

Geospatial Education at the GIS–GeoAI Interface: A PRISMA-Guided Bibliometric Mapping of a Scopus Corpus, 2002–2025

Sony Nugratama Hijrawadi*¹ , Epon Ningrum^{1,2} , Nandi^{1,2} , Lili Somantri^{1,2} 

¹Doctoral Study Program in Geography Education, Faculty of Social Sciences Education, Universitas Pendidikan Indonesia, Indonesia

²Geographic Information Science Study Program, Faculty of Social Studies Education, Universitas Pendidikan Indonesia, Indonesia

ARTICLE INFO

Article History:

Received: July 01, 2026

Revision: September 29, 2026

Accepted: September 30, 2026

Keywords: Geospatial Information;
Geography Education;
Geographic Information Systems;
Geospatial Artificial Intelligence

Corresponding Author

E-mail:

sony.nugratama@upi.edu

ABSTRACT

Geospatial information is used in education as disciplinary content and as a learning technology, while computational geospatial research increasingly employs artificial intelligence, machine learning, deep learning, and remote sensing. This study maps the publication performance and thematic structure of a broad Scopus corpus at the interface of geospatial technology and education from 2002 to 2025. A PRISMA-guided review and bibliometric analysis were conducted on 125 documents from 68 sources using bibliometrix and Biblioshiny in R. The corpus showed an annual publication growth rate of 10.99%, an average of 11.93 citations per document, and 2.81 authors per document. The Journal of Geography was the most productive source, while De Lázaro-Torres and De Miguel González were the most productive authors. Co-word analysis identified an educational GIS cluster, a geospatial technology and learning cluster, and a computational geospatial cluster containing GeoAI-related terms. The increased visibility of the computational cluster in 2022–2025 indicates an emerging thematic orientation, not evidence that GeoAI has replaced GIS-based education or already dominates educational practice. Because the search expression included the broad term learning and the corpus retained several technical geospatial records, the findings should be interpreted as an exploratory map of the education–technology interface. The proposed instructional sequence is therefore a theory-informed research proposition that requires empirical validation.

INTRODUCTION

Recent advances in geospatial information technologies have significantly transformed the way people perceive, understand, represent, and make decisions about spatial phenomena. Geospatial information, defined as data that is referenced to specific locations on the Earth's surface, has become a critical knowledge infrastructure that underpins decision-making across a wide range of sectors, including regional planning, disaster risk reduction, transportation, and precision agriculture (Saipiatuddin et al., 2026; Sajjad, 2021; Tomlinson, 2013).

In educational contexts, geospatial information has two analytically distinct roles: it may be the content to be learned (learning about spatial data, mapping, GIS, and spatial reasoning), or it may function as a pedagogical tool used to support inquiry and the development of spatial thinking. A third category must be distinguished from both: technical geospatial research that uses machine learning or other computational methods without investigating learners, teachers, curricula, or educational outcomes. In this study, GeoAI refers operationally to artificial-intelligence methods applied to georeferenced data or spatial problems; GeoAI counts as educational research only

when the record includes an explicit educational setting, actor, process, or outcome. This distinction is essential because the co-occurrence of educational and computational terms does not by itself demonstrate pedagogical integration (Golledge, 2002).

Studies of GIS in educational settings report benefits for spatial analysis, map literacy, geographic inquiry, and problem solving (Battersby, 2005; Milson & Earle, 2007; Nielsen et al., 2011). WebGIS and digital atlases have also been examined in secondary education (De Lázaro-Torres et al., 2017; De Miguel González & De Lázaro-Torres, 2020), while GIS is established in parts of higher-education curricula (Cox et al., 2019; Hupy, 2011). By contrast, several frequently cited GeoAI sources concern technical geospatial applications rather than education directly (Bai et al., 2023; Gahegan, 2020; Ito & Biljecki, 2021). They are therefore interpreted here as indicators of a technological frontier adjacent to educational research, not as direct evidence of teaching effectiveness or curriculum adoption.

Although the literature on geospatial information in education continues to expand, few studies systematically map the field's intellectual structure, including key contributors, leading publication outlets, thematic evolution, and emerging research directions. Such mapping is essential for at least three reasons. First, this field is inherently multidisciplinary, bringing together geography, geographic information science, educational technology, and computer science. Consequently, novice researchers often struggle to identify foundational references, influential scholars, and major research streams. Second, the rapid pace of technological innovation—from desktop GIS and WebGIS to Geospatial Artificial Intelligence (GeoAI)—necessitates the continuous updating of research landscapes to capture emerging trends and shifts in scholarly focus. Third, developing geospatial-information-based learning models requires identifying core themes, promising research areas, and existing knowledge gaps to ensure the novelty and

relevance of newly developed educational frameworks and instructional models.

In addition, the limited development and implementation of geospatial information in education can be attributed to the relatively low levels of teacher capacity and readiness. These challenges are closely associated with teachers' motivation, professional experience, and confidence in using geospatial technologies, even though curriculum frameworks and external support mechanisms have become increasingly favorable in many educational contexts (Bernhäuserová et al., 2022; Humble, 2023; Misařová et al., 2024; Shakhislam et al., 2024). Other major barriers include inadequate infrastructure, limited technical support, and research designs that remain narrow in scope and fragmented across disciplines (Baker et al., 2015; Bernhäuserová et al., 2022; Bondarenko, 2025; Konstantakatos & Galani, 2022). Although the educational benefits of geospatial information technologies are widely recognized, the field still needs a more systematic, long-term, interdisciplinary research agenda to realize their transformative potential in education fully.

Previous reviews provide important but differently bounded evidence. (Bernhäuserová et al., 2022) synthesize barriers to GIS implementation in education; (Konstantakatos & Galani, 2022) examine GIS in geographical and environmental education; and (Bondarenko, 2025) reviews GIS-based geography teaching over a more restricted period. The present study differs by combining PRISMA-guided selection, performance analysis, and science mapping across 2002–2025 to examine the interface between geography/GIS education and computational geospatial themes. This is a bounded contribution rather than a claim to be the first or exhaustive review. The analysis describes thematic visibility and relationships in the retrieved corpus; it does not test an epistemological paradigm shift or the effectiveness of a learning model. Its practical relevance lies in identifying propositions that curriculum developers and researchers can subsequently test,

principally in relation to SDG 4. Connections to SDGs 11 and 13 are conditional on instructional applications involving urban, disaster, or climate problems.

Bibliometric analysis is a quantitative approach that can map the development of a scientific field by assessing publication performance and visualizing intellectual structures within the literature (Aria & Cuccurullo, 2017; Donthu et al., 2021). When combined with a Systematic Literature Review (SLR) following PRISMA guidelines (Haddaway et al., 2022; Page et al., 2021), this approach enables a transparent, replicable, and comprehensive synthesis of existing knowledge. Based on the aforementioned background, this study aims to: (1) examine the publication performance of geospatial information research in education from 2002 to 2025; (2) identify the most influential sources, authors, and documents; (3) map the thematic structure and evolution of research topics; and (4) formulate a future research agenda to support the development of geospatial-information-based learning models.

RESEARCH METHODS

This study employed a Systematic Literature Review (SLR) design combined with bibliometric analysis. The SLR approach ensured transparency and reproducibility in the literature selection process, while bibliometric analysis quantified publication performance and mapped the field's intellectual structure (Donthu et al., 2021; Zupic & Čater, 2015). The selection process followed the PRISMA 2020 framework (Page et al., 2021), which consists of four stages: identification,

screening, eligibility assessment, and inclusion. The PRISMA protocol was originally developed in the health and medical science (Page et al., 2021) and has since been widely adopted across diverse research areas worldwide, including business and management research (Donthu et al., 2021; Zupic & Čater, 2015), geographical and environmental education (Bernhäuserová et al., 2022; Konstantakatos & Galani, 2022), and GIS-based geography teaching (Bondarenko, 2025), demonstrating its robustness as a framework for transparent and replicable literature selection. Figure 1 presents the PRISMA 2020 flow diagram used in this study, generated following Haddaway et al. (2022).

Data were retrieved from Scopus through TITLE-ABS-KEY combinations linking geospatial terms (including “geospatial information,” “geospatial technology,” and “geographic information system”) with education-related terms (including “education,” “teaching,” “learning,” and “curriculum”). The search covered 2002–2025, English-language records, and the subject areas Social Sciences, Earth and Planetary Sciences, Environmental Science, and Multidisciplinary Studies. The available audit record did not preserve the exact executable query string and retrieval date; therefore, this article alone cannot replicate the search exactly. The standalone word “learning” also creates a predictable false-positive pathway through phrases such as “machine learning” and “deep learning.” These limitations are treated as constraints on corpus validity rather than concealed as methodological certainty.

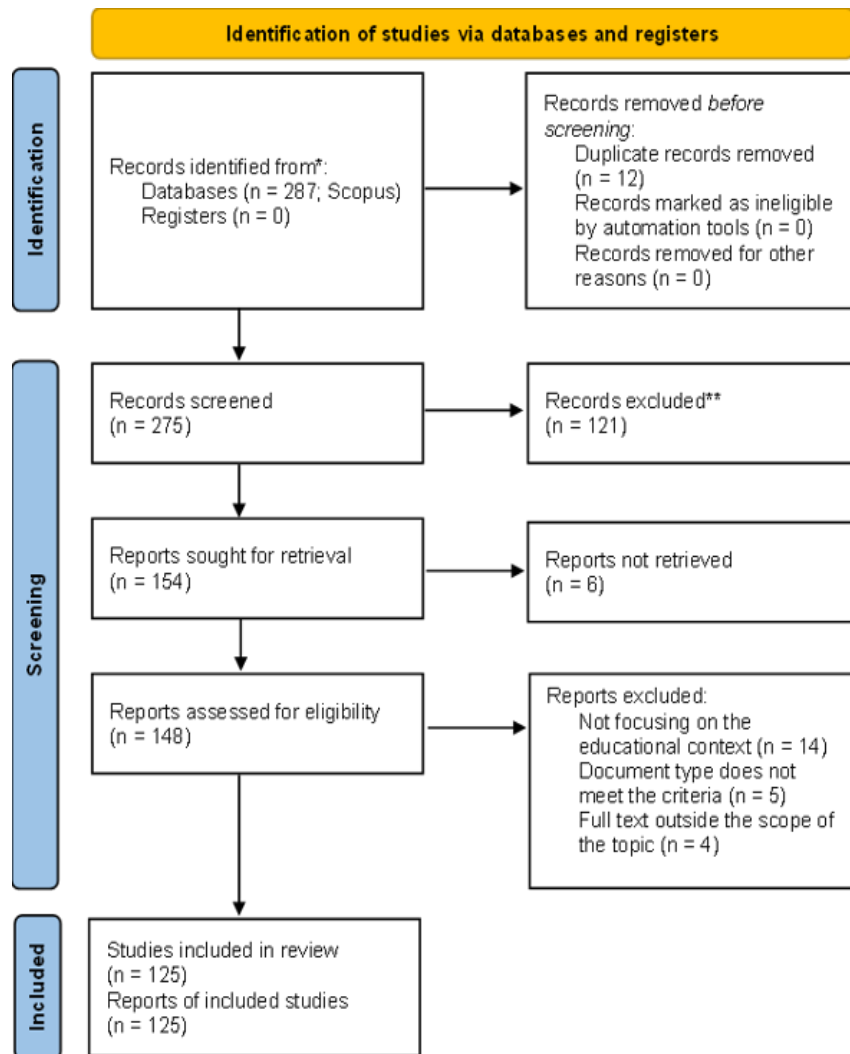


Figure 1. PRISMA Flow Diagram for Article Identification and Selection
 Source: Authors' elaboration based on the PRISMA 2020 protocol
 (Haddaway et al., 2022; Page et al., 2021)

The analytical file contained 125 records from 68 Scopus-indexed sources. Contrary to the earlier protocol wording, the exported corpus was not limited to journal articles and reviews: it comprised 84 journal articles, 18 book chapters, 9 books, 9 conference papers, and 5 records of other document types. We therefore corrected the eligibility description to match the dataset actually analyzed. Records were screened for an apparent relationship between geospatial information and education. However, the surviving corpus also contained technical applications in transportation, urban analytics, disaster management, land use, and related domains. The review protocol was not registered, and

the available audit trail does not document the number of screeners, independent duplicate screening, conflict resolution, or the specific deduplication operation. Accordingly, we report the study as a PRISMA-guided bibliometric mapping rather than a fully reproducible systematic review. We used Bibliometrix and the Biblioshiny interface in R for performance indicators, Bradford analysis, citation indicators, trend topics, keyword co-occurrence, thematic mapping, Walktrap clustering, and MCA (Aria & Cuccurullo, 2017). The retained bibliographic vocabulary was not subjected to a fully documented thesaurus, stemming, or synonym-merging workflow; variants such as "GIS,"

“geographic information systems,” “geospatial,” “geospatial,” “student,” and “students” may therefore appear separately. The precise software versions, field selection, frequency thresholds, normalization, pruning, Walktrap settings, and MCA parameters were not archived and should be supplied from the original analytical environment before publication. Citation values are interpreted as descriptive Scopus-export indicators at the time of data retrieval; comparisons may still be affected by publication age, field, source visibility, and document type. Because the current file does not permit a reproducible reanalysis, the following results are retained as descriptive outputs of the original mixed corpus. Claims that depend on an education-only corpus or robustness testing are explicitly qualified.

RESULTS AND DISCUSSION

General Characteristics and Publication Performance

The research corpus consisted of 125 documents from 68 sources published between 2002 and 2025 and authored by 309 researchers. It included 84 journal articles (67.2%), 18 book chapters (14.4%), 9 books (7.2%), 9 conference papers (7.2%), and 5 records of other document types (4.0%). The annual publication growth rate was 10.99%; average document age was 7.24 years; average citations per document were 11.93; and the corpus contained 41 single-authored documents. These indicators describe the mixed corpus retrieved by the original search. They should not be generalized as estimates of education-specific research until the records have been rescreened with explicit educational eligibility criteria.

Table 1. Main Information of the Research Dataset

Description	Result
Timespan	2002–2025
Sources	68
Document	125
Annual Growth Rate (%)	10,99
Average Document Age (Year)	7,24
Average Citations per Document	11,93
Author’s Keywords	417
Keyword Plus	618
Numbers of Authors	309
Single-Authored Documents	41
Average Authors per Document	2,81

(Source: Biblioshiny Analysis Result, 2026)

For descriptive purposes, annual production can be divided into an initiation period (2002–2014), a consolidation period (2015–2021), and an acceleration period (2022–2025), with output peaking at 14 publications in 2024 (**Figure 2**). These period labels summarize the observed publication curve; they do not establish that a technological change caused the growth. Because recent technical machine-learning

records may have entered through the broad search term “learning,” the apparent acceleration of GeoAI-related themes requires confirmation in an education-only sensitivity corpus.

Average annual citation rates varied by publication year, with relatively high values for records published in 2021 and 2023. Citation indicators are descriptive and should not be read as direct evidence of

novelty, educational relevance, or research quality because exposure time, field, source visibility, and document type affect them.

Normalized citation values partly address publication-year exposure but do not eliminate these differences.

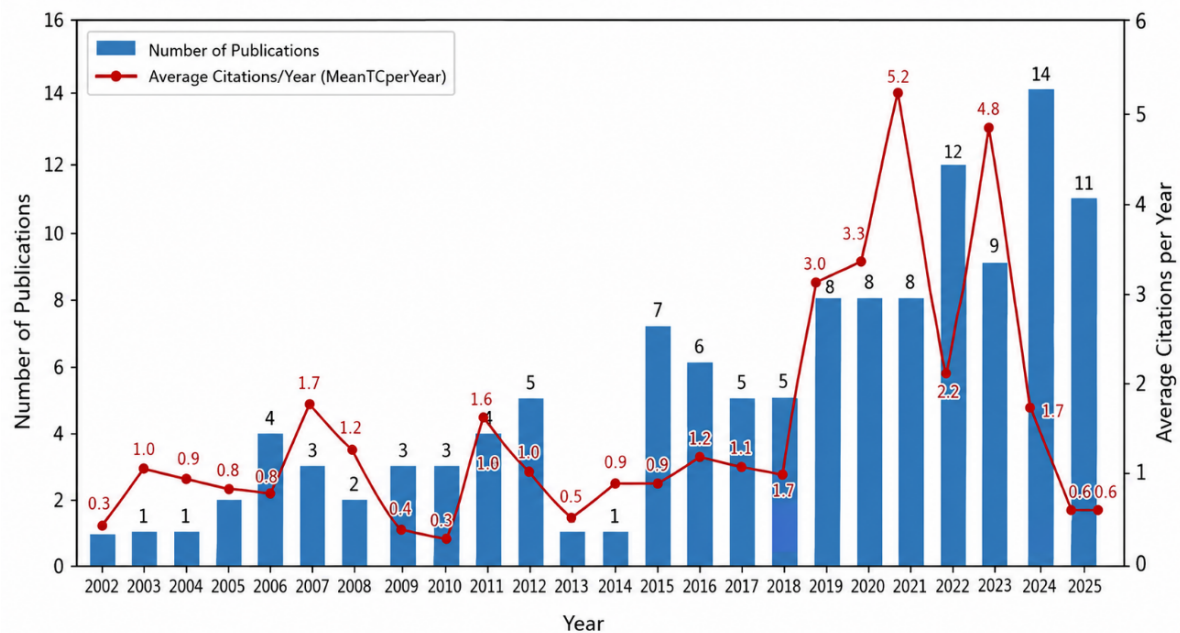


Figure 2. Annual Publications and Average Citations per Year, 2002–2025
 (Source: Biblioshiny Analysis Results, 2026)

Taken together, the production and citation indicators show growth and changing thematic composition within the retrieved corpus. They do not, by themselves, demonstrate improved research quality, educational adoption, or a paradigm shift from GIS to GeoAI.

Most Relevant Sources and Bradford's Law

The source analysis revealed that the Journal of Geography was the most productive publication outlet, contributing 10 documents, followed by the Journal of Geography in Higher Education with five documents. Four additional sources each published three documents: ISPRS Archives, International Journal of Geographical Information Science, International Research in Geographical and Environmental

Education, and Journal of Map and Geography Libraries.

Bradford's Law analysis confirmed that the ten most productive sources constituted Zone 1 (the core zone), collectively accounting for 35 documents, or 28.0% of the entire corpus. This pattern is consistent with Bradford's proposition that a relatively small number of core journals concentrate a substantial proportion of the literature within a particular research field.

The core zone contains both geography-education outlets and technical geographic-information-science outlets. This composition demonstrates that the search retrieved an interdisciplinary corpus, but it should not be interpreted as proof that pedagogy and computation are integrated within individual studies.

Table 2. Ten Most Relevant Sources (Zone 1 of Bradford's Law)

No	Source	Articles
1	Journal of Geography	10
2	Journal of Geography in Higher Education	5

No	Source	Articles
3	Int. Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS Archives)	3
4	International Journal of Geographical Information Science	3
5	International Research in Geographical and Environmental Education	3
6	Journal of Map and Geography Libraries	3
7	Annals of the Association of American Geographers	2
8	British Journal of Educational Technology	2
9	Cartography and Geographic Information Science	2
10	Education Sciences	2

(Source: Data Processing Results in R, 2026)

Most Productive and Influential Authors

Among the 309 authors represented in the dataset, De Lázaro-Torres and De Miguel González emerged as the most productive scholars, each contributing five publications. Demirci, Golledge, Kerski, Van der Schee, and Wang followed, each with three publications. In terms of local scholarly impact, De Lázaro-Torres and De Miguel

González also ranked highest, achieving an h-index of 4 and accumulating 90 and 108 local citations, respectively. These findings highlight the Spanish research group's sustained influence in advancing studies on WebGIS implementation and geography education at the secondary school level (De Lázaro-Torres et al., 2017; De Miguel González & De Lázaro-Torres, 2020).

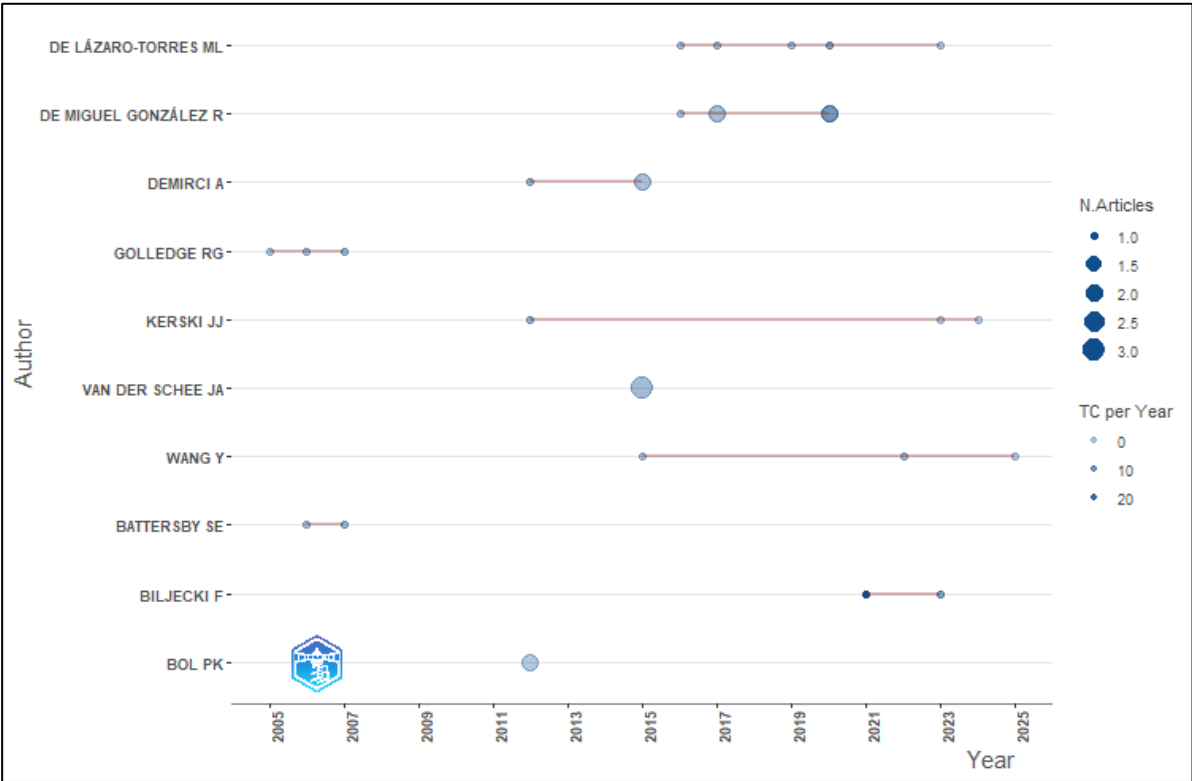


Figure 3. Authors’ Production over Time, 2005–2025
(Source: Biblioshiny Analysis Results, 2026)

Among the core authors, Golledge recorded 147 citations across three publications, consistent with the continuing visibility of work on spatial thinking and geospatial cognition. (Ito & Biljecki, 2021) recorded the highest m-index (0.40) and 165 citations in the dataset, reflecting strong citation visibility for recent technical work in urban analytics and computational geospatial science. These indicators should

not be interpreted as evidence of influence on education without document-level assessment. The metadata also reported an international-collaboration rate of 0%, but the underlying indicator definition and country-level collaboration table were not retained. The value is therefore reported without substantive interpretation and should be verified from author-affiliation countries before publication.

Table 3. Authors with the Highest Local Impact

Author	h-index	g-index	TC	NP
(De Lázaro-Torres et al., 2017)	4	5	90	5
(De Miguel González & De Lázaro-Torres, 2020)	4	5	108	5
(Kerski et al., 2013)	3	3	83	3
(Golledge, 2002)	3	3	147	3
(Favier & Schee, 2014)	3	3	35	3
(Ito & Biljecki, 2021)	2	2	165	2
(Battersby, 2005)	2	2	129	2
(Milson & Earle, 2007)	2	2	111	2

Note: TC = total citations; NP = number of publications. Source: Biblioshiny Analysis Results, 2026

Most Influential Documents

The most globally cited document in the retrieved corpus was Ito and Biljecki (2021), which examined cycling infrastructure using street-view imagery and geospatial computing. It received 141 citations (28.2 per year) and had the highest normalized total citation score (5.40). Marsh et al. (2007), which addresses geospatial concepts in geography education, followed with 83 citations, while Reynard and Shirgaokar (2019), which applies machine learning to transportation-related Twitter data, received 71 citations.

These rankings illustrate the coexistence of educational and technical

geospatial research within the retrieved corpus. Educational studies address spatial thinking, geographic concepts, and GIS-supported learning, whereas technical studies examine computational methods and spatial applications without necessarily investigating educational processes or outcomes. The latter's citation visibility indicates their influence within the mixed corpus; it does not establish their influence on teaching, curriculum development, or student learning. Education-specific citation rankings would require document-level eligibility assessment and subsequent recalculation.

Table 4. Documents with the Highest Global Citations

Document	Year	TC	TC/Year	NTC
Ito K & Biljecki F – Transp. Res. Part C	2021	141	28,20	5,40
Marsh MJ et al. – Ann. Assoc. Am. Geogr.	2007	83	4,37	1,83
Reynard D & Shirgaokar M – Transp. Res. Part D	2019	71	10,14	3,48
Tomlinson RF – Thinking About GIS (book)	2012	61	4,36	4,55
Milson AJ & Earle BD – J. Geogr.	2007	50	2,63	1,10

Ehlers M – Int. J. Digit. Earth	2008	47	2,61	2,00
Bai L et al. – ISPRS J. Photogramm. Remote Sens.	2023	46	15,33	3,18
Gahegan M – Int. J. Geogr. Inf. Sci.	2020	46	7,67	2,37
Battersby SE et al. – J. Geogr.	2006	46	2,30	3,76
Sajjad M et al. – Appl. Geogr.	2021	45	9,00	1,72

Note: TC = total citations; NTC = normalized total citations. Source: Biblioshiny Analysis Results, 2026

Keyword Analysis and Topics Trend

The keyword frequency analysis (Figure 4) identified “GIS” as the most frequent term, with 39 occurrences, followed by “teaching” (26), “geography education” (22), “learning” (20), and “geo-spatial” and “geographic information systems” (18 each). These frequencies indicate the substantial representation of GIS and educational terminology in the retrieved corpus. However, the separate occurrence of synonymous or closely related terms also reflects the absence of a fully documented vocabulary-normalization procedure.

Computational terms, including “remote sensing” (14 occurrences), “machine learning” (11), and “deep learning” (8), were also prominent. Their presence indicates the visibility of

computational geospatial themes within the mixed corpus rather than demonstrated integration into educational practice. In particular, “learning” may refer to either an educational process or a computational method, making its interpretation dependent on the context of individual records.

The aggregate keyword distribution therefore identifies educational and computational strands within the same corpus. It does not establish that individual studies connect these strands through instructional design, curriculum implementation, or the assessment of learning outcomes. Such integration requires document-level content assessment using explicit educational-context criteria.

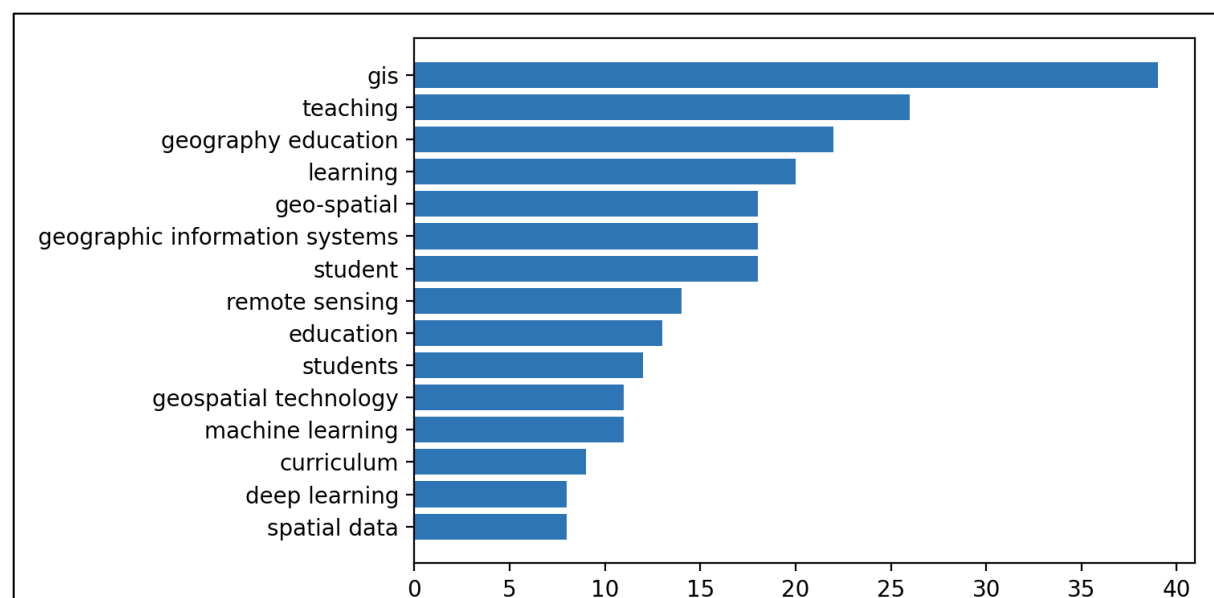


Figure 4. Most Frequently Occurring Keywords in the Geospatial Information and Education Research Dataset (Source: Biblioshiny Analysis Results, 2026)

The topic-trend output (Figure 5) summarizes the timing of terms within the retrieved corpus. Because the vocabulary was not fully normalized and the query

allowed false positives through the word “learning,” interpret the output as exploratory thematic visibility rather than a definitive evolution of geospatial education.

The period 2015–2019 was marked by a growing emphasis on “teaching,” “geospatial technology,” “GIS,” and “student,” indicating a shift toward pedagogical implementation and the evaluation of educational outcomes. During this phase, research increasingly focused on how geospatial technologies could enhance learning processes, spatial thinking, and student engagement within geography education.

During 2020–2025, computationally oriented terms—including “machine learning,” “geospatial,” “remote sensing,” “learning systems,” “artificial intelligence,” and “deep learning” —became more visible. This is evidence of an emerging orientation in the broad corpus, not evidence that GeoAI dominated educational practice or replaced GIS education

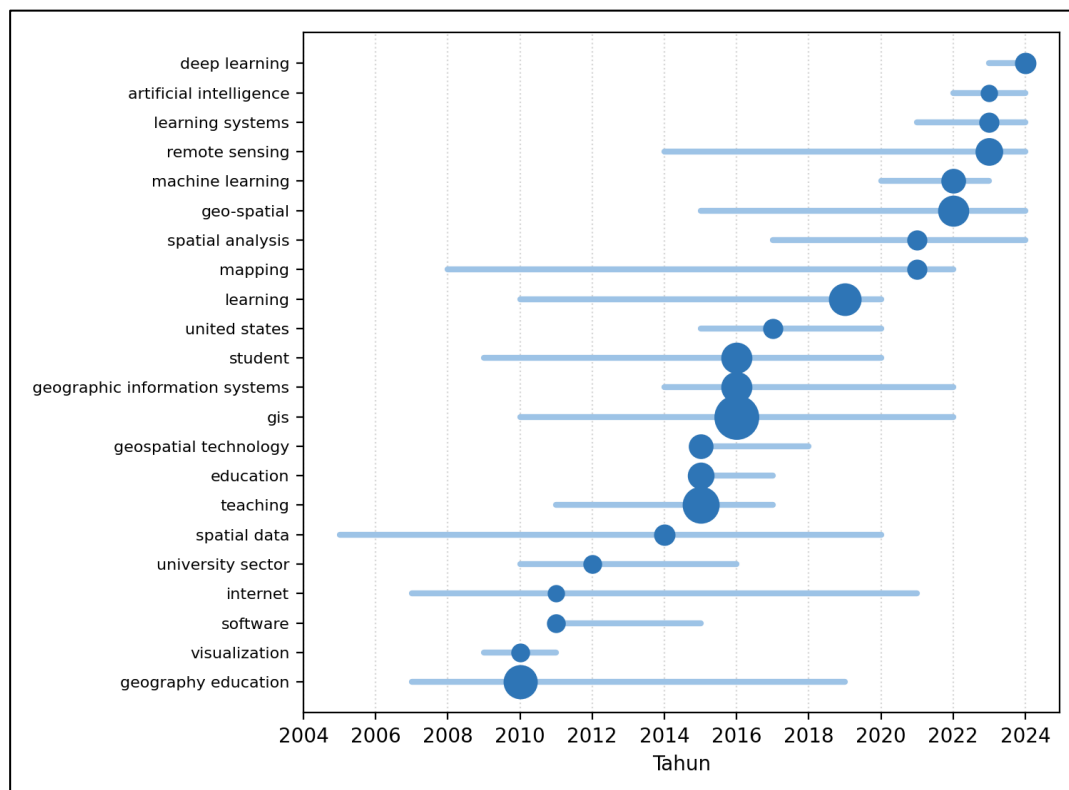


Figure 5. Temporal Evolution of Research Topics in Geospatial Information and Education (2007–2025) (Source: Biblioshiny Analysis Results, 2026)

Thematic Structure: Co-Word Network and Thematic Map

The co-occurrence network analysis of keywords, conducted using the Walktrap clustering algorithm, identified seven thematic clusters within the research corpus. The thematic map (**Figure 6**) is divided into four quadrants: (1) Motor Themes, representing highly developed and influential themes; (2) Basic Themes, representing fundamental and widely connected themes; (3) Niche Themes, representing specialized but relatively isolated themes; and (4) Emerging or Declining Themes, representing either

newly emerging topics or areas experiencing a decline in scholarly attention.

The thematic map is structured around two axes. The horizontal dashed line represents Density (Development Degree), which indicates a theme's internal development and maturity. The vertical dashed line represents Centrality (Relevance Degree), which reflects the importance of a theme and its degree of connection to other themes within the broader field of geospatial information research.

In the thematic-map output, “geo-spatial,” “remote sensing,” and “machine learning” occupy the Motor Themes

quadrant, indicating relatively high centrality and density within this specific network configuration. This network position is conditional on the original corpus, retained lexical variants, and undocumented analytical settings; it must not be equated with pedagogical effectiveness or field-wide dominance.

In contrast, the lower-right quadrant (Basic Themes) contains two major thematic

groups that form the field's conceptual foundation. These themes are highly connected to the broader research landscape but exhibit lower internal development compared to motor themes. As a result, they function as essential knowledge bases that support ongoing research while continuing to provide opportunities for further theoretical and methodological advancement.

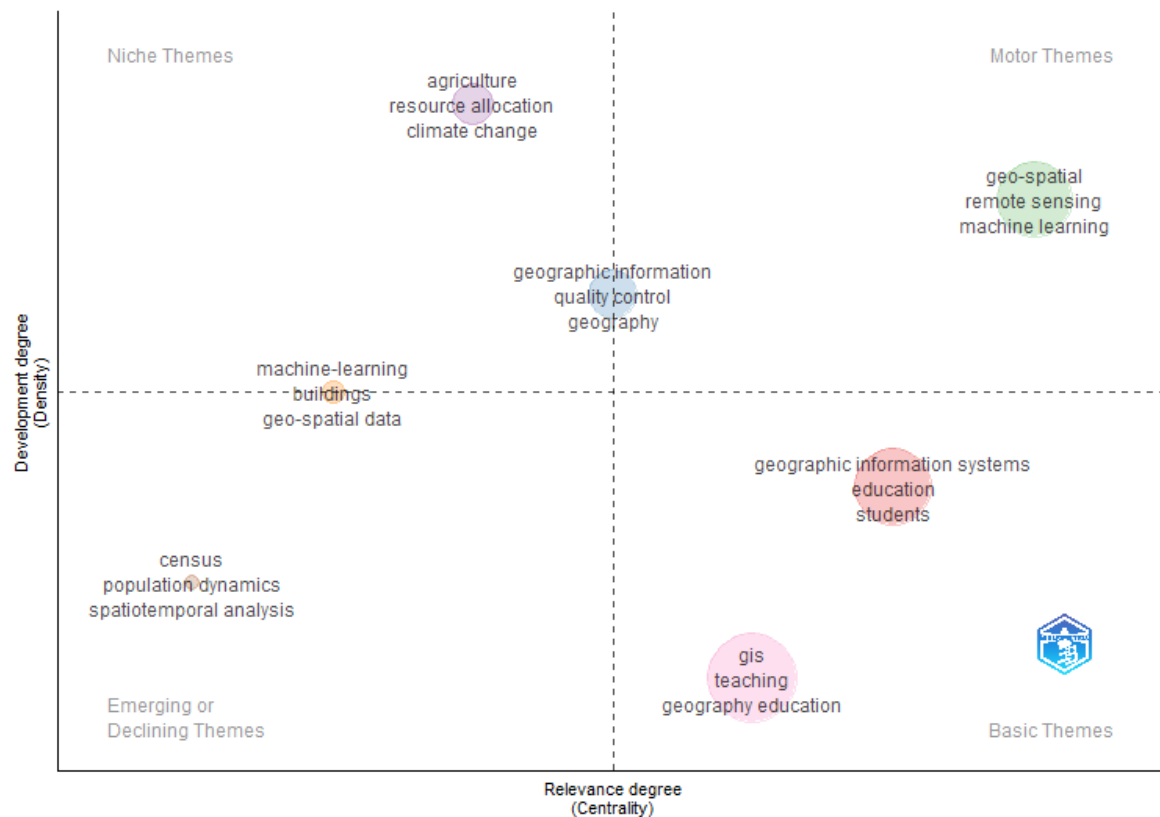


Figure 6. Thematic Map of Author Keywords (Source: Biblioshiny Analysis Results, 2026)

Based on **Figure 6**, three major research clusters were identified from the keyword co-occurrence network derived from article keywords. Cluster 1, GIS and Geography Education, represents the largest thematic cluster and is anchored by the keywords "GIS" (betweenness centrality = 3,225.0), "teaching," "geography education," "learning," "student," "curriculum," "higher education," and "spatial analysis." This cluster reflects the core research domain, characterized by high centrality and density, and focuses on integrating GIS into curricula, teaching practices, and learning processes across various educational levels. The prominence of these keywords indicates

that geography education has historically been the primary context for applying geospatial technologies in educational research.

Cluster 2, Geographic Information Systems and Geospatial Technologies in Education, comprises keywords such as "geographic information systems" (betweenness centrality = 2,771.3), "education," "students," "geospatial technology," "learning systems," "mapping," "spatial cognition," "spatial thinking," and "professional development." This cluster connects cognitive dimensions, particularly spatial thinking and spatial cognition, with technological and

pedagogical dimensions, including learning systems and teacher professional development. The cluster's structure aligns closely with the spatial thinking framework proposed by [Golledge et al. \(2008\)](#) & [Marsh et al. \(2007\)](#), emphasizing geospatial technologies as tools for fostering spatial reasoning and geographic competencies.

Cluster 3, Computational Geospatial Science, is centered on “geospatial” and includes remote sensing, machine learning, deep learning, artificial intelligence, satellite imagery, decision-making, disaster management, land use, and urban planning. Its composition confirms that several nodes are technical application domains rather than explicitly educational constructs. The cluster is therefore interpreted as a technological frontier adjacent to the educational clusters, not as a validated GeoAI-in-education cluster.

In addition to these three primary clusters, we identified several supporting clusters, including themes related to agriculture and sustainable development, machine learning applications for urban data, census and population dynamics, and geographic information and photogrammetry. These supporting clusters reflect the broad range of application

domains in which geospatial information is currently utilized and demonstrate the multidisciplinary character of the field.

The thematic map analysis further shows that “geo-spatial,” “remote sensing,” and “machine learning” fall within the Motor Themes quadrant, indicating that these topics have both high relevance and strong internal development within the geospatial research landscape. In contrast, themes such as “GIS,” “teaching,” “geography education,” “education,” “students,” and “geographic information systems” are located within the Basic Themes quadrant. This positioning suggests that integrating GIS and geospatial information into geography education is a fundamental and highly connected research area, while still offering substantial opportunities for future theoretical, methodological, and pedagogical development.

Taken together, the maps suggest increased visibility of computational geospatial themes alongside a persistent GIS and geography-education foundation. This pattern is described as a thematic expansion or emerging orientation. It does not establish a paradigm shift, replacement of GIS, or integration of GeoAI into curricula.

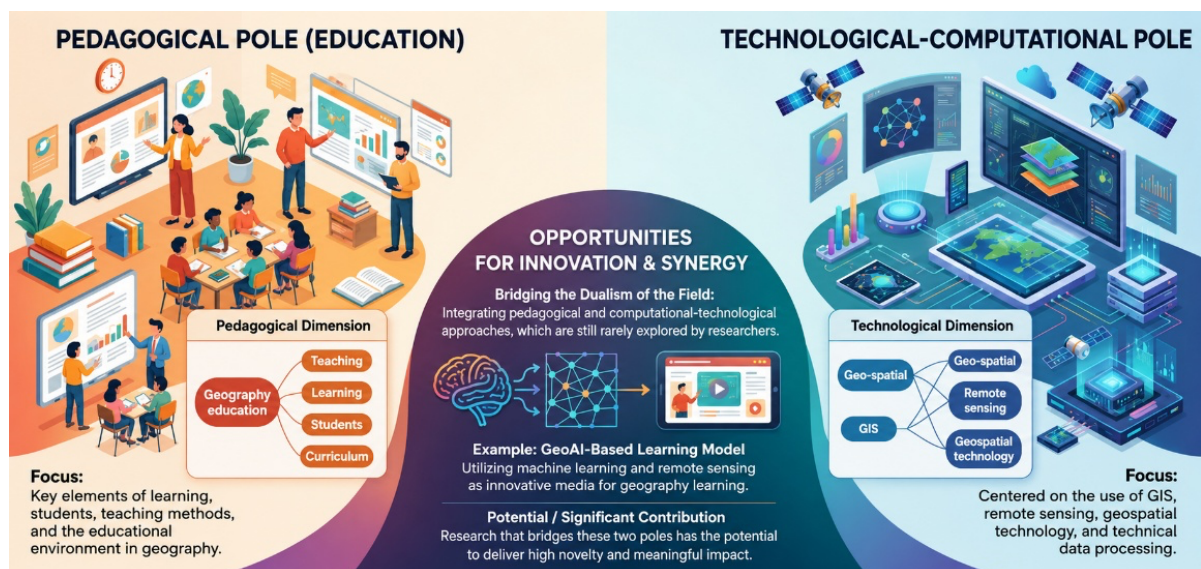


Figure 7. Interpretive Schematic of Pedagogical and Computational Poles Suggested by Multiple Correspondence Analysis (MCA) (Source: Authors' interpretive visualization based on the reported Biblioshiny MCA output, 2026)

The reported MCA suggests two broad conceptual poles: a pedagogical pole associated with geography education, learning, students, and teaching, and a technological-computational pole associated with geospatial terms, remote sensing, geographic information systems, and geospatial technology. **Figure 7** is an author-prepared interpretive schematic rather than a direct analytical output. Because the MCA input fields, thresholds, software version, and settings were not archived, treat this structure as provisional until the analysis is reproduced directly from a documented pipeline.

The bibliometric patterns can inform—but do not empirically validate—propositions for geospatial-information-based learning models. Educational GIS, spatial thinking, and map literacy provide a theory-supported pedagogical foundation, while the computational cluster identifies technologies for future instructional research.

These foundational elements are reflected in Cluster 1, which includes keywords such as GIS, teaching, geography education, learning, student, curriculum, and spatial analysis, as well as in the Basic Themes quadrant. Consequently, the initial stage of instructional design should focus on strengthening learners' conceptual and operational understanding of spatial concepts, including location, spatial patterns, spatial relationships, map interpretation, and the use of basic GIS or WebGIS applications.

Second, once spatial thinking and fundamental GIS competencies have been established, learning models can progressively incorporate more advanced geospatial technologies. Findings from Cluster 3 indicate that geospatial, remote sensing, machine learning, deep learning, artificial intelligence, and satellite imagery have emerged as rapidly developing themes and occupy the Motor Themes quadrant. Therefore, GeoAI should be positioned as an advanced stage of learning rather than an introductory component. Students can progress from map exploration and spatial data interpretation, through spatial pattern

analysis and WebGIS-based investigations, to interpreting remote sensing imagery and applying machine learning to spatial problem-solving.

Third, the relationship between the thematic clusters and the field's conceptual structure suggests that future learning models should explicitly bridge the pedagogical and technological-computational poles. The pedagogical pole encompasses geography education, learning, students, and teaching, whereas the technological-computational pole includes geospatial, remote sensing, geographic information systems, geospatial technology, machine learning, and artificial intelligence.

A progressive instructional sequence is proposed for future validation: (1) spatial concepts and map literacy; (2) foundational GIS and WebGIS competencies; (3) geospatial data analysis for authentic spatial problems; and (4) optional advanced work with remote sensing, machine learning, and GeoAI. This sequence is a normative, theory-informed proposition; keyword clusters do not demonstrate prerequisite relations, developmental appropriateness, or learning effectiveness.

Compared with the cited reviews, the present study offers a longer temporal window and combines performance analysis with science mapping. [Bernhäuserová et al. \(2022\)](#) focus on GIS implementation barriers, [Konstantakatos and Galani \(2022\)](#) on GIS in geographical and environmental education, and [Bondarenko \(2025\)](#) on GIS-based geography teaching. The present contribution should therefore be understood as complementary and exploratory, not as a verified first or exhaustive map.

Implications for Learning Model Development and Future Research Agenda

The analysis generates research propositions rather than tested instructional implications. First, future models may be anchored in spatial thinking and GIS competencies. Second, GeoAI-related technologies should be investigated as potential extensions, with educational value

assessed directly rather than inferred from keyword centrality.

Third, prior educational studies of WebGIS, digital atlases, and mobile learning can inform the design of active and inquiry-based activities. Fourth, cross-national collaboration warrants further examination, but the previously reported 0% international-collaboration value is not interpreted here because the indicator definition and country-level evidence were not preserved in the analytical audit trail.

Based on these gaps, future research should prioritize developing and validating learning models that explicitly integrate GeoAI, remote sensing imagery, machine learning, and geospatial analytics within

geography and Earth science education. Furthermore, future studies should investigate geospatial literacy and spatial data literacy as essential twenty-first-century competencies, conduct design-based research on the educational effectiveness of WebGIS, geospatial dashboards, and digital twins, and explore teacher professional development strategies that support the sustainable integration of emerging geospatial technologies into educational practice. Collectively, these directions offer a promising pathway to bridge the longstanding divide between pedagogical and technological-computational domains.

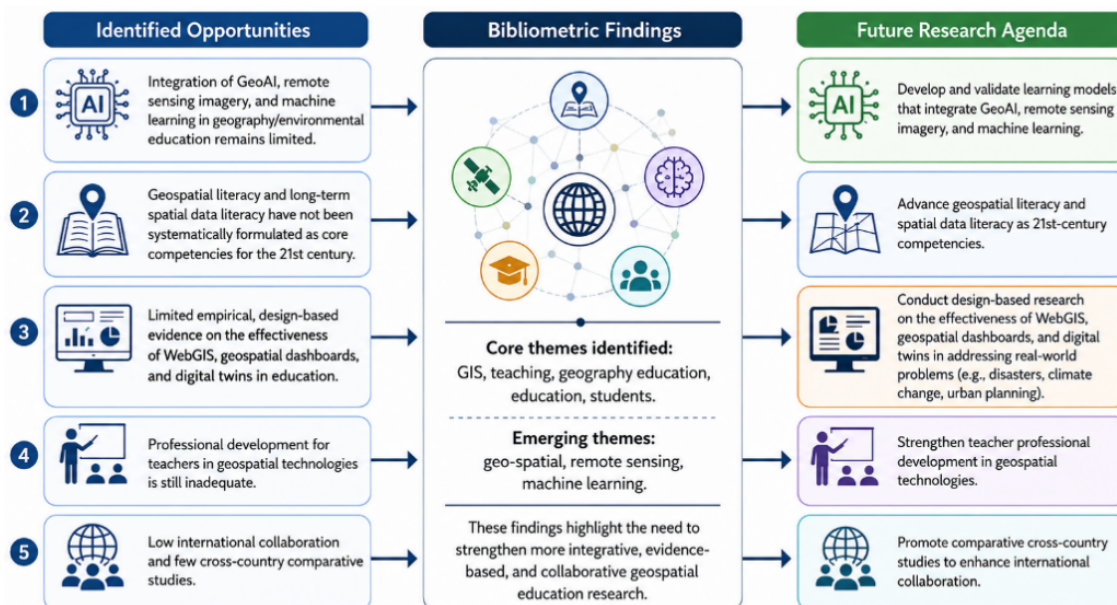


Figure. From Identified Opportunities to Future Research Agenda through Bibliometric Insights

Figure 8. Identified Opportunities for the Future Research Agenda
 (Source: Authors' elaboration based on bibliometric analysis results, 2026)

The cluster analysis derived from the bibliometric mapping reveals that a key future research priority lies in bridging two thematic domains that have evolved largely in parallel: the GIS-Geography Education cluster and the GeoAI cluster. The GIS-Geography Education cluster represents the field's established pedagogical foundation, encompassing research on GIS integration in teaching and learning, spatial thinking development, map literacy, geography education, curriculum design, and students'

ability to interpret and analyze spatial data. In contrast, the GeoAI cluster, which includes topics such as remote sensing, machine learning, deep learning, artificial intelligence, satellite imagery, and geospatial analytics, reflects a more recent and computationally oriented research trajectory.

The separation between the two clusters suggests a candidate research gap rather than proving one. Educational GIS studies address pedagogy and spatial

competence, while many computational-cluster records address technical image analysis, spatial modeling, land-use classification, urban planning, disaster risk, or decision support. Document-level screening is needed to determine how often the two domains are genuinely integrated.

Such models should not position GeoAI as an isolated technological component, but rather as an advanced extension of foundational geospatial literacy. The initial stages of instruction should emphasize spatial thinking, map literacy, understanding of location, spatial patterns, spatial relationships, and the use of basic GIS or WebGIS tools. Subsequent stages may incorporate remote sensing data, satellite imagery, geospatial dashboards, and spatial analyses centered on authentic real-world problems. At more advanced levels, learners can be introduced to fundamental concepts of machine learning, deep learning, and GeoAI through contextualized applications, such as disaster vulnerability assessment, land-use change detection, urbanization analysis, climate change studies, and environmental degradation monitoring.

Future research should move beyond general recommendations regarding the importance of GeoAI in education and instead address more specific questions. For example, how can GeoAI be integrated into geography education without neglecting the foundational principles of spatial thinking and GIS competencies? How can instructional models help students understand the relationships among spatial data, spatial processes, and evidence-based decision-making? To what extent are such models effective in enhancing geographic skills, geospatial literacy, and data-driven problem-solving abilities? Addressing these questions would contribute to a more robust and pedagogically informed integration of emerging geospatial technologies into educational practice.

This more focused research agenda offers substantial added value because it directly addresses the gap identified through the bibliometric analysis. The GIS–Geography Education cluster serves as the

pedagogical foundation, while the GeoAI cluster represents the technological frontier of innovation. Learning models that connect these two domains can significantly contribute to geography education by ensuring that strong pedagogical principles, measurable learning outcomes, and alignment with twenty-first-century educational needs support technological innovation.

Based on the identified research gaps, five priority directions for future research are proposed: (1) Development and validation of learning models that integrate GeoAI, remote sensing imagery, and machine learning within geography and Earth science education. (2) Investigation of geospatial literacy and spatial data literacy as essential twenty-first-century competencies across educational levels. (3) Design-based research examining the effectiveness of WebGIS, geospatial dashboards, and digital twins in problem-based learning environments focused on real-world spatial issues such as disasters, climate change, and urban planning. (4) Teacher professional development initiatives aimed at strengthening competencies in geospatial technologies and GeoAI applications. (5) Cross-national comparative studies designed to enhance international collaboration and broaden the geographical diversity of research contributions.

Collectively, these five research directions provide a strategic roadmap for advancing the field and may serve as valuable entry points for researchers interested in geospatial information, geography education, and emerging geospatial technologies.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

CONTRIBUTION AUTHOR

SN. Contributed to conceptualization and study design, literature searching and screening, data curation, bibliometric analysis, interpretation of the findings, preparation of

visualizations, and writing the original manuscript draft. EN. Provided academic supervision and critically reviewed and revised the manuscript. NN. Contributed to developing the methodological framework, validating the analytical approach, and critically revising the manuscript. LS. Contributed to methodological refinement, validation of the analytical results, and critical review and editing of the manuscript.

CONCLUSION

This PRISMA-guided bibliometric study provides an exploratory map of 125 Scopus records published between 2002 and 2025 at the interface of geospatial education and computational geospatial research. The retrieved corpus showed an annual publication growth rate of 10.99%, with increased output after 2022. The Journal of Geography was the most productive source, while De Lázaro-Torres and De Miguel González were the most productive authors. The analyses identify educational GIS themes alongside increasingly visible computational themes involving remote sensing, machine learning, and artificial intelligence. These patterns characterize the mixed corpus; they do not demonstrate a transition from GIS education to GeoAI-based practice or establish pedagogical integration. The study contributes by identifying relationships and questions for subsequent education-specific content analysis and empirical research. Its proposed instructional progression remains a proposition requiring validation.

This study has substantial limitations. It used only Scopus, and the exact executable query, retrieval date, software versions, screening audit trail, deduplication procedure, thesaurus, network thresholds, normalization, clustering settings, and MCA parameters were not preserved in the available records. The broad term “learning” can retrieve technical machine-learning studies without educational content, and the final corpus contains books, book chapters, conference papers, and technical application studies despite the earlier journal-only eligibility wording. Lexical variants were not fully normalized, citation comparisons

remain sensitive to exposure time and document type, and no education-only or parameter-sensitivity analysis was available. Consequently, the findings are exploratory. Before publication as a definitive systematic bibliometric review, the corpus should be rescreened using explicit educational-context criteria; the query and analytical code should be archived; and all tables, figures, and interpretations should be recalculated against the final education-specific dataset.

FUNDING

This research was supported by the Indonesia Endowment Fund for Education (LPDP) through the Indonesian Education Scholarship Program (Beasiswa Pendidikan Indonesia/BPI), administered by the Ministry of Higher Education, Science, and Technology, Republic of Indonesia. The financial support facilitated the research, manuscript preparation, and publication of the study. The authors conducted the research as part of their doctoral studies.

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