crevier, 1993). Following each AI winter, artificial intelligence regained momentum due to advancements in hardware and the introduction of new algorithms, allowing research in the field to continue progressing (Nilsson, 2010; Russell & Norvig, 2016). Over time, artificial intelligence research has diversified significantly, encompassing numerous subfields. Among the key research areas, though not limited to those listed here, are machine learning, deep learning, natural language processing, autonomous systems and robotics, generative AI, and computer vision, which remain at the forefront of artificial intelligence research (Littman et al., 2021).

As a result of the rapid advancement and diversification of research areas, artificial intelligence technologies are now employed across various sectors, including healthcare, education, security, automotive, finance, and media (Hashim et al., 2022). Adopting an interdisciplinary approach, artificial intelligence has influenced multiple scientific domains, including the humanities (Frankish & Ramsey, 2014). One of the most significant applications of artificial intelligence is undoubtedly scientific research. Researchers utilize artificial intelligence, an effective tool for developing research methodologies, analysing data, and constructing research models, at various stages of the academic research process. Given its ability to continuously improve, AI's role in scientific research is expected to expand progressively.

2.1. Geography Meets Artificial Intelligence

The discipline of geography has continuously evolved since its inception (Özgen, 2010). It has undergone a series of stages, including establishment, identity formation, institutionalization, development, and building competence (Tanrıkulu & Gümüşçü, 2021). Today, geography actively engages with technological advancements and seeks to adapt to the opportunities they present. In this context, it can be argued that the stages of development and competence in geography are ongoing, with the integration of artificial intelligence into geographical research serving as a key indicator of this progression.

The integration of artificial intelligence into geography began in the 1980s, with one of the pioneering studies, J. E. Dobson's "Automated Geography" (1983). Drawing on the rapid advancement of analytical methods and computer technology for spatial analysis, Dobson highlighted automation as a transformative force in geography. Expanding on this perspective, Cowen (1983) argued that geographers should act as the architects of automation rather than merely using it as a tool like a carpenter. Furthermore, he cautioned against fully automating geographical analysis, emphasizing the need for human oversight in the process.

A year later, T. R. Smith investigated whether artificial intelligence could be used to address geographic issues. This study evaluated the present state and prospects of AI, emphasizing its potential to improve geographers' problem-solving and creative thinking skills, rather than offering an empirical or methodological application (Smith, 1984). Following this research, Nystuen (1984) accepted Smith's viewpoint on the potential of AI to solve geographic issues, but he raised issues with theoretical ambiguity and an unduly cautious approach. Following Dobson and Smith's arguments that AI could be more than just a tool for processing data in geography, Couclelis (1986) claimed that AI, a relatively new methodology in the field, could have a more transformative role and should be given more thought by geographers.

After some initial studies that examined the current state and prospects of artificial intelligence in geography, research on the interaction between AI and geography gained noticeable momentum between 1985 and 1990. During this period, much of the attention was directed toward two main areas: Geographic Information Systems (GIS) and Remote Sensing (RS). One of the early examples of this emerging interest is the study by Estes et al. (1986), in which the potential use of AI techniques in remote sensing processes was explored. Shortly after, the Association of American Geographers organized the International Geographic Information Systems (IGIS) Symposium (November 15 to 18, 1987). This symposium

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was particularly notable for featuring a dedicated session on GIS, an essential component of geography, focusing on spatial analysis and artificial intelligence. During this session, well-known geographers such as John R. Borchert, Nicholas R. Chrisman, M. Dobson, Donna J. Peuquet, and K. Ord discussed about how AI can be used in spatial analysis.

In this plenary session, chaired by D. Marble, Borchert provided an overview of the evolving geoscientific missions, while Chrisman discussed the challenges faced in GIS research due to advances in computer technologies. Peuquet highlighted the opportunities that artificial intelligence offers for GIS applications, emphasizing artificial intelligence as a powerful tool to address the shortcomings that GIS faces. Dobson, reflecting critically on the research and theoretical discussions of GIS at the time, expressed both the appeal and potential of artificial intelligence for enhancing GIS. Finally, Ord explored the challenges and future potential of statistical modelling for spatial processes, given the ongoing developments in statistical methods (IGIS, 1987 Vol. I: 93-139). Furthermore, the symposium featured a paper on the successful application of semantic processes in GIS (Robinson & Lundberg, 1987) and another paper (Frank et al., 1987) that looked favourably at the adaptability of AI to GIS applications.

The same year, in parallel with the perspectives and research presented in symposium sessions, some ideas regarding how artificial intelligence solutions could expand the scope of GIS were discussed by McKeown (1987). The following year, Fisher et al. (1988) examined the role of artificial intelligence in geographic data processing, emphasizing expert systems and image processing as areas of particular interest to geoscientists. Subsequently, at a broader level, Fisher (1989) and Tikunov (1990) discussed the current and potential applications of AI and expert systems in geography, considering a range of perspectives and contexts.

Between 1990 and 2000, the number of studies examining the interaction between artificial intelligence and geography increased, accompanied by significant shifts in research focus. While earlier studies concentrated on theoretical foundations, assessing the current status, and exploring potential effects, there was a notable transition toward the practical application of artificial intelligence as a methodological approach and technique (Ritter & Hepner, 1990; Lees & Ritman, 1991; Openshaw & Wymer, 1991; Fabricius & Coetzee, 1992; Civco, 1993; Barbanente et al., 1992; Black, 1995; Openshaw, 1995; Huang & Jensen, 1997; Gahegan, 2000), with a few exceptions (Openshaw, 1992; S. Openshaw & C. Openshaw, 1997).

In the 2000s, the adoption of artificial intelligence as an applied methodological approach and technique in geographical research accelerated. Various AI algorithms and techniques were employed across a wide range of studies with diverse foci (Rigol et al., 2001; Li & Yeh, 2002; Pijanowski et al., 2005; Naderi & Raman, 2005; Laffan et al., 2005; Badariotti et al., 2007; Christodoulou et al., 2009; Steiniger et al., 2010; Lamovec & Ostir, 2010; Wan et al., 2012; Hagenauer & Helbich, 2012; Doherty et al., 2013; Jachowski et al., 2013; Rienow & Stenger, 2014). A visual representation of the development of the interaction between geography and artificial intelligence is provided in Figure 1.

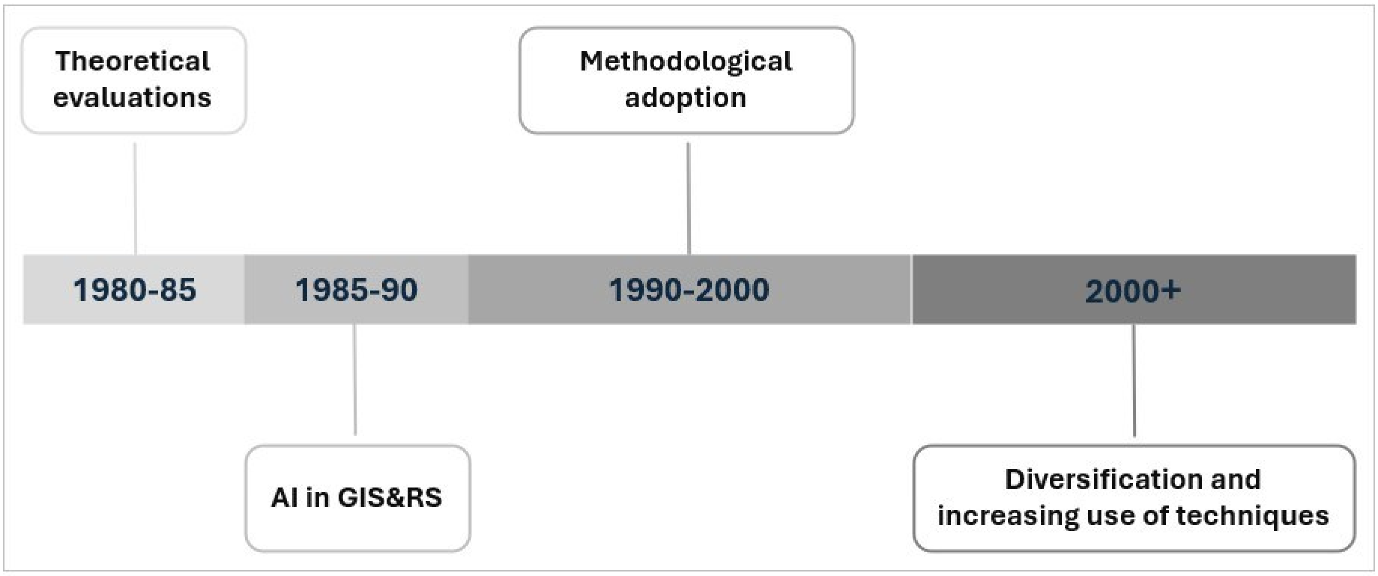

Figure 1. Evolution of geography and AI interaction.

In general terms, the period from 1980 to 1985 focused on evaluating the current state and potential of artificial intelligence in the field of geography. This initial interest was followed by attempts to create AI-based solutions for GIS and RS from 1985 to 1990. In the following decade, from 1990 to 2000, the use of artificial intelligence in geographic research became more common. This included developing theoretical frameworks and practical methods. Throughout the 2000s, the range of AI techniques used and the number of studies applying these methods increased steadily.

3. Data and Method

Through its multiple functions, scientific databases such as WoS and Scopus have significantly facilitated researchers in having easy access to the huge amounts of bibliometric data needed. The existence of various software packages to analyse the data further helps researchers gain comprehensive insights into the field, identify gaps, and put forth ideas for further studies (Donthu et al., 2021). Successful analyses performed on bibliometric indicators allow for evaluating and characterizing scientific knowledge production, related domains, research activities, and broader trends (Linnenluecke et al., 2020). Such analyses are composed of a variety of methods for data collection, analysis, and interpretation, and visualize the essence of the current standing of any research area while providing insights useful for prognosticating future developments (Ninkov et al., 2022; Pessin et al., 2022; Kraus et al., 2024).

The study adopted an AI-powered bibliometric framework that increased the efficiency, depth, and interpretive power of analyses compared to traditional bibliometric analyses. Firstly, pyBibX, used as the primary analysis tool in the study, surpassed previous bibliometric analysis tools (such as VOSviewer and Scientopy) in terms of analytical scope (Pereira et al., 2025). This AI-powered tool not only replicated the descriptive analyses offered by traditional tools but also supported advanced analytical-semantic capabilities such as topic modelling, semantic embedding, and automatic text summarization. This added both quantitative and qualitative depth to bibliometric analyses.

Secondly, the use of natural language processing techniques provided an advantage over traditional methods in processing textual data such as titles, abstracts, and keywords. Specifically, pyBibX is integrated with language models such as BERT and generative AI systems such as ChatGPT and Gemini. This advantage enabled tasks such as automatic text summarization, calculating semantic similarities between terms, contextually tagging topics, and automatically identifying representative documents. Consequently, while traditional bibliometric analyses are often limited to basic statistical and visualization capabilities, the AI-powered approach used in this study offered advanced techniques for modelling topics and temporal dynamics, text analysis, and semantic relationship extraction, significantly increasing the depth of insights into the interaction between geography and AI.

The data analysis began with basic analyses, covering general information such as titles, abstracts, keywords, authors, institutions, countries, collaborations, and publication sources. Beyond these basic analyses, comprehensive topic modelling was performed using BERTopic, a technique that uses BERT-based document embeddings from the Sentence-Transformers library for clustering-based topic extraction. Finally, natural language processing capabilities were employed to interpret and evaluate the outputs of the analysis and modelling.

3.1. Data Collection and Filtering

The study data were obtained from the widely recognized WoS database, which was chosen due to its inclusion of the highest-quality and most-cited studies in literature (Harzing & Alakangas, 2016). Additionally, WoS offers easy and accessible access to bibliometric data, making it a preferred and reliable data source for many studies (Liu et al., 2014; Chen et al., 2015; Zhao et al., 2019; Kahraman, 2022; Yılmaz, 2024).

In line with the objectives of this study, a query was conducted in the WoS Core Collection using six leading terms for the period between 2015 and 2024. These terms relate to the main pillars of present-day AI research and the main subfields within AI research: Artificial Intelligence, the most generic or umbrella term to address the generality of AI-related research. Machine Learning, the most dominant form of AI, as well as a subfield of AI focusing on statistical learning. Deep Learning is a dominant, prominent subfield of ML that is based on neural networks. Neural Networks, the base architectures that enable deep learning and AI to operate. Generative AI is a relatively new area (e.g., GPT, DALL-E) with increasing cross-domain collaborations. Natural Language Processing, an important area of application, particularly relevant for text-related research (e.g., geospatial text-mining, social media mining). The combination of these keywords helps encompass both the foundational and the rapidly emerging areas of AI research, without narrowing the queries, and redundancies. The query is as follows:

Topic = ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "generative AI" OR "natural language processing") - Date Range (Publication Date) = (2015-01-01 to 2024-12-31)

Following the query, the WoS categories "Geography" and "Geography, Physical" were selected, and the document type was refined to "article," with "retracted publication" excluded. As a result of the query and filtering, a total of 5,471 studies were retrieved. The records of the retrieved studies were exported in the Bibtex (bib) format. Export date = (2025-03-15) – Query link = (*https://www.webofscience.com/wos/woscc/summary/65c7453c-c353-4e01-996c-36d1ae73a464-018032a8cd/relevance/1*).

Exported the .bib file containing the studies belonging to these selections and was observed with pyBibX and Bibliometrix. It was observed that all article records included small counts of articles in press and other studies (article; book chapter, article; proceeding papers—as presented in WoS). To reflect the most current scientific output in the field of research and to ensure the integrity of the analysis, publications with "article in press" status have been included in the study. On the other hand, other types of studies, such as book chapters and proceedings , can also make original contributions to the field, like journal articles. Excluding these studies from the dataset would overlook the dynamics and significant scientific outputs of the field; therefore, these studies were also retained (Figure 2).

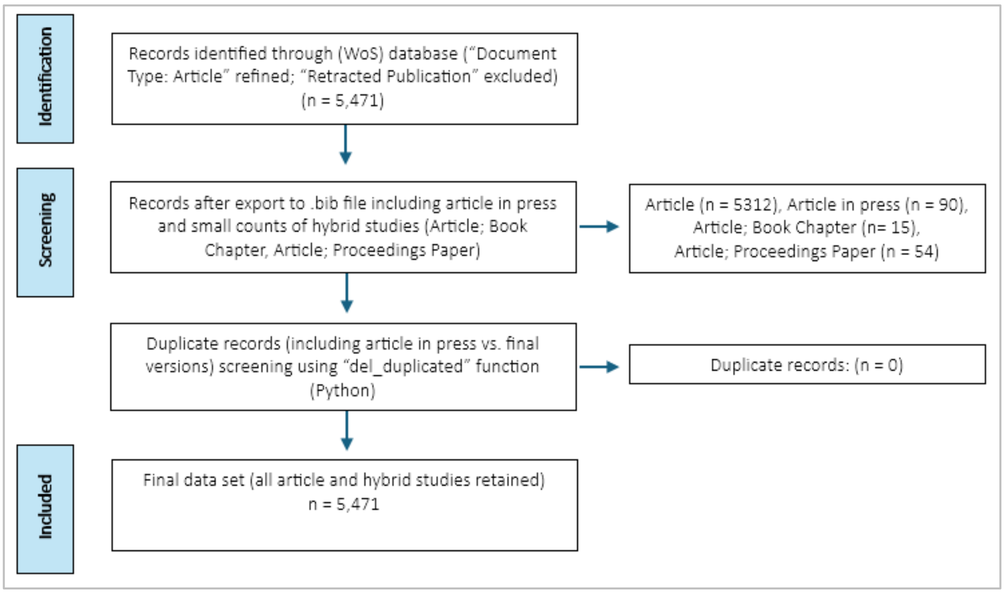

Figure 2. Inclusion and exclusion criteria flow chart

Although the WoS query is limited to studies in the "Geography" or "Geography, Physical" categories (n = 5,471), it is important to note that WoS uses multi-category indexing. For example, a study may include 4 WoS categories: "Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology," and the study may be found under these categories. As a result, it was observed that a portion of the retrieved studies were already classified in complementary categories such as Remote Sensing (n = 3,732), Geosciences, Multidisciplinary (n = 1,181), and Environmental Sciences (n = 168). This overlap indicates that our analysis data covers a certain portion of AI-focused research published in the fields of remote sensing, geosciences, multidisciplinary, and environmental science. Additionally, it was found that the 5,471 studies were presented in a total of 42 unique categories and 55 different categorization variations in WoS (Appendix A, Figure A1).

3.2. Basic Analysis and Scientific Mapping

Basic analyses were conducted using the data obtained from the studies, and scientific maps were generated. In this process, the Bibliometrix software, developed in the R programming language, and the pyBibX 4.7.9 library, developed in Python and supporting AI-powered analysis, were utilized. Both tools are distinguished by their specific features.

Bibliometrix was selected for this study due to its statistical algorithms, comprehensive data visualization capabilities, and advanced user interface (Aria & Cuccurullo, 2017). However, the primary analysis was conducted using pyBibX, as it surpasses its predecessors in analytical scope and introduces AI-assisted techniques for enhanced interpretation (Pereira et al., 2025). The integration of artificial intelligence in bibliometric analysis provides pyBibX with a distinct advantage, significantly improving efficiency and analytical depth (Uysal et al., 2024). As outlined by Pereira et al. (2025), the key strengths of pyBibX include:

- *Diverse Data Sources*: pyBibX can integrate and process data from multiple sources, including Web of Science (WoS), Scopus, and PubMed.
- *Advanced Analysis Features*: pyBibX supports a wide range of analyses, including topic modeling, embeddings, and text summarization, in addition to replicating the functionalities of various previous tools such as Scientopy, Bibliometrix, and VOSviewer.
- *Enhanced Visualization*: pyBibX presents analysis results in an intuitive and visually appealing manner using techniques such as Sankey diagrams, projections, word clouds, evolution plots, treemaps, bar plots, and network visualizations. Moreover, it allows customization of visual elements, including data quantity, font style and size, and frame width.
- *Artificial Intelligence Integration*: pyBibX incorporates AI capabilities more effectively than its predecessors. These include topic modelling, word embedding, text summarization, general NLP tasks, and integration with generative AI models (e.g., ChatGPT, Gemini) and language models (e.g., BERT).

In analyses conducted using comprehensive data from studies between 2015 and 2024, exploratory data analysis (EDA) was performed as an initial step. Subsequently, various aspects of the studies, including titles, abstracts, keywords, authors, affiliations, countries, collaborations, and publication sources, were analysed. The results of these analyses were visualized using graphs, tables, treemaps, co-occurrence networks, bar plots, and evolution plots.

3.3. Topic modelling enriched with Natural Language Processing (NLP)

To comprehensively identify themes and topics in publications from the 2015–2024 period, the topic modelling technique was utilized. pyBibX enables topic modelling in bibliometric data by leveraging the advanced BERTopic model. Topic modelling is a statistical approach that identifies latent topics within a text collection and is widely applied in machine learning and natural language processing tasks (Guo et al., 2017). Several techniques, including LDA, LSA, Top2Vec, and BERTopic, have been developed for topic modelling in large text corpora (Egger & Yu, 2022). BERTopic was selected for this study due to its distinct advantages, such as versatility and stability across different domains, support for multiple types of topic modelling (e.g., guided, dynamic, online), automatic topic count detection, multilingual analysis capabilities, and extensive parameter tunability (Grootendorst, 2022).

Dynamic topic modelling and annual topic modelling were conducted using the abstracts of 5,471 publications over a ten-year period. Dynamic topic modelling was applied to examine the evolution of topics over time and to understand how different topics emerged and changed throughout the years. Additionally, annual topic modelling was performed separately for each year to provide a more detailed analysis of topic distributions and trends across specific time periods. The steps followed in the topic modelling process, the tools used, and the parameters are provided in Appendix B, Table B1.

Word embedding-based NLP capabilities were utilized to facilitate a more comprehensive analysis of the identified topics. These functions allowed for a deeper investigation of thematic content during the topic modelling process. For instance, the "similar_topics" function was used to identify topics semantically related to a given query (word) and to calculate their similarity scores. Subsequently, the "topics_representatives" function retrieved the most representative studies for any given query, which significantly aided in interpreting the thematic focus of each cluster. Furthermore, the "similarity calculation" function calculated the semantic similarity between specific terms, providing a deeper understanding of their relationships within the dataset. To complement this, the "find_doc" function retrieved the most relevant documents for a given set of target words. The complete code, including all functions used in the topic modelling process, is available on GitHub[1].

3.4. Sensitivity Analysis Design

To present the sensitivity of our findings, a sensitivity analysis was conducted. The main dataset initially included only two WoS categories ("Geography" and "Geography, Physical") to capture the disciplinary basis of geographical research. However, to assess how counts, sources, and topics changed, the search was expanded to include additional WoS categories ("Remote Sensing," "Geosciences, Multidisciplinary," and "Environmental Sciences"). Additionally, a parallel dataset including the "Environmental Sciences" category was obtained from Scopus. There are no "Geography," "Geography, Physical," "Remote Sensing," or "Geosciences, Multidisciplinary" categories in Scopus, and it was observed that AI-geospatial focused studies were gathered under a single category, "Environmental Sciences." Subsequently, the same filtering, preprocessing, and

[1] https://github.com/burakoglakci/TopicFlow-Advanced-NLP-Pipeline-for-Bibliometric-and-Scientometric

BERTopic-based topic modelling procedures were applied to these expanded datasets. This approach allowed us to assess whether the observed publication patterns, sources, and thematic structures were consistent across different data sources and classification schemes.

4. Findings

As mentioned in the previous section, the keywords "artificial intelligence," "machine learning," "deep learning," "neural networks," "generative AI," and "natural language processing" were queried for the period between January 1, 2015, and December 31, 2024. The Web of Science (WoS) category was filtered to include only "Geography" and "Geography Physical," resulting in a dataset of 5,471 studies. The findings obtained from the analyses conducted on the bibliometric data are provided below.

4.1. Exploratory Data Analysis (EDA)

Table 1 provides an overview of the general information on publications, authors, and collaborations. From 2015 to 2024, a total of 5,471 studies were published across 166 different sources, exhibiting an annual growth rate of 38.16% and an average age of 3.29 years. The total number of citations is 107,111, with an average of 19.58 citations per study. The total number of keywords used across the studies is 13,770. The authorship and collaboration aspects are also noteworthy. The total number of authors is 18,170, and nearly all the studies are multi-authored (96.81%), while only a small percentage (3.19%) are single-authored. The studies originated from 124 different countries and 3,990 institutions, with an international collaboration rate of 30.03%. The number of publications increased slowly from 2015 to 2017. However, starting in 2017, there was a noticeable increase in the number of articles published. 2024 was the year in which approximately one-fourth of the articles in the last 10-year period were published.

Table 1. Details of publications (2015-2024)

Publications		**Authors and Collaborations**	
Timespan	2015-2024	Total number of authors	18,170
Sources (journal, book, etc.)	166	Single-authored documents	174
Documents	5,471	Multiple-authored documents	5,297
Annual growth rate (%)	38.16	Countries	124
Document average age	3.29	Institutions	3,990
Average citations per document	19.58	Average collaboration index	4.79
Total number of citations	107,111	International co-authorship (%)	30.03
Author's keywords	13,770		
Keywords plus	5,805		

4.2. Textual Patterns in Studies: Analysing Titles, Abstracts, and Keywords

4.2.1. Titles

Titles, abstracts, and keywords are fundamental components that reflect the content of a study, offering readers essential preliminary information. When analysing the top 20 lemmatized[2] most frequently used words (unigrams) in the titles of the studies, it becomes evident that the words are related to both artificial intelligence and geography (Appendix C, Figure C1). The most frequently used word in the titles was "learn" (9.9%), followed by "use" (9.6%) and "network" (8.3%). Other commonly used words, each appearing in 5-6% of the titles, include "image," "deep," "data," and "sense." The top 20 most recurring words and the co-occurrence of the most frequently used terms in the titles suggest that machine learning, deep learning, neural networks, and remote sensing techniques are prevalent in geography studies. The terms "image," "classification," "detection," "urban," and "imagery" offer insights into the primary research topics (Figure 3). This trend illustrates how remote sensing, originally developed for mapping and military applications, has expanded across various fields, particularly with technological advancements such as the development of satellite systems, and has been further enhanced by artificial intelligence techniques.

4.2.2. Abstracts

Being more detailed than titles and keywords, abstracts serve as an initial overview of the study. Therefore, the words in the abstracts were analysed as trigrams (Appendix C, Figure C2). The results of this analysis offer more specific insights into the methods employed. For instance, the convolutional neural network (CNN), a widely used algorithm in machine learning and deep learning, is frequently mentioned. Additionally, phrases such as "deep learn(ing) base(d)" and "machine learn(ing) algorithm(s)" suggest that the research methodologies are grounded in these domains. When analysing the co-occurrence network of the abstracts, it is evident that there is a greater number of terms and more interconnected relationships (Figure 4). The data, techniques, models, and results are closely linked. Two notable points emerge from the analysis. First, the primary data sources in the studies are remote sensing images and data. Second, it is evident that model performance evaluations and recommendations

[2] Lemmatization is an important text pre-processing technique in NLP that reduces words to their base form. This process was implemented with the spaCy.

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are frequently included in the studies. These evaluations and recommendations are commonly applied across various learning types (supervised, unsupervised, reinforcement) in artificial intelligence.

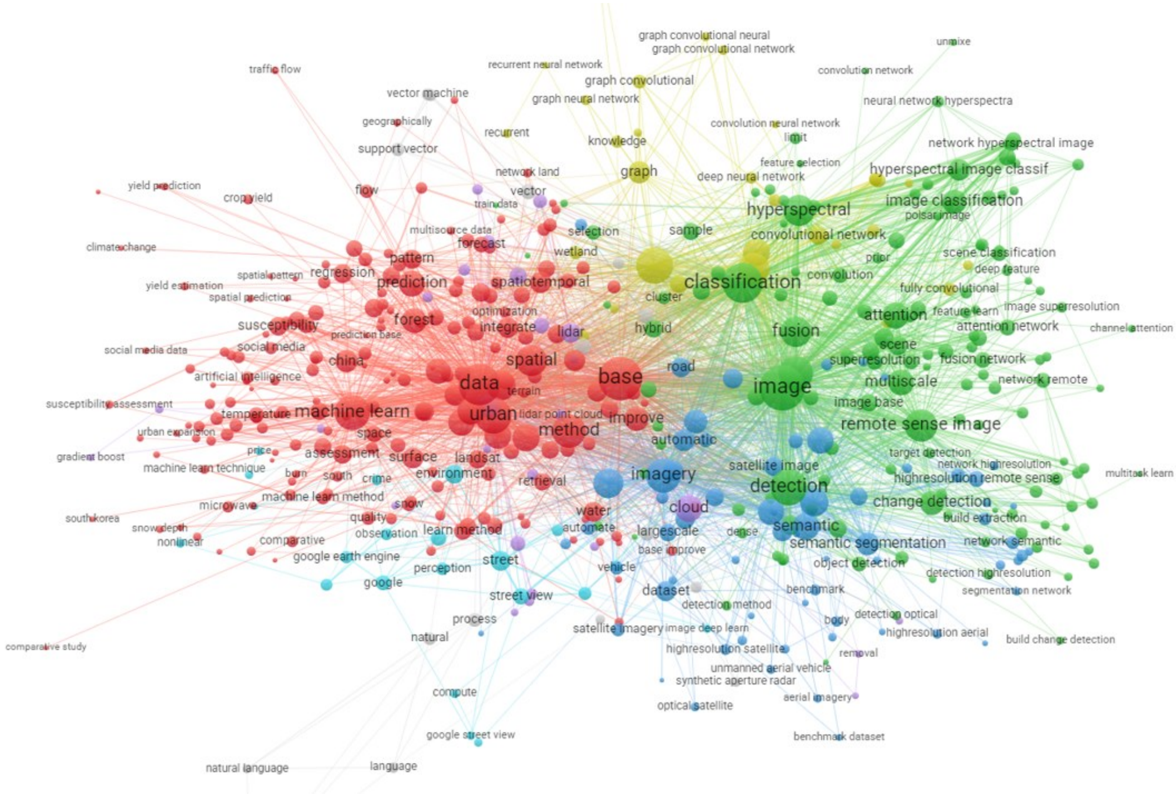

Figure 3. Co-occurrence network analysis of titles (lemmatized)

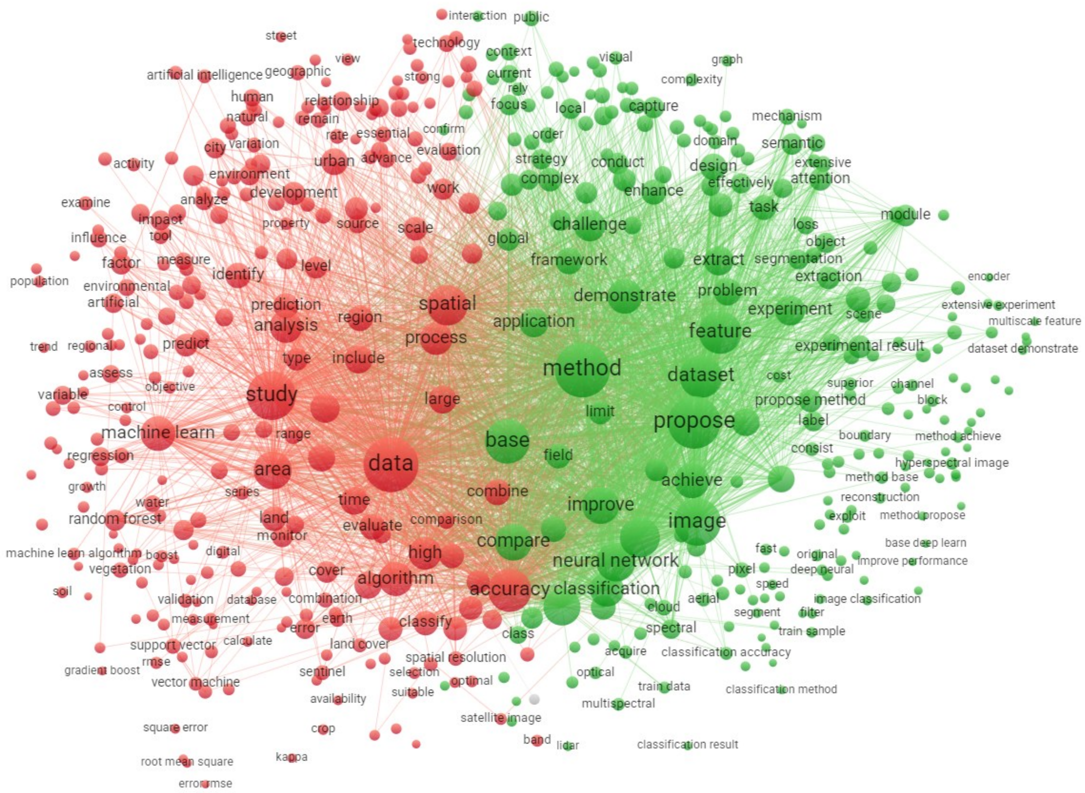

Figure 4. Co-occurrence network analysis of abstracts (lemmatized)

4.2.3. Keywords

Keywords are essential terms that provide insight into the content of a topic and are interconnected with one another. Scientific journals typically limit the number of keywords to 3 to 5. These selected keywords represent the core focus of the study. An analysis of the keywords in the studies (Appendix C, Figure C3), reveals that “learn,” “network,” “image," “deep,” and “sense” are the top 5 most frequently recurring words. As reflected in the titles and abstracts, these keyword trends indicate that the primary focus of the studies is on analysing remote sensing data through learning (machine and deep) techniques. An analysis was conducted to examine the evolution of the ten most prominent keywords over time. During the first two years of the period, classic keywords such as "random forest," "machine learning," and "remote sensing" were commonly used. However, from 2017 onwards, terms such as "deep learning," "convolutional neural networks," "semantic segmentation," and "feature extraction" became more prevalent (Figure 5). This shift indicates a diversification in the techniques employed in the research methods.

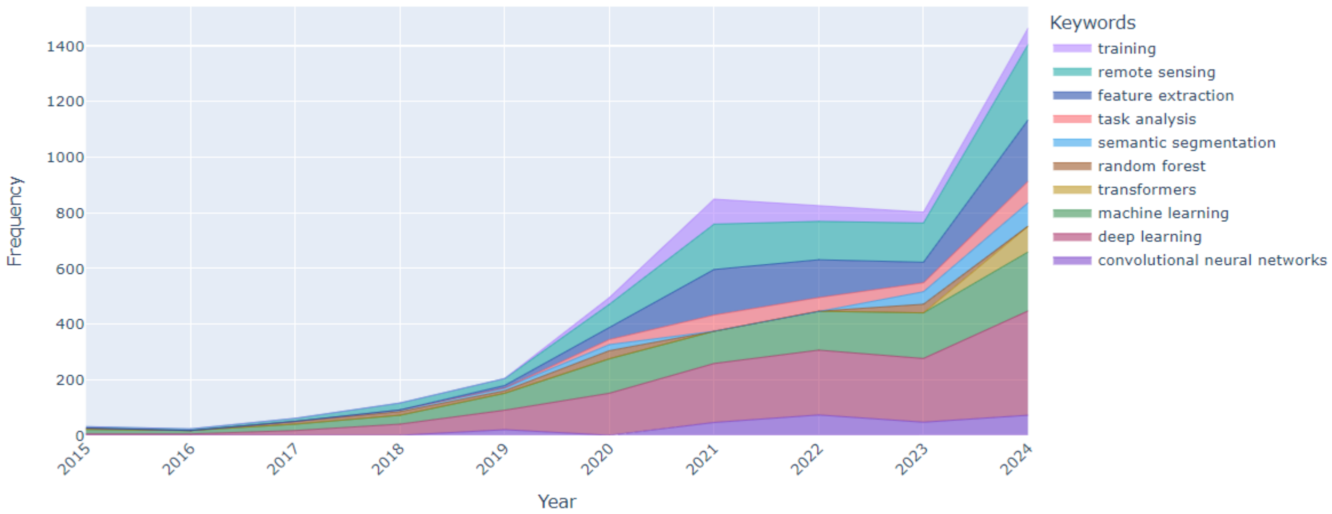

Figure 5. Evolution of the top 10 recurring keywords over time

4.3. Mapping Scientific Contributions: Authors-Affiliations, Collaborations, and Publishing

4.3.1. Authors-Affiliations

The number of authors contributing to studies on the interaction of geography and artificial intelligence from 2015 to 2024 is notably high, with a total of 18,170 authors. The ten most productive authors during this period are shown in (Appendix C, Figure C4). "Liangpei Zhang," "Fan Zhang," and "Lizhe Wang" are the top three authors. Among the ten most productive authors, only "Liangpei Zhang" and "Jonathan Li" have publications from 2015, while the productivity of the other authors begins in 2017 and continues thereafter. Additionally, there are no publications from the ten most productive authors in 2016. Despite the high volume of multi-authored studies, international co-authorship remained at 30.03%. When examining the countries of the corresponding authors (Table 2), the multiple-country publication (MCP) rates for China and the USA, countries with the highest number of publications, are 23.5%. However, the single-country publication (SCP) rates for these countries are considerably high, at 76.5%. In contrast, the countries with the highest MCP rates include the United Kingdom (49.6%), Spain (44.6%), Italy (42.9%), and Germany (40.2%).

Table 2. Corresponding Author's Countries (Top 10)

Country	Articles	Articles %	SCP	MCP	MCP %
China	2647	48.4	2024	623	23.5
USA	617	11.3	472	145	23.5
Germany	224	4.1	134	90	40.2
Korea	135	2.5	96	39	28.9
United Kingdom	131	2.4	66	65	49.6
Canada	124	2.3	80	44	35.5
Italy	119	2.2	68	51	42.9
India	114	2.1	91	23	20.2
Spain	101	1.8	56	45	44.6
Australia	97	1.8	60	37	38.1

When examining the institutions in which the analysed research is produced, the universities in the top 10 are particularly notable (Appendix C, Figure C5). All these universities are in China, with the first two located in Wuhan city. The "University of Chinese Academy of Sciences," "Beijing Normal University," and "Peking University" are in Beijing, the capital of the country. China has recognized artificial intelligence as a sector of strategic importance, which is reflected in the high number of patents related to artificial intelligence and the extensive research conducted in the field (Khanal et al., 2024). These factors further support the findings of this analysis.

4.3.2. Collaborations

Studies during the 2015-2024 period demonstrate extensive collaboration across various regions and countries. Table 3 presents the top 10 countries with frequent collaboration. China and the USA have the highest number of international connections. In addition to their bilateral cooperation, both countries engage in substantial collaboration with European nations. European countries, in turn, exhibit strong cooperation both among themselves and with other continents. Conversely, Africa shows relatively fewer connections, indicating more limited opportunities for international cooperation with this region. According to Table 3, China has collaborated with a larger number of countries, demonstrating a broader and more diverse range of international partnerships. The most frequent collaborations for China involved the USA, the United Kingdom, Germany, and Canada. Apart from China, the USA's most frequent collaborations were with the United Kingdom and Canada. This indicates that China had a significant global impact on research during the ten-year period, with its extensive and varied international cooperation shaping the field.

Table 3. Countries' Collaboration Frequency (Top 10)

From	To	Frequency
China	USA	306
China	United Kingdom	123
China	Germany	75
China	Canada	68
USA	United Kingdom	60
USA	Canada	51
China	Australia	49
China	France	45
China	Japan	44
China	Italy	39

4.3.3. Publishing: Most relevant sources

The 5,471 studies analysed were published across 166 different sources, indicating a concentration of research in select publication outlets. As shown in the top ten most relevant sources (Appendix C, Figure C6), studies are particularly concentrated in three journals. Notably, one-third of all articles were published in the “IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing”. As the title suggests, this journal specializes in earth observations and remote sensing applications. The prominence of "remote sensing" as the most frequently used term pair in the previous sections aligns with this journal's dominance in the publication of related studies. Following this journal are the “ISPRS Journal of Photogrammetry and Remote Sensing” and the “ISPRS International Journal of Geo-Information”, both of which also focus on remote sensing topics. A common feature of the top 10 journals in which the most frequently published research appears is that they are all related to the field of geography. Considered from a broader perspective, these journals focus on technological (such as geographical information systems and digital applications), urban, and environmental issues. More specifically, the shared themes among these journals include remote sensing, technology, geographical information systems, environmental studies, coastal research, urban systems, city planning, and human-environment interaction. Figure 6 presents the number of studies published in the top ten sources of scientific production over the years. From 2015 to 2018, the number of publications in each journal showed a slow but steady increase. However, starting in 2019, there was a significant rise in production, particularly in three of the journals. The "IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing" consistently led in terms of the number of publications across all years, except for 2018 and 2019.

4.4. Tracking Research Themes: Topic Modelling

One of the primary objectives of this study is to identify the key themes of relevant studies published between 2015 and 2024, as well as to highlight areas where future research is needed. The findings from various analyses related to this objective are presented in this chapter. The analyses conducted to identify these themes primarily utilized the abstracts of the studies, as abstracts provide essential insights into the purpose, methodology, findings, and conclusions of the study. To analyse the evolution of topics over time and how topics were represented at different periods, dynamic topic modelling and topic modelling by year were performed using the abstracts of 5,471 publications from 2015 to 2024. Dynamic modelling was used to track the development of topics over time. The top ten prominent topics throughout the period, as identified by BERTopic, are presented in Figure 7.

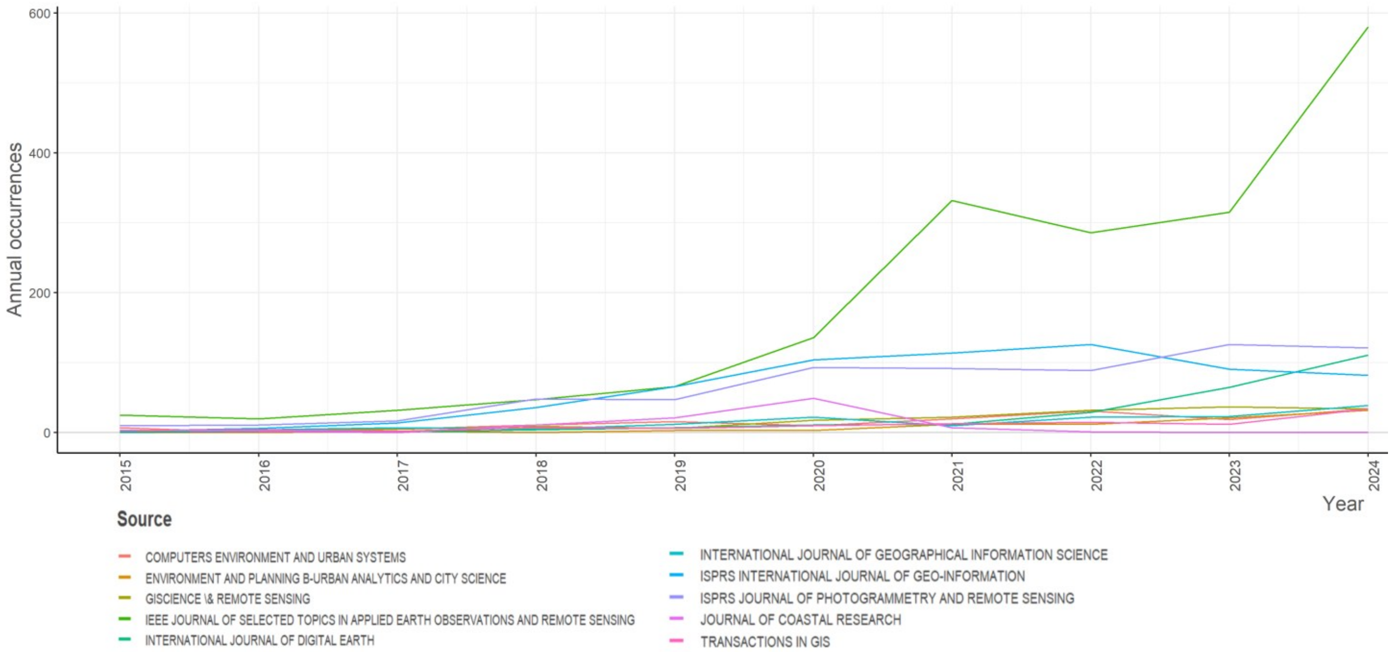

Figure 6. Sources' production over time (per year)

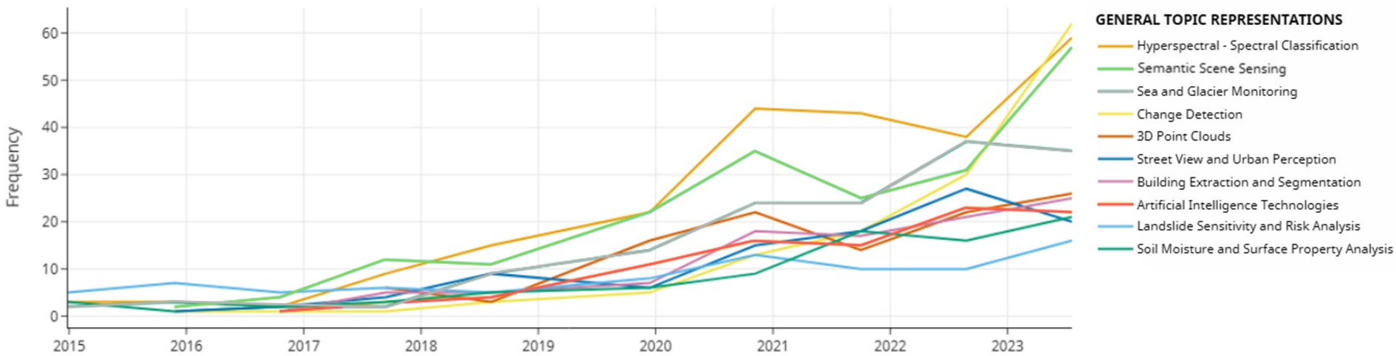

Figure 7. Topics over time (2015-2024)

Almost all the significant topics show an increasing trend over the period, with a particularly notable rise after 2020. Topics such as "classification of hyperspectral images," "semantic scene sensing for remote sensing," "change detection," and "3D point clouds" reflect the growing interest in image processing and remote sensing. The increase in research on urban sensing and building extraction underscores the emphasis on city-oriented studies, while the rise in artificial intelligence technologies indicates a strong adaptation to technological advancements. Additionally, the continued focus on landslide susceptibility research highlights the ongoing importance of natural disaster studies. To further explore these topics by year, topic modelling specific to each year was conducted, allowing for the identification of the prominent themes each year. The results of this yearly modelling are shown in Figure 8, where the first four topics of each year are presented. The ranking of prominent topics varies from year to year, demonstrating the evolving interest in different research areas over time.

This analysis reveals several important insights. The analysis and classification of remote sensing imagery dominated much of the period, reflecting its central role in the field. Other frequently researched topics include landslide susceptibility, urban change and development, and various elements of cities. By 2021, technology-integrated topics such as change detection, object detection, geography and artificial intelligence, and social media analysis began to gain more importance. Change detection and object detection, for example, are closely linked to the "image recognition" domain within artificial intelligence. Social media analysis, which was first observed in 2017, continued steadily in 2021, 2022, and 2023, indicating the growing use of spatial data derived from social media platforms (such as post location, user location, or mentioned location) in research. From 2021 onward, themes related to geography and artificial intelligence, along with social media analysis, persisted, while new topics emerged, including model proposals, disaster research, and mobility studies. In conclusion, while certain themes recurred throughout the decade, this period has been marked by diversity and a broad range of topics. Research in both geography and AI has evolved in parallel, with the two fields increasingly complementing one another.

5. Conclusions and Discussion

This study provides an overview of the status, trends, themes, and international collaborations within the interaction of artificial intelligence and geography over the last decade, based on WoS data and analysed using AI-powered methods. During this period, geography research incorporating artificial intelligence algorithms and techniques gained substantial momentum. The annual volume of studies has demonstrated a steady increase, with research output at the intersection of artificial intelligence and geography surging significantly from 2020 onwards. The distribution of research across 124 countries, coupled with rising collaboration rates, underscores the global interest in this domain. Concurrently, this quantitative growth has been matched by the evolution and diversification of research methodologies and focal topics. .

This intense interaction between geography and artificial intelligence will only increase with the expansion of research in the field of artificial intelligence. We believe that this study provides important insights into making sense of this increasingly intense and complex interaction between geography and artificial intelligence. A bibliometric view of this interaction over the last decade and assessments of the current situation and future potential for geography are presented below.

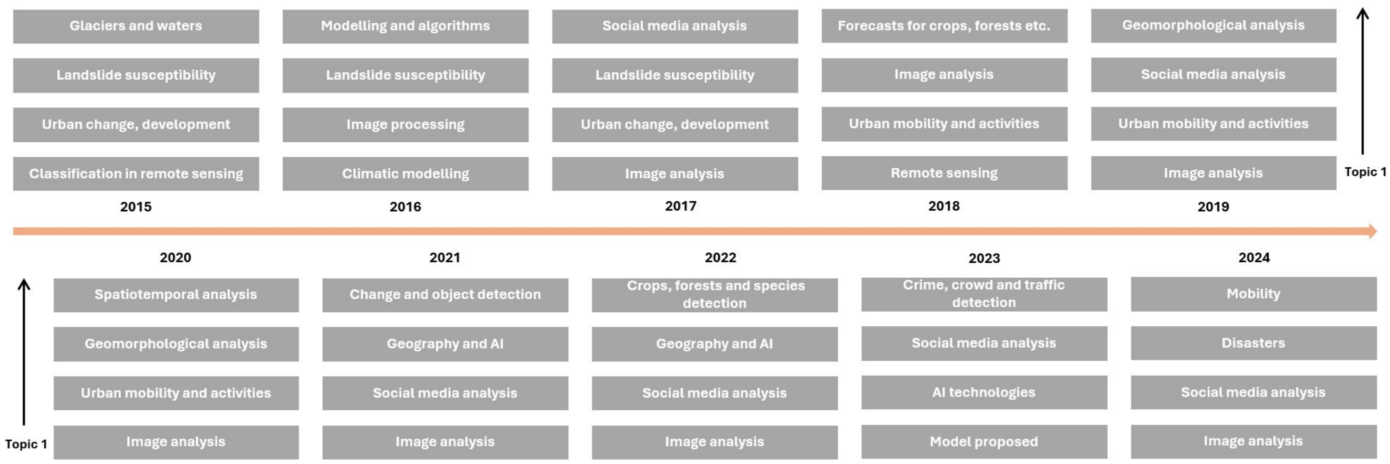

Figure 8. The top 4 topics by year (2015-2024)

5.1. Global Trends in AI-Geography Research: Productivity, Collaboration, and Key Players

Globally, China and the USA led the field in terms of research output in the interaction between artificial intelligence and geography. China took the lead in 2015 and maintained this position throughout the period, consistently achieving the highest productivity numbers. From 2015 onwards, China was closely followed by the USA, with an increasing number of countries from Europe, South America, Asia, Africa, and Australia contributing to the research. At both the single-country and multiple-country publication levels, the top three countries based on corresponding authors were China, the USA, and Germany. Although China and the USA are the leaders in terms of research output, the rates of multi-country publications are low, and most of the research collaborations have taken place at the national level. In terms of international cooperation, the UK, Spain, Italy, and Germany are the leading countries.

In terms of institutional output, Wuhan University, China University of Geosciences, and the Aerospace Information Research Institute Chinese Academy of Sciences were the top three institutions contributing the most publications. A significant portion of all publications appeared in journals such as the "IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing", the "ISPRS Journal of Photogrammetry and Remote Sensing", and the "ISPRS International Journal of Geo-Information". This highlights the strong tendency of publications toward technical journals and underscores the significant interest in remote sensing and geographic information systems (GIS) within geography research.

5.2. Evolving Methodologies, Thematic Shifts, and Future Prospects in AI-Geography Research

- Changes and improvements in technical and data

Artificial intelligence has triggered a significant methodological transformation in geography research with its data processing capacity and modelling capabilities. As can be seen from the titles, abstracts, and keywords, the studies in the period 2015-2024 are technically based mostly on machine learning, deep learning, and remote sensing. In the early years of the period, machine learning algorithms, particularly standard algorithms such as random forest, support vector machine, as well as artificial neural networks and classification, were used. These techniques played a significant role in GIS and remote sensing research. Over time, the range of techniques expanded, incorporating more advanced machine learning and deep learning algorithms, neural networks, data analytics, feature extraction, and transformers. Along with this diversification of methods, there was a concerted effort to improve the success rates of these techniques. Although model evaluations were not commonly seen in geography research in the past, the results indicate a growing adoption of such evaluations. Furthermore, in addition to traditional satellite imagery, new and diverse data sources, such as training datasets, social media data, and web platforms, have also been incorporated into research. These trends highlight that advancements in artificial intelligence are being closely followed and effectively integrated into the methodological frameworks of geography research.

- Expanding research themes

The focus of research themes has evolved significantly over the years, alongside the ongoing themes. In the early years of the period, classical geographical analyses such as remote sensing practices, natural hazards, and climate studies were dominant, whereas, over time, approaches like artificial intelligence, data science, and social media analysis have become more integrated into geographical research. A notable trend is the concentration of topics within the realm of "physical geography", one of the two primary branches of geography. Image analysis has remained a recurring topic almost every year, pointing to the continued importance of remote sensing and image processing in geographical studies. These analyses are closely linked to detecting and forecasting climatic phenomena, agricultural yields, and land-use changes. Social media data analysis has also emerged as a recurring theme, highlighting the growing relevance of geography to digital social data. The detection and prediction of environmental and natural hazards have consistently been a key focus. Topics related to urban change, development, and mobility reflect a growing emphasis on urban studies. Furthermore, the emergence of the title "Geography and AI" in 2021 and the inclusion of "AI technologies" in 2023 indicate a strengthening integration of geography with artificial intelligence, signalling a deeper convergence between the two fields.

- *The Imbalance Between Physical and Human Geography*

The findings show that the reflections of AI applications in geography are largely concentrated in the fields of physical geography and remote sensing. While topics such as remote sensing, land classification, susceptibility analysis, and disaster management make extensive use of machine learning and deep learning techniques, the potential of AI in human geography studies has not yet been fully explored. Indeed, a limitation stands out in the integration of artificial intelligence techniques into human geography analyses. However, considering the multidimensional structure of geography, urban and social analyses, spatiotemporal analyses, migration models, examination of spatial inequalities, political (election) outcome, and many other topics can be addressed further with natural language processing, machine learning, and big data analytics. In future studies, increasing interdisciplinary collaborations and using new algorithms for qualitative and mixed data analysis will be an important step in encouraging the integration of human geography with artificial intelligence. Addressing the social, cultural, economic, and other dimensions of human geography through artificial intelligence could provide valuable insights and contribute to a richer understanding of this field.

- *Future Projections: The Co-Evolution of Geography and AI*

Soon, some specific approaches and issues for the interaction between geography and artificial intelligence may be noteworthy.

(1) Autonomous GIS: This approach, introduced in 2023 in line with the promising capabilities of Large Language Models (LLMs) and generative artificial intelligence (GAI), offers an automated framework for solving spatial problems. The autonomous GIS approach envisions GIS evolving beyond being merely an analysis tool into an intelligence capable of perceiving, deciding, and solving spatial problems on its own (Li & Ning, 2023). Central to this vision is the use of LLMs as “reasoning cores” that interpret natural language queries, automatically gather relevant data, design multi-step geoprocessing pipelines, and generate visualizations—all without requiring expert GIS knowledge (Li et al., 2025). Early implementations, such as *GIS Copilot*—a prototype integrated with QGIS—demonstrate this potential by enabling users to perform complex spatial analyses through simple text commands (Akinboyewa et al., 2025).

Li & Ning (2023) emphasize that autonomous GIS should achieve five key goals: self-generation, organization, verification, execution, and growth. This framework signals a paradigm shift in GIS science, as the system is no longer a passive platform but an active “geo-intelligence.” However, achieving full autonomy still presents technical and methodological challenges, particularly in advanced multi-step workflows (Akinboyewa et al., 2025). Nevertheless, these developments advance the democratization of geographic analysis, lowering technical barriers and expanding access to spatial insights for non-expert users.

(2) Spatial AI: An approach that involves the use of general AI applications to understand spatial patterns, where machines are given spatial reasoning capabilities. Spatial AI is important for advanced robotics, smart cities, geospatial analysis, augmented and virtual reality, and interactive monitoring and evaluation applications (Se, 2024). This approach encompasses various forms of spatially enabled AI, such as geospatial artificial intelligence-GeoAI (Papadimitriou, 2025). Spatial AI handles a wide array of spatial data that goes beyond geographical data, including robotic sensing, augmented reality, and mobile sensor data. Nevertheless, in the context of geography, the integration of Spatial AI is primarily manifested through the framework of GeoAI (Janowicz et al., 2022; Shi et al., 2025; Liu et al., 2025; Kang et al., 2025; Mai et al., 2025; Walker & Winders, 2025). Therefore, GeoAI can be seen as the tangible expression of Spatial AI within geography.

(3) Geospatial AI (GeoAI): The origins of the term “GeoAI” can be traced back to the 2017 ACM SIGSPATIAL conference (Mao et al., 2017). GeoAI, a variation of spatial AI, includes a combination of GIS and AI technologies, with a more specific focus on geographic data. This approach, which uses artificial intelligence as an innovative way to solve spatial problems (Li & Hsu, 2022), aims to develop a new generation of machines that can imitate the human ability to perceive the environment and reason spatially, and can perform location-based analyses thanks to this ability (Gao et al., 2023). GeoAI analyses geographic data from maps, satellite imagery, GPS data, and other sources, primarily using machine learning and deep learning techniques (VoPham, 2018; Janowicz et al., 2020; Boutayeb et al., 2025). As a result, GeoAI enables automated spatial analysis, real-time geographic insights, and scalable processing of large-scale geographic datasets that would be impractical with traditional GIS methods.

GeoAI includes two approaches, “symbolic” and “subsymbolic,” like the distinction in artificial intelligence (Mai et al., 2022; 2025). In Symbolic AI, geographic knowledge and relationships are represented through logical rules and a predefined knowledge base, such as ontologies and partial knowledge graphs (Janowicz et al., 2022). Explainability, knowledge representation, and logical inference are the fundamental features of symbolic GeoAI. On the other hand, Subsymbolic GeoAI relies on connectionist models, such as artificial neural networks, that learn patterns and correlations from large datasets. This approach particularly incorporates machine learning and deep learning techniques (Janowicz et al., 2020; Mai et al., 2022; 2025). Data-driven pattern recognition and the “black box” tendency can be listed as characteristics of this approach. As expected, GeoAI involves applying AI models to solve geospatial problems, which naturally includes the two aforementioned approaches. However, there is a unique methodological core that distinguishes it from general artificial intelligence research: “spatially explicit modelling.” This core is the explicit inclusion of space and place into the AI model that is created or developed (Li et al., 2024).

Consequently, GeoAI plays a significant role in advancing geographical analysis, Earth observation, and GIS to a new level. This also presents significant challenges. Integrating the dynamics of diverse geographic applications and the unique characteristics of space into AI models requires an effort beyond current capabilities. Therefore, resolving these integration challenges constitutes a key research focus for the future success of GeoAI (Song et al., 2023).

(4) Ethics, Algorithmic-Geographic Biases and Geo-Alignment: “Ethical issues intersect uniquely with the field of Geography and GIS due to the nature and impact of geoinformation, data gathering and the power of cartographic visualization” (EuroGEO, 2024, p. 10). The concept of ethics refers to a set of behavioural principles that distinguish right from wrong within a given social system (Siau & Wang, 2020). With the rapid development of artificial intelligence (especially GeoAI) in geography research, concerns about ethical issues have also increased (Griffin, 2020; Zhao et al., 2021). Ethical issues at the intersection of AI and geography can be categorized under five headings. a. Commodification: Models, data,

and outputs generated using AI are used in intensive commercial activities. b. Responsibility: As AI accelerates mapping and the automation of analysis, the resulting output is experiencing a significant explosion. This growth raises the question of who is responsible for inaccurate, misleading, or illegal outputs. c. Geoprivacy: Providing models with large amounts of social data (e.g., social media) as training and analysis data can potentially expose individuals' personal information or bias specific groups. d. Justice and Equity: This issue highlights the potential for AI to negatively impact social and environmental justice. e. Transparency and Explainability: Models that incorporate deep learning techniques, in particular, face challenges in understanding how decisions are made, how the process operates, and many other aspects. This challenge is described as the black box problem (Kang et al., 2024).

AI models have the potential to learn and even amplify existing biases in training data. This potential typically includes data bias and algorithmic bias. In data bias, unbalanced or incomplete training data can lead artificial intelligence models to learn and reinforce stereotypes, which can result in underrepresentation. However, in algorithmic bias, AI models may be prone to bias due to biases inherent in the algorithmic structures. This is exemplified by model developer bias (Janowicz et al., 2025). For geographic analysis-models, in addition to those mentioned, there is another type of bias: "Geographic Bias." This is a type of bias frequently encountered but less studied in GeoAI research. For example, a lack of geographic diversity or data imbalance in the training data of models developed within GeoAI can lead to inconsistencies in model performance for certain geographic regions (Liu et al., 2022; Ramaswamy et al., 2023). Furthermore, Manvi et al. (2024) demonstrated that LLMs exhibit systematic bias against regions with low socioeconomic status.

Finally, at the intersection of ethics and bias is the vision of "Geo-Alignment," which aims to ensure that AI systems behave in a way that aligns with societal norms, values, and goals, and bases this alignment on spatially explicit patterns. Geo-Alignment refers to the requirement that the outputs of AI systems be sensitive to spatial and temporal context. Geo-alignment predicts that nearby regions will have similar alignment needs by analyzing factors such as spatial dependence. Through this prediction, it goes beyond the pluralistic alignment approach (Janowicz et al., 2025).

Recent developments will necessitate geographers to cooperate more with AI. However, this cooperation also brings with it ethical dilemmas, reliability issues arising from the manipulation of geographic data, and both algorithmic and geographic biases. These challenges threaten the transparency and credibility of geographic decision-making processes and risk severing ties with the discipline's theoretical roots. Therefore, to fully capitalize on the potential of this new era, it is critical for geographers to consciously navigate AI by developing ethical and context-sensitive frameworks such as "Geo-Alignment."

(5) The black box problem and explainable AI (XAI): The term "black box" refers to the fact that the complex inner workings of artificial intelligence models are not easily understood or visible to humans. While the relevant models produce a result based on input data, it remains unclear how and which factors they consider. Moreover, models may produce different results for different users (Bathaee, 2018). This lack of transparency constitutes an important limitation for the discipline of geography, which focuses on understanding the cause-and-effect relationships of spatial processes. As stated in an article by the USA agency The Defense Advanced Research Projects Agency (DARPA): "There is an inherent tension between machine learning performance (predictive accuracy) and explainability; often the highest performing methods (e.g., deep learning) are the least explainable, and the most explainable (e.g., decision trees) are less accurate" (DARPA, 2016, p. 7). The use of architecture defined as black boxes and the concerns due to this opacity have led to the necessity of looking inside these boxes (Carabantes, 2020).

In this context, it is very important for future studies to focus on the explainable AI approach that makes it understandable how artificial intelligence models make decisions. The explainable AI approach, simply put, aims to put the models and algorithms of artificial intelligence in a "glass box" (Rai, 2020; Arrieta et al., 2020). However, the application of explainable AI in the geospatial framework has been limited. Despite this limitation, there are sixteen different explainable AI approaches that have been used or have the potential to be used in geospatial applications, ranging from rule-based explanations to quote visualizations and audio, to neuron-based explanations, prototypes, and critiques (Xing & Sieber, 2023). Nevertheless, there are efforts to integrate the explainable AI approach into geography, remote sensing, and GeoAI. Abdollahi & Pradhan (2021) used SHAP, an explainable AI method, to interpret vegetation classification results from a convolutional neural network (CNN). Behl et al. (2021) applied LIME to analyse misclassified earthquake-related tweets from Italy and Nepal, identifying keywords influencing usefulness predictions. Guo et al. (2021) reduced CNN training and inference time in land-use classification through neuron and layer pruning. Zhou et al. (2022) enhanced geolocation accuracy of tweets by integrating Volunteered Geographic Information (VGI) into Graph Neural Networks. Li (2022) compared XGBoost with geographically weighted regression to predict the spatial distribution of ride-hailing demand.

Explainable AI appears to be an important approach that aims to reconcile predictive power with interpretability. For geographers, the adoption of explainable AI can be considered not merely a technical concern but also an epistemological imperative.

5.3. Sensitivity Analysis: Core Geography and the Broader Interdisciplinary Landscape

Regarding publication counts , while the main dataset focused on geography contains a more limited number of studies, a higher volume of AI-focused studies was observed in the other three fields (Remote Sensing; Geosciences, Multidisciplinary; Environmental Sciences). While the studies in the main dataset concentrate on core geographical topics, it is evident that most studies in the other three fields are centred on technical/applied areas. A significant increase in the number of authors, countries, and journals was also noted, supporting an expansion of global participation. One of the most striking findings is that, despite the expanded scope of the research, the international collaboration rate remained stable at approximately 30% across all datasets. This can be interpreted as a general characteristic of the field.

Sources, although China and the USA led the top ten countries with the most publications in the main dataset, European countries such as Germany, the UK, Italy, and Spain were also included. In the extended analyses (WoS and Scopus), China and the USA continued to lead significantly. However, it is noteworthy that India and Iran, which were not on the list, rose to the top five. The journals with the most publications in the main dataset were technical journals directly related to geography, GIS, and remote sensing. The list in the expanded WoS analysis still includes technical journals focused on remote sensing. In the Scopus analysis, however, there is a noticeable change, with environmental, sustainability, and energy-focused journals ranking at the top.

The topics in the main dataset focused on various application areas of geography, including remote sensing and image analysis, landslide susceptibility, urban change and development, climate modelling, and spatiotemporal analysis, among others. In the expanded WoS analysis, the most dominant topic each year was "AI, methodology, and model developments." This indicates that the focus in case studies was more on the development of artificial intelligence methodology than on geographical problems. In the Scopus analysis, the main topics were similarly "AI-Based Methodology" and "Neural Network Architectures." In other words, the focus was again on the methodology itself. Two important points emerge here: 1) The original analysis comprehensively revealed the interaction between "geography and artificial intelligence," and the topics come from the fundamental sub-disciplines of geography. 2) Sensitivity analyses have shown how research in other fields uses artificial intelligence with a focus on technical/applied practices. It can be concluded that the focus here is on developing artificial models to solve and explain specific environmental or technical problems rather than geographical problems.

The sensitivity analysis confirms the reliability of the underlying trends observed in the original findings—namely, the dominant role of AI methodologies, the leadership of China and the USA (publications and international collaboration), the central importance of remote sensing, and the dynamics of international collaboration. However, it also reveals that a substantial portion of AI–geospatial research extends beyond the core of geography, taking place within interdisciplinary domains such as environmental sciences, engineering, and remote sensing.

Funding: This research received no external funding.

Data Availability Statement: The bibliometric data used in the research can be accessed using relevant keywords from the Web of Science (WoS) database. https://www.webofscience.com/wos/

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Category Numbers (High to low) + Total:

Rank	Web of Science Category	Count
1	Engineering, Electrical \& Electronic; Geography, Physical; Remote Sensing; Imaging Science \& Photographic Technology	1839
2	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science \& Photographic Technology	749
3	Computer Science, Information Systems; Geography, Physical; Remote Sensing	641
4	Geography, Physical; Remote Sensing	455
5	Geography	449
6	Geography, Physical; Geosciences, Multidisciplinary	279
7	Computer Science, Interdisciplinary Applications; Engineering, Environmental; Environmental Studies; Geography; Operations Research \& Management Science; Regional \& Urban Planning	153
8	Computer Science, Information Systems; Geography; Geography, Physical; Information Science \& Library Science	147
9	Environmental Sciences; Geography, Physical; Geosciences, Multidisciplinary	97
10	Environmental Studies; Geography; Regional \& Urban Planning; Urban Studies	96
11	Ecology; Environmental Studies; Geography; Geography, Physical; Regional \& Urban Planning; Urban Studies	69
12	Geography, Physical	53
13	Economics; Geography; Transportation	51
14	Ecology; Geography, Physical	46
15	Computer Science, Information Systems; Geography, Physical	42
16	Environmental Sciences; Environmental Studies; Geography; Regional \& Urban Planning; Urban Studies	35
17	Ecology; Geography, Physical; Geosciences, Multidisciplinary	34
18	Geography; Geography, Physical	25
19	Environmental Sciences; Geography; Geography, Physical; Remote Sensing	20
20	Economics; Environmental Studies; Geography; Regional \& Urban Planning	20
21	Geography; Geography, Physical; Remote Sensing	16
22	Environmental Studies; Geography	14
23	Environmental Sciences; Geography, Physical; Geosciences, Multidisciplinary; Meteorology \& Atmospheric Sciences	10
24	Geography, Physical; Geosciences, Multidisciplinary; Paleontology	9
25	Geography; Political Science	9
26	Computer Science, Information Systems; Geography; Geography, Physical; Remote Sensing	9
27	Environmental Studies; Geography; Regional \& Urban Planning	9
28	Geography; Regional \& Urban Planning	8
29	Green \& Sustainable Science \& Technology; Geography, Physical	8
30	Economics; Geography	7
31	Development Studies; Economics; Geography	7
32	Forestry; Geography, Physical	7
33	Education \& Educational Research; Geography	7
34	Geography, Physical; Geology	7
35	Geography; Regional \& Urban Planning; Transportation	5
36	Geography; Urban Studies	4
37	Demography; Geography	4
38	Business; Economics; Geography	4
39	Environmental Sciences; Environmental Studies; Geography	4
40	Geography; Geosciences, Multidisciplinary; Urban Studies	3
41	Area Studies; Geography	3
42	Environmental Sciences; Geography, Physical	2
43	Geography; Water Resources	2
44	Green \& Sustainable Science \& Technology; Environmental Studies; Geography; Regional \& Urban Planning; Urban Studies	2
45	Anthropology; Geography; Sociology	1
46	Green \& Sustainable Science \& Technology; Geography, Physical; Remote Sensing	1
47	Geography; Sociology	1
48	Geography; Public, Environmental \& Occupational Health; Remote Sensing	1
49	Computer Science, Information Systems; Computer Science, Interdisciplinary Applications; Geography; Geography, Physical; Information Science \& Library Science	1
50	Geography; Social Sciences, Interdisciplinary	1
51	Geography; Transportation	1
52	Geography, Physical; Geology; Oceanography	1
53	Computer Science, Information Systems; Geography; Remote Sensing	1
54	Geography, Physical; Oceanography	1
55	Environmental Studies; Geography; Regional \& Urban Planning; Public Administration	1
–	TOTAL	5471

Figure A1. WoS categories and categorization variations in the dataset

Appendix B

Table B1. Topic modeling stages, tools, parameters & descriptions

Stage	Tool	Parameters & Descriptions
Data Preparation	Custom Python Function	Source column: \`Title\` or \`Abstract\` Cleaning: Null entries and texts with fewer than 3 words are filtered out.
Text Embedding	SentenceTransformer	Model: \`all-MiniLM-L6-v2\` Description: Converts texts into semantically rich numerical vectors.
Dimensionality Reduction	UMAP	n_neighbors: 15 n_components: 5 metric: 'cosine' random_state: 42 Description: Reduces the dimensionality of vectors to optimize for clustering while preserving semantic structure.
Clustering	HDBSCAN	min_cluster_size: 10 min_samples: 5 cluster_selection_method: 'eom' Description: Groups similar documents to form topics and identifies outliers (topic-1).
Topic Representation	CountVectorizer (with c-TF-IDF)	ngram_range: (1, 2) (Unigrams & Bigrams) stop_words: 'english' min_df: 2 (Minimum document frequency) max_df: 0.95 (Maximum document frequency) Description: Extracts keywords and keyphrases that best describe each topic cluster.
BERTopic Configuration	BERTopic	min_topic_size: 10 nr_topics: 'auto' (Automatically determines the number of topics) top_n_words: 10 (Number of keywords per topic) calculate_probabilities: True

Appendix C

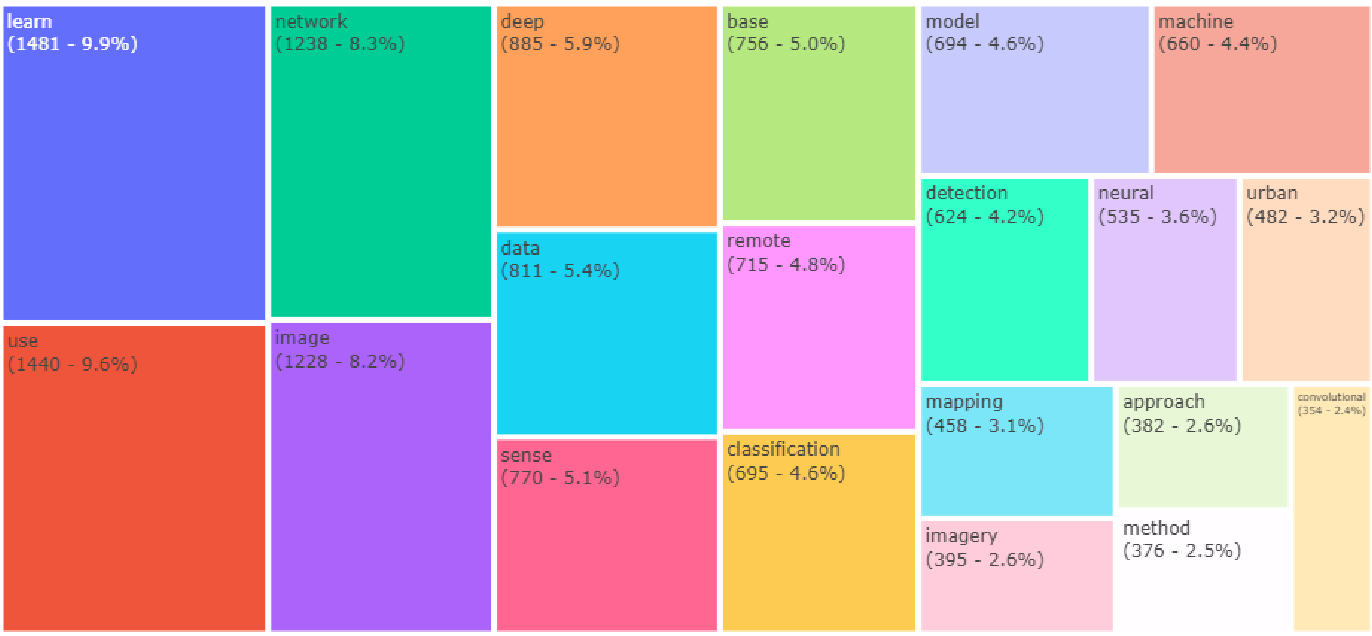

Figure C1. Treemap of the top 20 most recurring words in the titles (lemmatized)

https://doi.org/10.48088/ejg.b.ogl.16.2.372.392

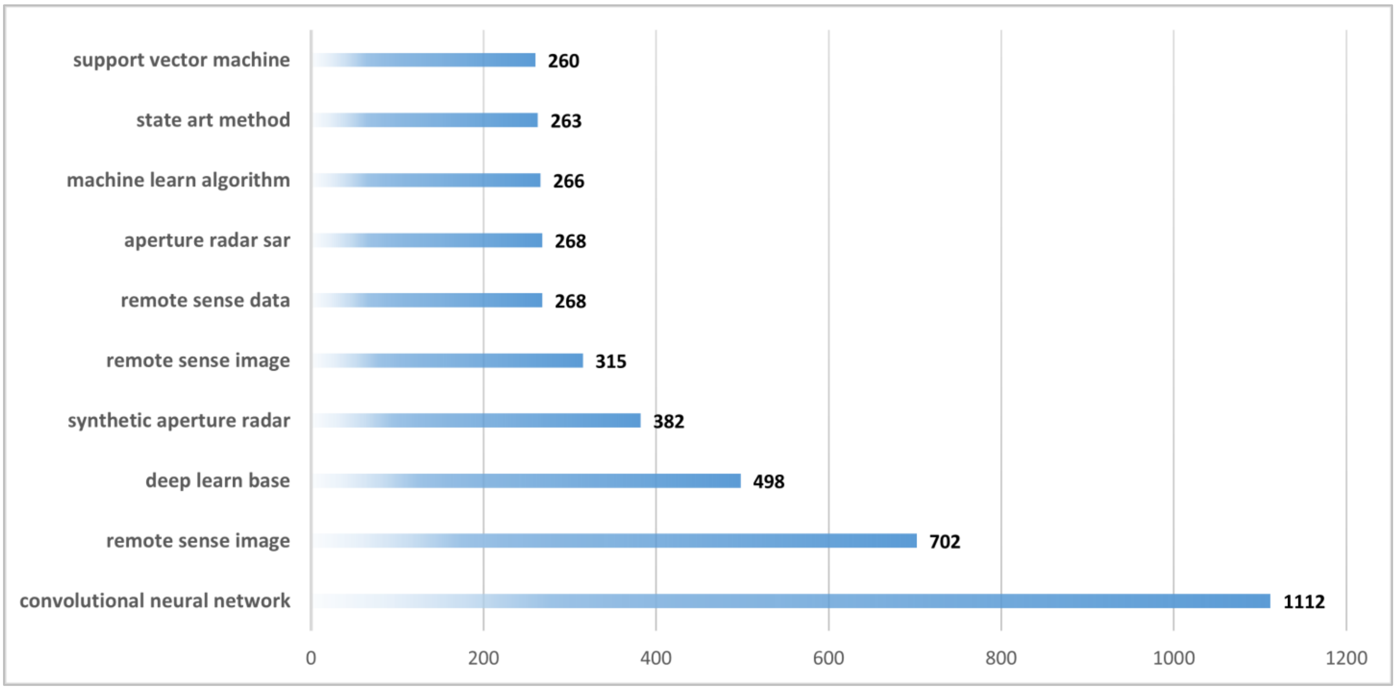

Figure C2. The most recurrent 3-word sequence in the abstracts (lemmatized)

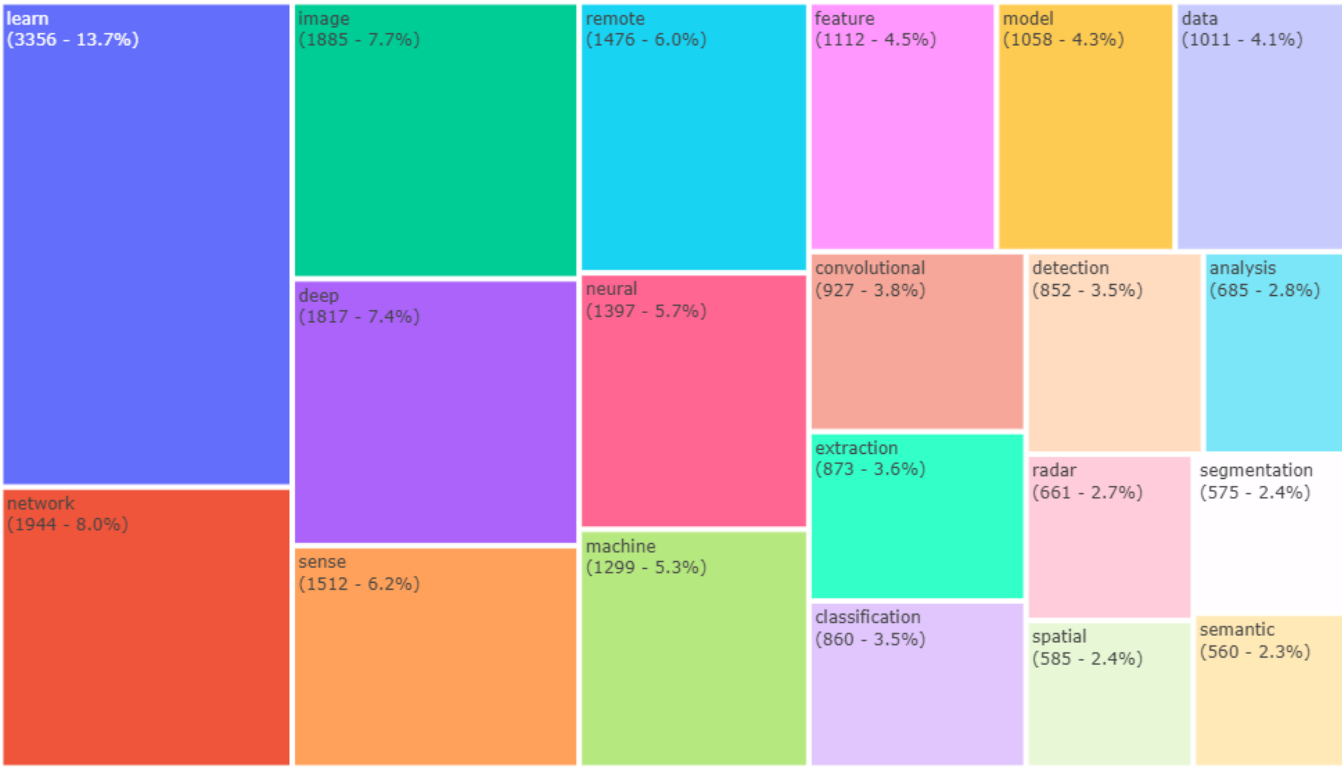

Figure C3. Treemap of the top 20 most recurring keywords in the abstract (lemmatized)

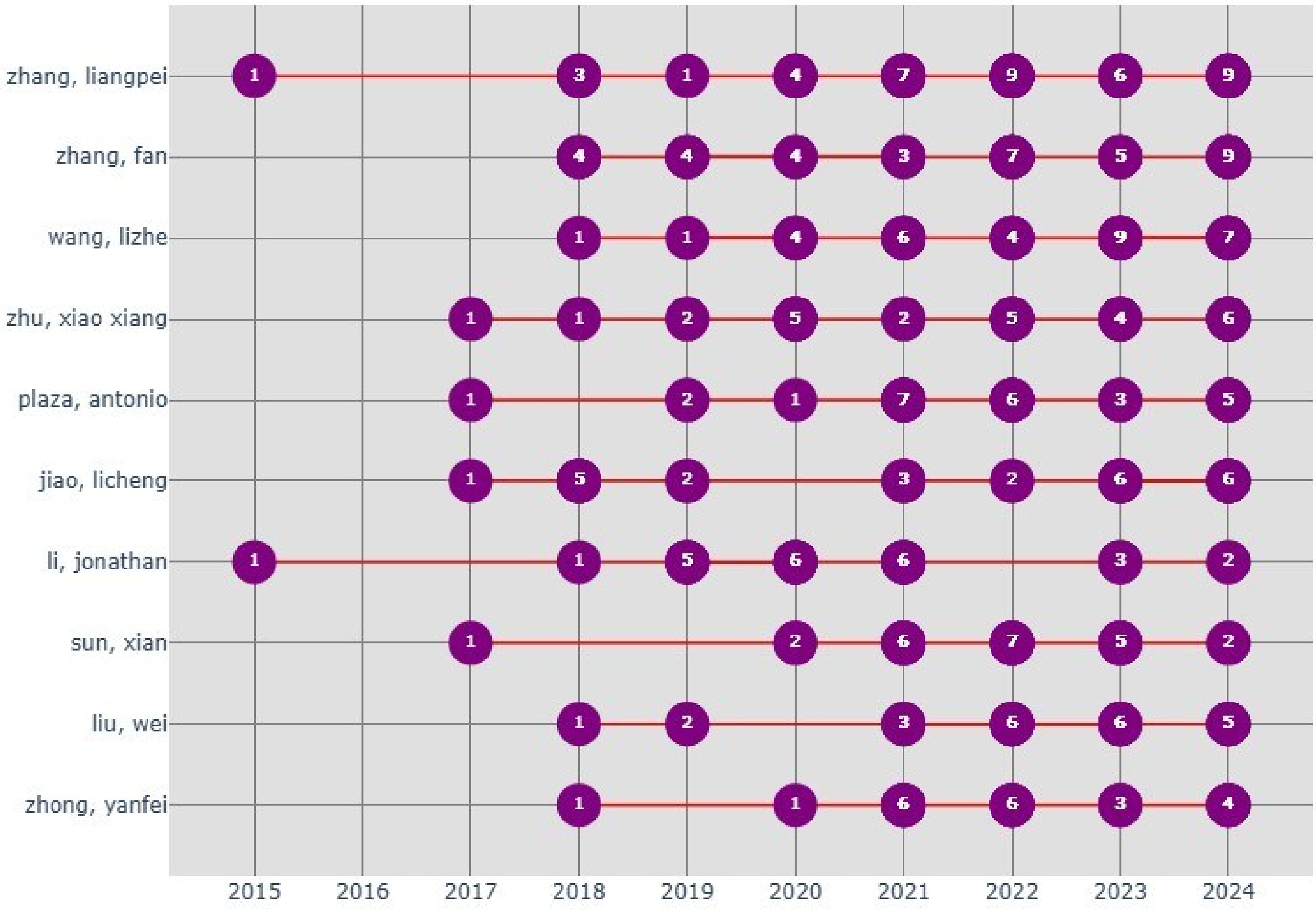

Figure C4. The most productive authors from 2015-2024

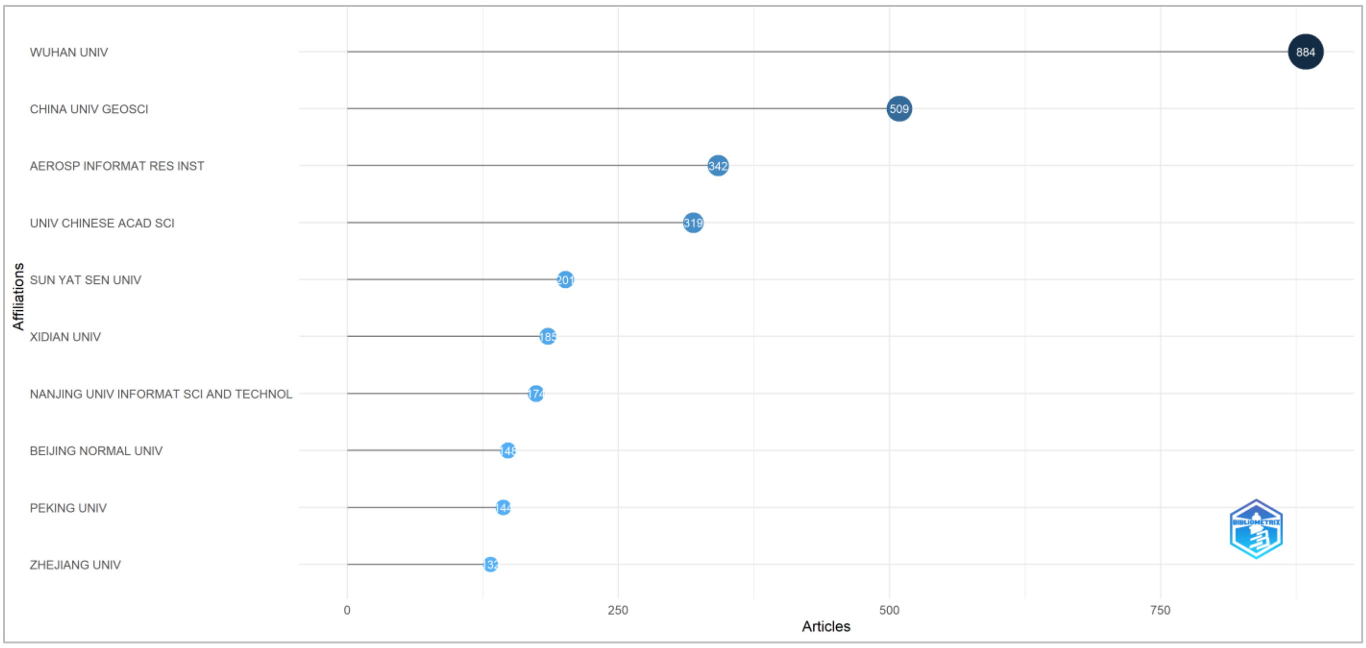

Figure C5. The 10 most productive organizations (2015-2024)

https://doi.org/10.48088/ejg.b.ogl.16.2.372.392

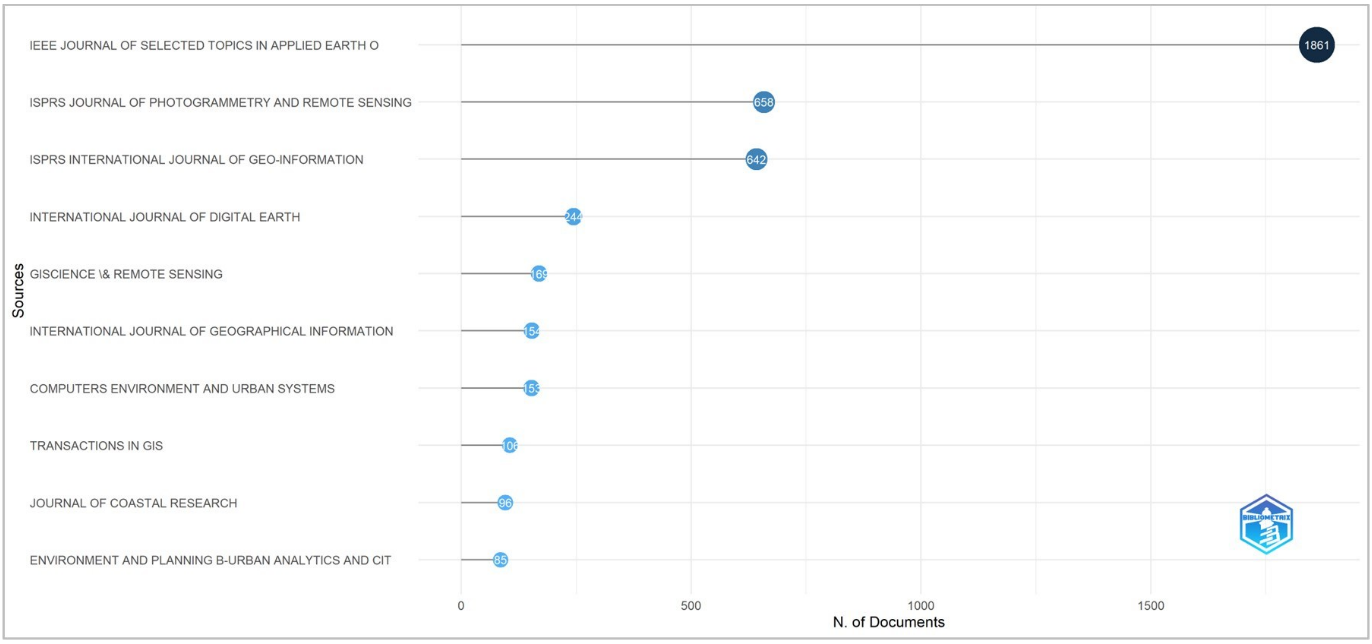

Figure C6. Most relevant sources (2015-2024)

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