

Monitoring And Assessing Wetlands Using Google Earth Engine: A Bibliometric Review (2017–2024)

Anugrah Anilkumar Nagaich^{1*}, Navneet Munoth²

¹Department of Architecture and Planning, Maulana Azad National Institute of Technology, Bhopal, Madhya Pradesh 462003, India, Email: aanagaich@gmail.com, ORCID: 0000-0001-6405-1585

² Department of Architecture and Planning, Maulana Azad National Institute of Technology, Bhopal, Madhya Pradesh 462003, India, Email: navneet.munoth@gmail.com, ORCID: 0000-0003-2704-1403

Abstract

This study presents a comprehensive bibliometric analysis of research papers focusing on wetland monitoring and assessment using Google Earth Engine (GEE) from 2017 to 2024. The analysis examined 308 publications from Scopus, revealing significant trends in publication patterns, geographic distribution, methodological approaches, and research impact. Results show a dramatic increase in publications since 2017, with peak growth occurring between 2022-2024. China emerged as the leading contributor (43% of publications), followed by the United States (20%) and Canada (10%). The analysis identified Earth and Planetary Sciences (27.7%) and Environmental Science (21.9%) as dominant subject areas. Remote Sensing emerged as the primary publication venue with 78 papers and 2,121 citations. The study revealed strong international collaboration networks among 56 key scholars, with Random Forest emerging as the most widely adopted classification method. The research highlighted significant advances in integrating multi-source data and machine learning techniques for wetland monitoring, while also identifying gaps in socio-ecological research and biodiversity monitoring. This analysis provides valuable insights into the evolution of GEE-based wetland research and suggests future directions for advancing the field.

Keywords: Wetland Assessment, Google Earth Engine (GEE), Bibliometric Analysis, Remote Sensing, Land-Cover Studies, Bibliometric Analysis.

1. INTRODUCTION

Wetlands are indispensable ecosystems that contribute to biodiversity conservation, water purification, carbon storage, and flood regulation. Despite their ecological significance, wetlands face escalating threats from climate change, deforestation, urbanization, and agricultural encroachment. Understanding and monitoring these ecosystems is critical to ensuring their sustainable management and conservation. Land use and land cover (LULC) assessments offer valuable insights into the spatial and temporal dynamics of wetlands, enabling researchers and policymakers to address these challenges effectively [1, 2].

The advent of advanced geospatial technologies, including remote sensing, geographic information systems (GIS), and global positioning systems (GPS), has revolutionized LULC studies. These technologies provide efficient tools for acquiring, processing, and analyzing data at various scales, supporting informed decision-making for wetland management. Moreover, cloud-based platforms like Google Earth Engine (GEE) have transformed land-cover assessment by providing unparalleled access to vast geospatial datasets, such as Landsat, MODIS, and Sentinel imagery, and offering powerful analytical capabilities. GEE's scalability, accessibility, and robust computational infrastructure allow researchers to analyze massive datasets over extensive spatial and temporal scales, making it an invaluable tool for wetland monitoring and management [3, 4].

1.1. Importance of Google Earth Engine for Land Cover Studies

Land-cover studies focus on the distribution and characteristics of various land types on Earth's surface, offering critical insights into environmental changes, natural resource management, and sustainable development planning [5]. These studies are particularly important for understanding the dynamics of ecosystems like wetlands, which are highly sensitive to anthropogenic pressures and climatic variations. LULC assessments help identify and quantify changes in wetland extent, vegetation composition, and hydrological regimes, providing a basis for developing conservation strategies and mitigating adverse impacts [6, 7].

The role of geospatial technologies in land-cover studies cannot be overstated. Remote sensing and GIS have traditionally enabled researchers to monitor environmental changes, map land cover types, and assess

ecosystem health with high precision. However, the emergence of GEE has taken these capabilities to the next level by integrating cloud computing with geospatial data analysis. GEE hosts petabytes of open-access satellite imagery and other geospatial datasets, allowing researchers to conduct time-series analyses, model land-cover changes, and identify trends over decades. Its user-friendly interface, combined with advanced machine learning algorithms, facilitates the creation of high-accuracy LULC maps, even in resource-constrained settings [8, 9].

1.2. Transformative Role of GEE in Wetland Studies

One of GEE's most significant contributions to wetland research is its ability to process and analyze extensive datasets efficiently. The platform's scalability enables the monitoring of large geographic areas and long-term temporal trends, which is essential for capturing the dynamic nature of wetlands [10]. GEE has been instrumental in various applications, including wetland mapping, biodiversity monitoring, vegetation health assessment, and urban expansion analysis. For instance, its time-series analysis capabilities provide critical insights into wetland degradation patterns and the drivers of change, such as land reclamation, pollution, and water extraction [11, 12].

Furthermore, the integration of machine learning techniques like random forests and support vector machines in GEE has enhanced the accuracy and reliability of wetland LULC classifications [13, 14]. These advancements allow researchers to create detailed maps and models that inform wetland restoration and conservation initiatives. GEE's extensive datasets and tools have also proven vital for studying the socio-economic and ecological impacts of wetland loss, making it an indispensable platform for addressing global environmental challenges [6, 15].

1.3. Importance of Bibliometric Analysis in Wetland Research

Bibliometric analysis is a quantitative research method used to evaluate and analyze scholarly literature within a specific domain. It provides insights into the evolution of research trends, author productivity, institutional contributions, citation impacts, and collaboration networks. By systematically examining metadata such as publication counts, citation patterns, and keyword occurrences, bibliometric analysis helps researchers understand the development and dissemination of knowledge in a particular domain [16, 17].

In the context of wetland studies, bibliometric analysis serves as an essential tool for assessing research output, identifying influential works, and tracking the adoption of emerging technologies such as Google Earth Engine (GEE). Given the increasing role of remote sensing and geospatial tools in environmental research, bibliometric analysis can highlight key contributions to the field, assess the impact of interdisciplinary research, and pinpoint areas requiring further exploration. By leveraging bibliometric techniques, this study contributes to a deeper understanding of the role of GEE in wetland research, offering valuable insights to guide future investigations and policy-making efforts aimed at wetland conservation and sustainable management [18].

This study explores the importance of assessments for wetlands and examines the transformative role of GEE in enabling comprehensive and scalable wetland monitoring. By leveraging bibliometric analysis, it aims to evaluate the current state of wetland research utilizing Google Earth Engine (GEE) to understand the research landscape, identify knowledge gaps, and propose future research directions by evaluating publication trends, identifying leading contributors, exploring international collaboration networks, and highlighting key research directions and knowledge gaps to guide future studies in this field.

To achieve our research aim, we pose the following research questions:

1. What is the global trend of scientific literature on wetlands using GEE?
2. What insights can be derived from the temporal and spatial distribution of such studies?
3. What has been the growth rate in the publication of articles in this domain?
4. How are international collaboration networks structured among countries and scholars?
5. Which scientific journals and research institutions have published the most articles on wetland research using GEE?
6. Which articles have had the highest impact on the research community, as indicated by citation counts?
7. In which research directions has GEE been most frequently utilized, based on keyword analysis?
8. What are the future research trends and knowledge gaps in the study of wetlands using GEE?

2. METHODOLOGY

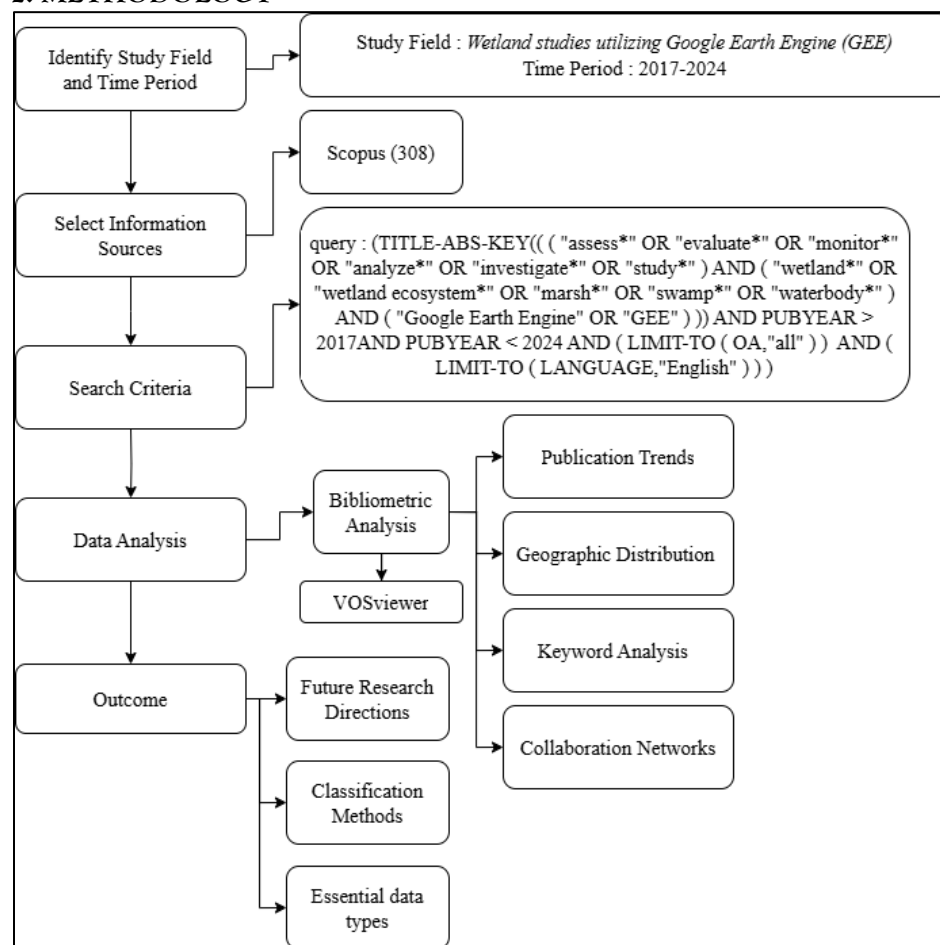


Fig. 1 Methodology Adopted for Study

This study (Figure 1) employs a bibliometric analysis approach to assess the research landscape of wetland studies utilizing Google Earth Engine (GEE) from 2017 to 2024. The methodology follows a structured workflow, beginning with the identification of the study scope and time period, selection of information sources, application of search criteria, data analysis, and interpretation of key outcomes. The study specifically focuses on the application of GEE in wetland-related research, including assessment, monitoring, evaluation, and analysis, covering a time span from 2017 to 2024 to capture recent advancements in the field.

To ensure a comprehensive collection of relevant literature, the study relies on Scopus, a well-established and widely recognized scientific database. A total of 308 documents were retrieved from Scopus using a structured search query incorporating keywords related to wetlands and Google Earth Engine. The search string included terms such as "assess," "evaluate," "monitor," "analyze," "investigate," and "study," combined with wetland-related terms like "wetland ecosystem," "marsh," "swamp," and "waterbody." Additionally, the inclusion of "Google Earth Engine" and "GEE" ensured that only studies utilizing this platform were considered. The search was refined to include English-language publications and both open-access and non-open-access studies, ensuring a broad yet relevant dataset.

Following data collection, the study employs bibliometric analysis techniques to evaluate various research trends. The analysis includes an examination of publication trends to assess the annual growth in research output, geographic distribution to identify key contributing countries and institutions, keyword analysis to uncover dominant themes and research focus areas, and collaboration network analysis to explore co-authorship patterns among researchers and institutions. For this purpose, VOSviewer, a specialized software for bibliometric visualization, is used to generate network maps illustrating keyword co-occurrence, research collaborations, and institutional contributions.

The insights derived from this bibliometric analysis help identify major trends in wetland research using GEE while also shedding light on potential gaps and future research directions.

2.1. Bibliometric Overview

The comprehensive bibliometric analysis (Table 1) of wetland research using Google Earth Engine reveals several key characteristics of the field's scholarly landscape. The dataset comprises 308 distinct document sources published between 2017 and 2024, representing a focused yet diverse body of literature. The temporal span coincides with the period of GEE's increasing accessibility and adoption in environmental research. The keyword analysis presents a rich vocabulary of research themes, with 1,630 author-designated keywords (DE) and 5,816 automatically indexed keywords (Keywords Plus), indicating the broad scope and multidisciplinary nature of the research field. This extensive keyword base suggests diverse applications and methodological approaches in GEE-based wetland studies.

The authorship patterns reveal a strong collaborative nature in this research domain. Out of 1,219 total authors, only 5 produced single-authored documents, while 1,214 participated in multi-authored works. This results in an average of 5.59 authors per document, with author appearances totaling 1,722, indicating that some researchers contributed to multiple publications. The Collaboration Index of 5.67 further emphasizes the field's highly collaborative nature, suggesting that complex wetland studies using GEE typically require diverse expertise and collaborative efforts.

The research impact is notable, with an average of 18.42 citations per document. This relatively high citation rate suggests that the research outputs have been well-received and influential within the scientific community. The citation patterns indicate that GEE-based wetland research has established itself as a significant subfield within environmental and geospatial sciences.

Table 1 Bibliometric Overview

Main Information	Value
Documents Sources	308
Timespan References	2017 - 2024
Author's keywords (DE)	1,630
Keywords Plus (ID)	5,816
Authors (Total number of authors)	1,219
Authors Appearances	1,722
Authors of single-authored documents	5
Authors of multi-authored documents	1,214
Authors per document	5.59
Co-Authors per Documents	5.59
Average citations per document	18.42
Collaboration Index	5.67

2.2. Analysis Methods

The collected bibliometric data was analyzed using VOSviewer, a widely used tool for network visualization in bibliometric studies. This software enables the graphical representation of relationships among authors, institutions, keywords, and countries, facilitating a deeper understanding of research trends and collaboration networks in wetland studies utilizing Google Earth Engine (GEE). VOSviewer was employed to generate co-authorship networks, illustrating research collaborations among scholars and institutions, as well as keyword co-occurrence maps, which highlight the most frequently used terms in the literature and their interconnections. Additionally, citation analysis was conducted to identify the most influential studies, journals, and researchers in this field. The software's clustering algorithm helped categorize research themes, allowing for the identification of dominant topics and emerging trends in wetland studies. Through these

analyses, the study provides a structured evaluation of the research landscape, offering valuable insights into scholarly contributions, evolving research priorities, and potential future directions in the application of GEE for wetland assessment.

3. RESULTS AND DISCUSSION

3.1 Publication Trends

Analysis of publication trends shows a significant increase in research output from 2017 (when GEE became widely available) to the present. This growth reflects the increasing adoption of GEE as a primary tool for wetland monitoring.

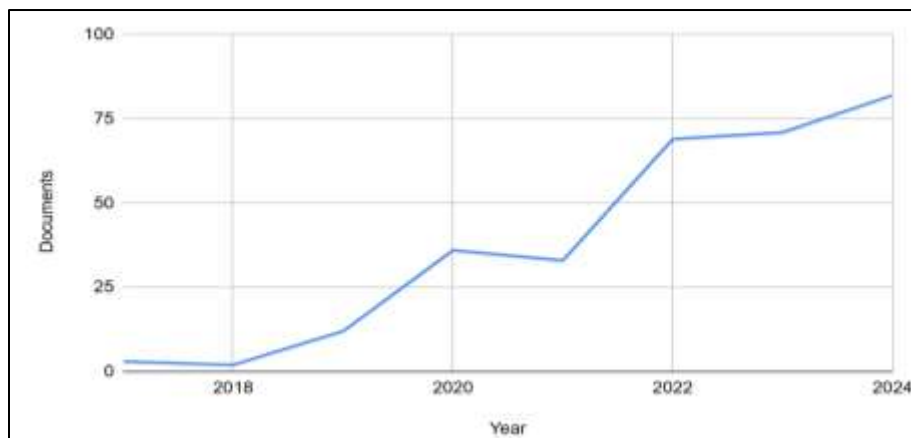


Fig. 2 Number of Documents per Year

Fig. 2 titled 'Number of Documents per Year' illustrates the annual trend in the publication of scientific articles related to wetland studies using Google Earth Engine (GEE). The x-axis represents the years from 2017 to 2024, while the y-axis denotes the number of documents published in each year. From 2017 to 2018, the number of publications remained minimal, indicating a lack of significant research activity in this domain during the initial years. However, starting around 2018-19, a gradual increase in the number of documents is observed, signaling a growing interest in applying GEE for wetland studies. A notable surge begins after 2019, with a sharp rise in publications observed between 2020 and 2024. This increase corresponds to the wider adoption of GEE as a robust tool for geospatial analysis and the growing global emphasis on addressing environmental challenges.

The peak in publications after 2021 reflects the enhanced accessibility and usability of GEE, along with its integration into advanced geospatial workflows for wetland assessment. This trend underscores the increasing recognition of GEE's potential to facilitate large-scale, efficient, and accurate analysis of wetlands. Furthermore, the rise in publications aligns with global environmental policy shifts, such as the emphasis on sustainable development and biodiversity conservation, which have likely fueled research in this area. Overall, the graph highlights the dynamic growth in scientific interest and research output in the application of GEE for wetland studies, particularly in recent years. This trend is indicative of the platform's transformative impact on the field of geospatial science and its pivotal role in addressing critical environmental challenges.

Table 2 Citation Trends by Year

Year	Papers	Average Citations
2017	3	95
2018	2	85
2019	12	83.08
2020	36	45.53
2021	33	25.58

2022	69	14.42
2023	71	8.52
2024	82	1.68

The analysis of citation trends from 2017 to 2024 (Table 2) reveals several significant patterns in the evolution of GEE-based wetland research. The data shows a clear trajectory in both publication volume and citation impact, reflecting the field's maturation and growing influence.

In the early years (2017-2018), despite relatively few publications (3 papers in 2017 and 2 in 2018), these papers achieved remarkably high average citation rates of 95 and 85 citations per paper, respectively. This high impact suggests these were seminal works that laid the foundational methodology for GEE applications in wetland research. The year 2019 marked a significant increase in research output with 12 publications while maintaining a high average citation rate of 83.08, indicating sustained quality and relevance of the research during this period.

A substantial surge in research activity occurred in 2020, with 36 publications averaging 45.53 citations per paper. This increase coincides with the wider adoption of GEE platforms and growing recognition of their potential in environmental monitoring. The following year, 2021, maintained similar publication levels with 33 papers, though the average citations decreased to 25.58, reflecting the natural citation lag for newer publications.

The field experienced its most productive period during 2022-2024, with annual publications rising significantly to 69, 71, and 82 papers respectively. The decreasing average citations for these recent years (14.42, 8.52, and 1.68) is a natural phenomenon due to the recency of the publications rather than a reflection of research quality. This dramatic increase in publication volume indicates the field's rapid expansion and the growing adoption of GEE as a primary tool for wetland research.

Several factors likely contributed to this growth trajectory:

1. Increased accessibility and user-friendliness of GEE platforms
2. Growing recognition of wetland conservation importance
3. Advancement in remote sensing technologies and data availability
4. Expansion of the global research community focused on wetland monitoring

3.2 Geographic Distribution

Research on wetland assessment using GEE shows distinct geographic patterns:

- Highest concentration of studies in North America and Asia
- Growing representation from Australia and Europe
- Limited studies from South America and Africa

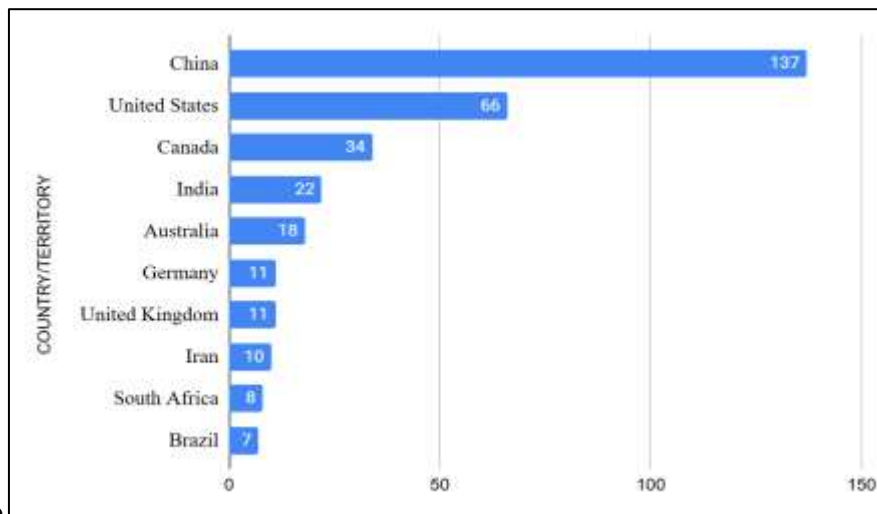


Fig. 3 Geographic Distribution of Documents

Fig. 3 titled ‘Geographic Distribution of Documents’ illustrates the distribution of research publications on wetland assessment using Google Earth Engine (GEE) across different countries or territories. The x-axis represents the number of documents, while the y-axis lists the contributing countries or territories. China leads significantly in the number of publications, with nearly 150 documents, indicating its strong research focus and utilization of GEE for wetland assessment. The United States follows as the second-highest contributor, highlighting its active role in geospatial and environmental research. Canada ranks third, reflecting its emphasis on environmental conservation and geospatial technologies.

India, Australia, and Germany also show considerable contributions, showcasing their engagement in leveraging GEE for wetland-related studies. Other countries such as the United Kingdom, Iran, South Africa, and Brazil contribute a smaller but noteworthy number of publications, underscoring a global interest in this research domain. This graph demonstrates the international collaboration and widespread adoption of GEE for wetlands research. It also highlights the dominance of countries with advanced geospatial research capabilities and environmental priorities. The findings emphasize the global relevance of geospatial technologies like GEE in addressing critical environmental challenges, with China and the United States leading these efforts.

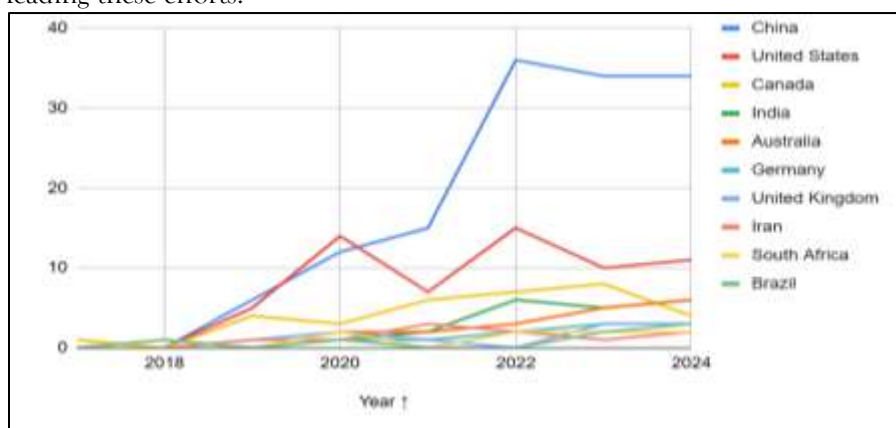


Fig. 4 Geographic Distribution of Documents across Years

The analysis of publication patterns across countries from 2017 to 2024 reveals (Fig. 4) distinct temporal and geographical trends in GEE-based wetland research. China emerged as the dominant contributor with 137 publications (43% of total output), followed by the United States with 63 publications (20%) and Canada with 33 publications (10%).

Early Development Phase (2017-2018)

The field's initial years showed limited geographic diversity, with only five countries contributing publications. The United States and Canada were early adopters in 2017, while 2018 saw contributions from India, Germany, and Brazil, indicating the gradual global spread of GEE adoption in wetland research.

Growth Phase (2019-2021)

A significant expansion occurred during this period, particularly in China, which published 33 papers across these three years. The United States maintained strong output with 26 papers, while Canada established itself as a major contributor with 13 publications. This period also saw increased participation from countries like Iran and Australia, broadening the global research base.

Maturation Phase (2022-2024)

The field entered a highly productive phase marked by:

- China's dramatic increase in output, averaging 34-36 papers annually
- Sustained high production from the United States (10-15 papers annually)
- Consistent contributions from Canada (4-8 papers annually)
- Emerging presence of India and Australia (5-6 papers annually)
- Growing participation from European nations (Germany, UK)

Regional Patterns and Collaboration

The geographic distribution reveals several important patterns:

1. Asian Dominance: Led by China and India (158 papers combined)
2. North American Strength: USA and Canada contributed 96 papers collectively

3. European Presence: Germany and UK together produced 21 papers
4. Emerging Contributors: South Africa and Brazil showing increasing engagement

This distribution reflects not only research capacity and funding availability but also the pressing need for wetland monitoring in different regions. The concentration of research in China and North America aligns with these regions' extensive wetland resources and technological capabilities.

3.3 Subject Area

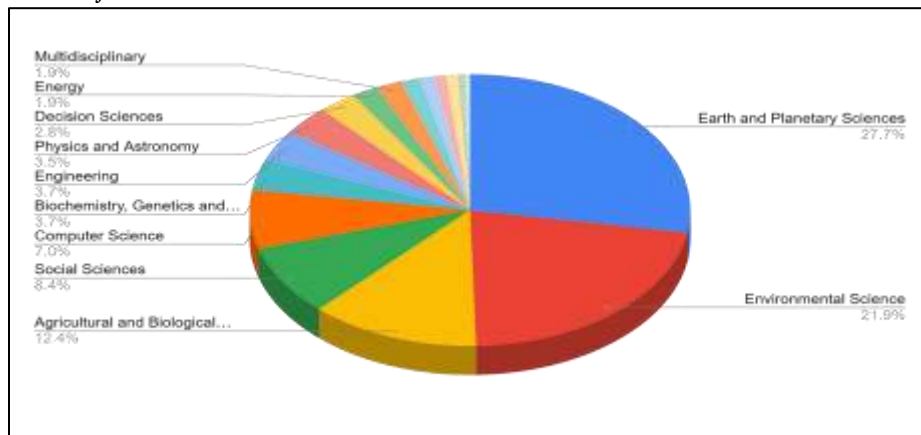


Fig. 5 Subject Area of Researches

The pie chart represents (Fig. 5) the distribution of research publications related to wetland assessment using Google Earth Engine (GEE) across various academic disciplines. The percentage share of each discipline highlights the interdisciplinary nature of the research.

The largest share of publications, 27.7%, belongs to the field of Earth and Planetary Sciences, reflecting the central role of geospatial tools like GEE in understanding and analyzing natural landscapes, including wetlands. Environmental Science follows closely with 21.9%, emphasizing the focus on ecological and sustainability studies. Other significant contributors include Agricultural and Biological Sciences (12.4%), showcasing research on the role of wetlands in agriculture and biodiversity, and Social Sciences (8.4%), which may involve human-wetland interactions, policy, and management studies. Computer Science accounts for 7.0%, indicating the computational and technical advancements used in GEE applications.

Smaller contributions come from disciplines like engineering (3.7%) and physics and astronomy (3.5%), reflecting applications of technical and theoretical models. Fields like Decision Sciences (2.8%), Energy (1.9%), and Medicine (1.4%) demonstrate niche applications. Multidisciplinary research (1.4%) bridges gaps between different scientific fields.

This graph underlines the diverse applicability of GEE in wetland studies, with the majority of research concentrated in environmental and earth sciences but also extending into social, agricultural, and computational domains. It showcases the integrated efforts of multiple disciplines in addressing wetlands-related challenges using geospatial technologies.

3.4 Journal Publication Distribution

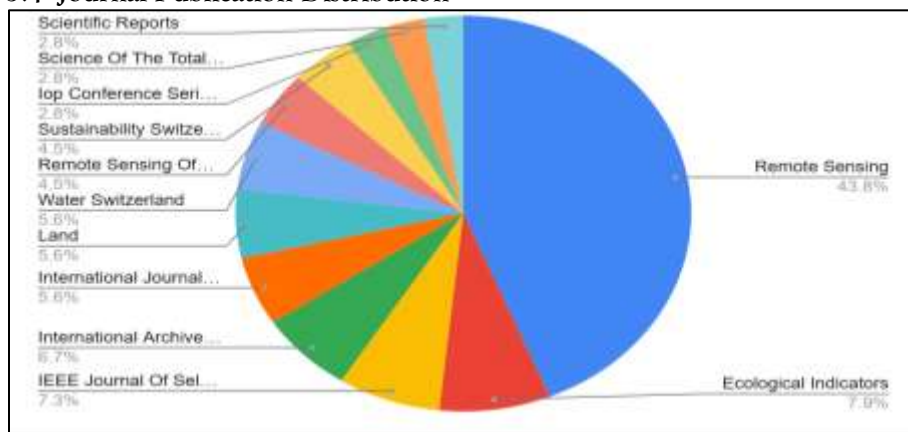


Fig. 6 Journal Publication Distribution

Table 3 Top 10 Journal Publication Distribution and Impact

Journal	Documents	Total Citations	Avg Citations
Remote Sensing	78	2,121	27.2
Ecological Indicators	14	406	29
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	13	172	13.2
International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	12	23	1.9
International Journal of Applied Earth Observation and Geoinformation	10	207	20.7
Land	10	62	6.2
Water (Switzerland)	10	113	11.3
Remote Sensing of Environment	8	490	61.3
Sustainability (Switzerland)	8	43	5.4
IOP Conference Series Earth and Environmental Science	5	16	3.2

The analysis of journal publications reveals distinct patterns (Fig. 6 & Table 3) in both publication volume and citation impact across different journals in the field of GEE-based wetland research. This distribution provides insights into the preferred publication venues and their relative influence in the field.

Leading Journals by Publication Volume

Remote Sensing emerges as the dominant publication venue with 78 documents, representing approximately 47% of the analyzed publications among the top 10 journals. This substantial lead over other journals demonstrates its position as the primary platform for GEE-based wetland research. The second tier of journals includes Ecological Indicators (14 papers) and IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (13 papers), collectively accounting for about 16% of the publications.

Citation Impact Analysis

The citation metrics reveal interesting patterns that don't always correlate with publication volume:

1. High Impact Journals:
 - Remote Sensing of Environment shows the highest average citation rate (61.3 citations per paper) despite having fewer publications (8 papers)
 - Remote Sensing leads in total citations (2,121) due to its high publication volume
 - Ecological Indicators maintains strong impact with 29 citations per paper average
2. Moderate Impact Journals:
 - International Journal of Applied Earth Observation and Geoinformation demonstrates solid impact (20.7 citations per paper)
 - IEEE Journal maintains steady influence (13.2 citations per paper)
 - Water (Switzerland) shows consistent performance (11.3 citations per paper)
3. Emerging and Specialized Venues:
 - Land and Sustainability (Switzerland) show growing contributions with moderate citation rates
 - International Archives of Photogrammetry shows lower citation rates (1.9) but maintains steady publication volume
 - IOP Conference Series provides an important venue for emerging research

3.5 Scholarly Contributions and International Collaboration

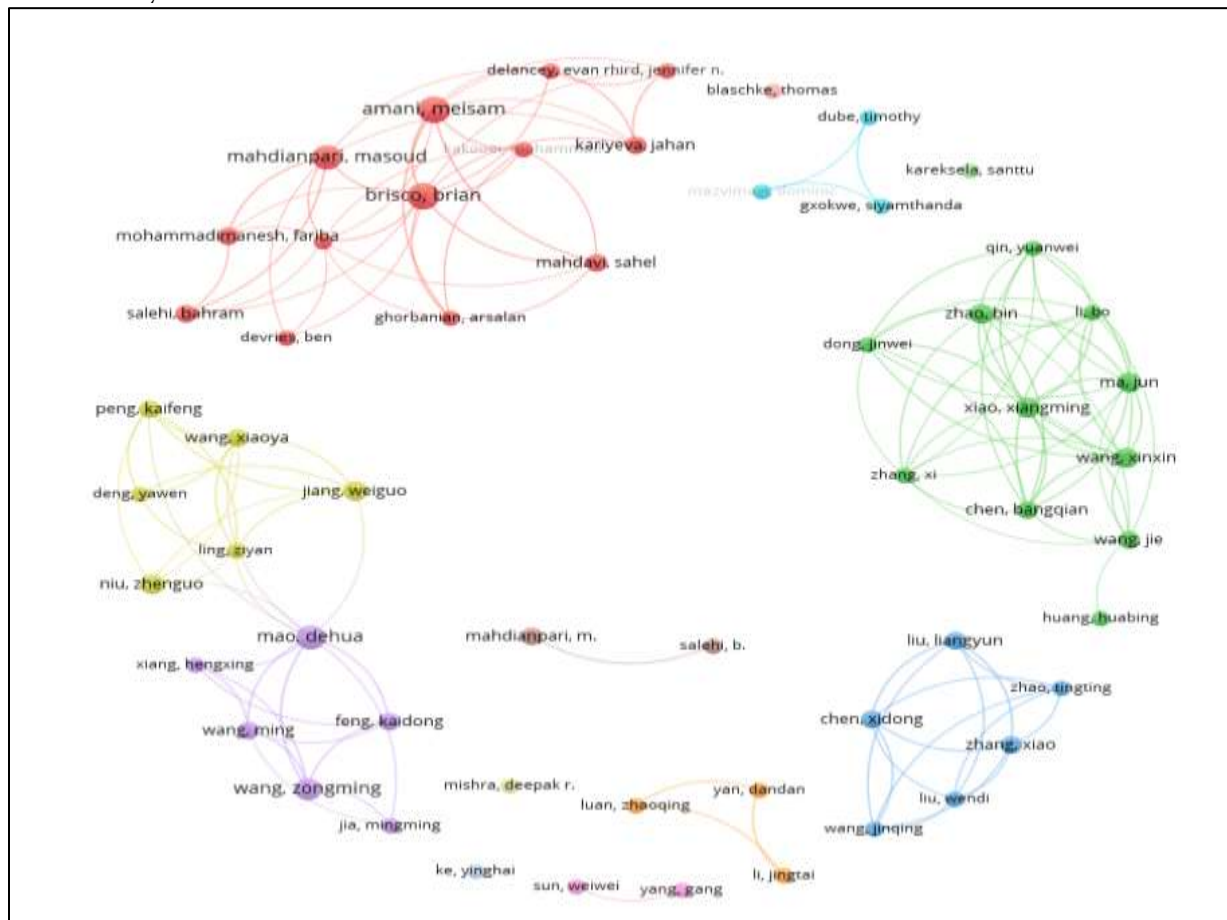


Fig. 7 International Collaboration Network of 56 Scholars (who published at least 3 articles related to GEE) Based on the Number of Publications (top) and the Number of Citations (bottom)

In the above Fig. 7, the node represents a scholar. The size of nodes is proportional to the number of publications and citations, whereas the thickness of lines between nodes is proportional to the strength of collaboration between scholars

The analysis of scholarly contributions highlights the involvement of 56 researchers who have published at least three articles on the application of Google Earth Engine (GEE) in land-cover assessment of wetlands. The collaboration network visualizes the interplay of publications and citations among these scholars.

Key contributors include Brian Brisco and Meisam Amani, each with eight publications and citation counts of 475 and 364, respectively. Dehua Mao follows with seven publications and 139 citations, showcasing consistent academic productivity. Other prominent researchers, such as Masoud Mahdianpari (7 publications, 425 citations) and Zongming Wang (6 publications, 109 citations), have significantly advanced the field through their research efforts.

The network map depicts the relationships among these scholars, with node sizes proportional to the number of publications and citations. Scholars like Xinxin Wang, Xiangming Xiao, and Bin Zhao emerge as key figures with high total link strengths, indicating strong collaboration ties. For instance, Xinxin Wang and Xiangming Xiao both boast five publications and 521 citations, underscoring their influence in the domain.

The thickness of connecting lines between nodes represents the strength of collaborative efforts. Notable collaborations include those among scholars such as Chen Bangqian, Chen Xidong, and Liangyun Liu, whose partnerships have led to high citation counts and impactful research.

This collaborative network underscores the importance of partnerships in driving innovation and progress in the field. By fostering deeper collaborations among emerging and established scholars, the academic community can further enrich the research landscape and enhance the global understanding of wetland ecosystems.

3.6 The Frequency, Growth, and Co-Occurrence of Keywords

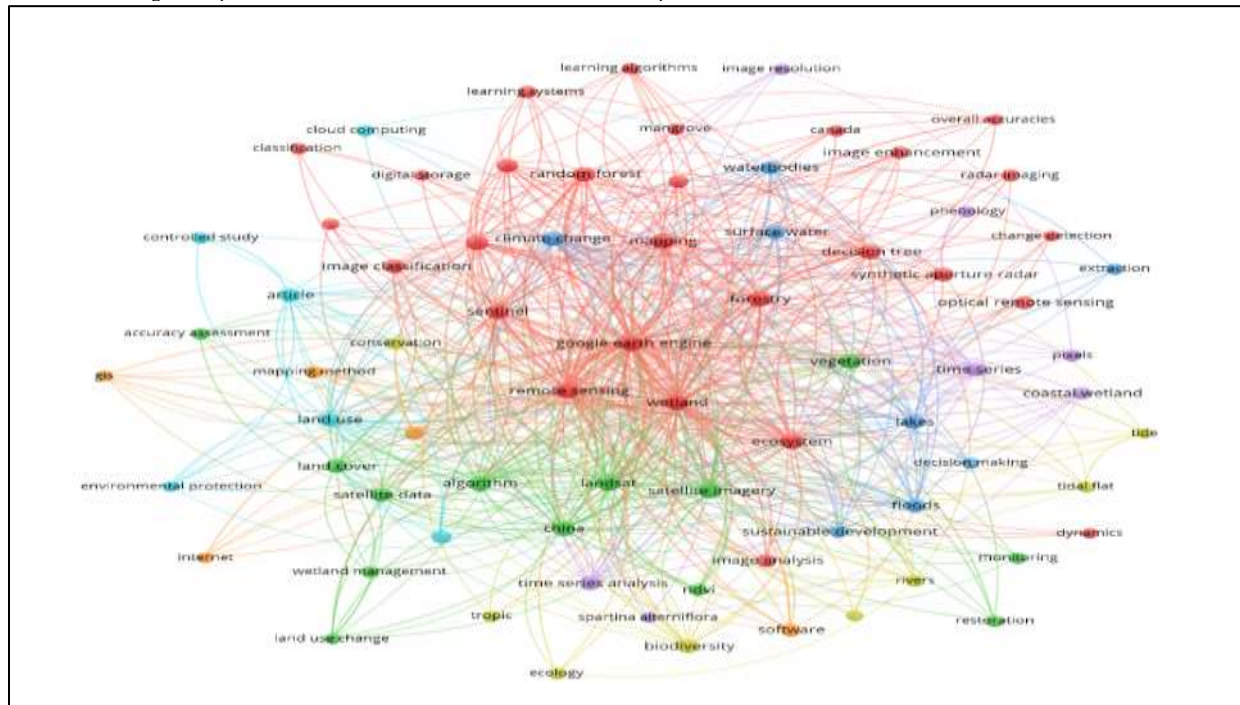


Fig. 8 The Co-Occurrence Network of 89 Most Frequent Keywords

The Fig. 8 shows the co-occurrence network of the 89 most frequent keywords. (1) the size of the node indicates the occurrence of the keyword (i.e., the number of times that the keyword occurs), (2) the link between the nodes represents the co-occurrence between keywords (i.e., keywords that co-occur or occur together), (3) the thickness of the link signals the occurrence of co-occurrences between keywords (i.e., the number of times that the keywords co-occur or occur together), (4) the bigger the node, the greater the occurrence of the keyword, and (5) the thicker the link between nodes, the greater the occurrence of the co-occurrences between keywords. Each color represents a thematic cluster, wherein the nodes and links in that cluster can be used to explain the theme's (cluster's) coverage of topics (nodes) and the relationships (links) between the topics (nodes) manifesting under that theme (cluster).

The co-occurrence network of keywords, visualized using VOSviewer, highlights the thematic structure of research in wetland assessment utilizing Google Earth Engine (GEE). The analysis identified several prominent clusters, each representing a major research theme:

1. Major Themes and Clusters:

- **Core Cluster:** Keywords such as "Google Earth Engine," "wetlands," and "remote sensing" form the central hub, reflecting the fundamental focus of the research field. These terms also show high total link strength, indicating their widespread use and interconnectedness across studies.
- **Technology and Methodology:** Keywords like "satellite imagery," "decision trees," "random forests," and "machine learning" dominate a cluster emphasizing the integration of advanced computational techniques for data analysis and classification.
- **Environmental Concerns:** Terms such as "climate change," "land use," and "sustainable development" form a cluster highlighting the role of GEE in addressing global environmental issues, including wetland conservation and restoration.
- **Geographic and Ecosystem-Specific Terms:** The inclusion of keywords such as "China," "coastal wetlands," "mangrove," and "tidal flat" reflects geographically or ecologically specific studies.

2. Emerging Topics:

- Smaller clusters or isolated terms, such as "*Spartina alterniflora*" (a coastal plant species), "NDVI," and "spatiotemporal analysis," suggest emerging niches. These areas could point to innovations in monitoring wetland vegetation and temporal changes.

3. Gap Analysis:

- Certain critical aspects are underrepresented or absent in the co-occurrence map. For example:

■ **Ecosystem Services:** Limited focus on quantifying specific benefits wetlands provides (e.g., carbon sequestration, water purification).

■ **Socio-Economic Integration:** Few studies explicitly address the socio-economic impacts of wetland degradation or restoration.

■ **Biodiversity Monitoring:** Keywords related to rare or endangered species monitoring are not prominent, indicating a potential gap.

These findings suggest that while the field is well-established in leveraging GEE for wetland mapping and monitoring, there is significant potential to expand research into socio-ecological dimensions and biodiversity conservation. Integrating these themes could enhance the field's relevance to policy and practical applications.

3.7 Author Keyword Impact Analysis

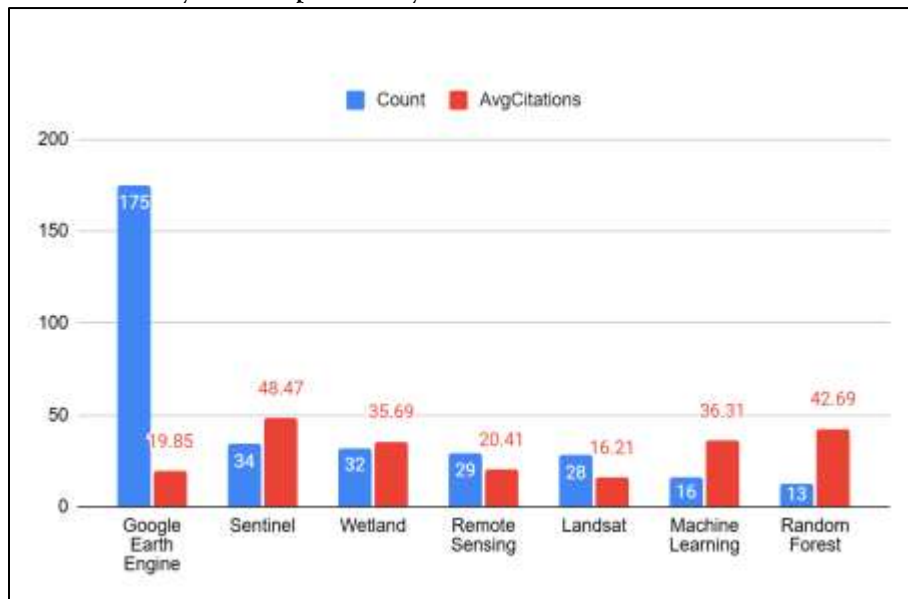


Fig. 9 Author Keyword Impact Analysis

A significant part of the analysis is the Author Keyword Impact Analysis (Fig. 9), where keywords are extracted from the "Author Keywords" field, and their occurrence counts and average citation impacts are calculated. The keyword impact analysis highlights the influence of frequently used author keywords within the wetland research domain, as measured by their occurrence and average citations. "Google Earth Engine" emerges as the most frequently used keyword, appearing 175 times with an average of 19.85 citations per article. This underscores its widespread adoption as a critical tool in geospatial and wetland studies.

"Sentinel" and "Wetland" are noteworthy for their high average citations of 48.47 and 35.69, respectively, indicating their significant impact in advancing research. Similarly, "Machine Learning" (16 occurrences) and "Random Forest" (13 occurrences) show substantial average citations of 36.31 and 42.69, reflecting the growing importance of artificial intelligence and data-driven approaches in wetland analysis.

Traditional remote sensing tools, such as "Landsat" (28 occurrences) and "Remote Sensing" (29 occurrences), continue to play a prominent role, though their average citation impact is comparatively lower at 16.21 and 20.41, respectively.

These insights reveal the pivotal keywords shaping wetland research and emphasize the critical areas where geospatial technologies and machine learning intersect with environmental studies.

3.8 Methodological Approaches

3.8.1. Classification Methods

Several classification methods can be used for large-scale provincial wetland studies, with varying degrees of success depending on the specific goals of the study, the data available, and the computational resources available.

3.8.2. Random Forest (RF)

Classification is a popular method for wetland mapping due to its efficiency and high potential [19]. The RF algorithm is an ensemble classifier that can effectively distinguish between spectrally similar land covers.

RF is beneficial because it is non-parametric, can process large, high classification accuracy, continuous and categorical data sets, is not sensitive to noise or overtraining, can provide ancillary information such as classification error and variable importance, and is computationally lighter than other tree ensemble methods [19].

Many studies have reported that the RF algorithm is superior to other commonly used classifiers for wetland mapping [20].

The RF algorithm has been successfully applied to classify wetlands across large areas within the Google Earth Engine (GEE) platform [20].

3.8.3. Object-based image analysis (OBIA)

OBIA methods use spatial information, extract additional features, and reduce the dataset. Object-based methods may be more accurate for wetland classification than pixel-based techniques when using high and medium-spatial-resolution data. However, the segmentation process should be done carefully to produce objects with appropriate size for classification [22]. Some studies have combined OBIA and RF classification methods to map wetlands [8, 19, 21].

3.8.4. Deep learning methods

Convolutional Neural Networks (CNNs) have shown great promise in wetland classification. Studies have demonstrated that deep learning results outperform other machine learning methods such as random forest. CNNs can achieve high wetland classification accuracies, but the accuracy can depend on the size of the study area. Deep learning algorithms can produce more accurate wetland/landcover classifications [23].

3.8.5. Other methods

Other methods that have been used for wetland classification include:

- Supervised machine learning algorithms
- Classification and Regression Tree (CART)
- Minimum Distance (MD) decision tree
- Multiple Classifier System (MCS) combining various machine learning algorithms
- Band thresholding of the short-wave infrared (SWIR) band

When choosing a method for large-scale provincial wetland studies, it is important to consider the following:

- Data availability: The technique should be compatible with the available remote sensing data, including optical, SAR, and DEM data [22].

- Field samples: A sufficient number of high-quality training samples is important for reliable classification [8, 20]. The lack of field samples can be a major issue for wetland mapping, particularly in remote areas [20].

- A generalized supervised classification scheme can be helpful for creating wetland inventory maps of provinces that lack field samples if land cover and wetland classes are similar [20].

- Computational resources: The method should be computationally efficient, especially for large study areas. Cloud-computing platforms such as GEE can help process large amounts of data [20].

- Accuracy: The method should provide a high level of accuracy in classifying different wetland types. The average producer and user accuracies for wetland classes can vary [24].

- Wetland complexity: Wetlands can be heterogeneous and fragmented, making them difficult to classify. The spectral similarity of differing wetland classes is also a challenge [21].

- The Canadian Wetland Classification System (CWCS): If the goal is to map wetlands based on the CWCS, it is important to use a method that can differentiate between the five main classes of bog, fen, marsh, swamp, and shallow water [20].

- Multi-temporal data: Using multi-temporal satellite images is helpful for improving the classification accuracy of dynamic landscapes and monitoring their changes over time [20].

- Object-based vs pixel-based methods: Object-based methods result in higher classification accuracy compared to pixel-based algorithms.

Ultimately, the best classification method for a large-scale provincial wetland study will depend on the specific requirements of the study and the resources available. A combination of different methods may also be used to achieve the best results.

Table 4 Essential data types and their information for wetland mapping, based on the provided sources

Data Type	Description	Key Information and Use
Optical Satellite Imagery	Data acquired from optical sensors on satellites (e.g., Landsat, Sentinel-2, MODIS).	- Essential for Land Use/Land Cover (LULC) change monitoring.
		- NIR band is useful for identifying vegetation and water.
		- SWIR band is helpful in detecting moisture contents in vegetation and soil.
		- Visible bands (especially red) can detect specific wetland classes (e.g., sphagnum moss in bogs).
SAR (Synthetic Aperture Radar) Imagery	Data acquired from SAR sensors (e.g., Sentinel-1, PALSAR).	- Unaffected by cloud cover, enabling regular monitoring.
		- Sensitive to soil moisture, vegetation structure, and inundation.
		- VV polarization is useful for detecting flooded wetlands, and VH polarization helps in discriminating between herbaceous and woody wetlands.
Elevation Data	Digital Elevation Models (DEMs) from sources like LiDAR or satellite data (e.g., CDEM).	- Important for identifying wetlands, as they are usually located in flat areas.
		- Can be used to derive topographic indices like the Topographic Wetness Index (TWI) and Topographic Position Index (TPI).
Field Data	In-situ data collected from wetland sites.	- Essential for training and validating remote sensing classifications.
		- Includes GPS points, photographs, and notes on dominant vegetation and hydrology.
Existing Wetland Inventories and Maps	Pre-existing wetland datasets and maps.	- Useful as reference data and for comparison.
		- Can be used to derive training samples.
Water Indices	Calculated from satellite imagery bands	-NDWI (Normalized Difference Water Index) and MNDWI (Modified Normalized Difference Water Index) are commonly used optically-based surface water indices.
Land Cover Data	Data on land cover types surrounding wetlands.	- Important for reducing the misclassification of non-wetland categories as wetland classes.

The integration of multi-source data, such as optical, SAR, and elevation data, is often recommended to improve the accuracy of wetland mapping and monitoring. Additionally, cloud computing platforms like Google Earth Engine (GEE) are frequently used for processing and analyzing large amounts of satellite data for wetland mapping applications.

4. FUTURE RESEARCH DIRECTIONS

Based on the provided sources, several areas for future research in wetland mapping and monitoring can be suggested:

- **Integrating multi-source data:** Combining data from various sources, such as optical, SAR (Synthetic Aperture Radar), and LiDAR, can improve the accuracy of wetland mapping [22].
 - SAR data is especially valuable for areas with frequent cloud cover, as it can penetrate clouds and provide data even in inclement weather [21].
 - The integration of Landsat and Sentinel data using platforms like Google Earth Engine (GEE) can help overcome the limitations of cloud cover [21].
 - Combining spectral information with texture information can significantly increase the accuracy of training sample migration methods for mapping and change detection [8].

- Future studies should explore more change factors, including the backscatter information of different wetland classes derived from SAR data, to refine workflows for migrating reference samples.
- Multi-temporal datasets help detect and understand wetland dynamics and trends over time [21].
- Exploring deep learning techniques:** Deep learning algorithms, such as Convolutional Neural Networks (CNNs), have shown promise for wetland classification, and further research is needed to explore their full potential [23].
- Future work should consider the application of deep learning for large-scale wetland mapping [25].
- While some studies have shown that deep learning methods can outperform other machine learning methods, more research is needed to assess their applicability in different environments.
- The combination of pixel-based and object-based classification techniques may also increase accuracy [25].
- Improving training sample selection:** Acquiring high-quality training and testing samples is crucial for accurate wetland mapping, particularly on a large scale.
- Future studies could explore more robust methods for automatically deriving training samples [21].
- More effort needs to be placed on obtaining reference data for other Invasive Aquatic Alien Plant (IAAP) species [24].
- A new method to achieve highly credible sample points may be used, especially for large and geographically diverse areas [26].
- A method for migrating training samples from a reference year to target years using histogram thresholding can be further explored.
- Developing and applying time-series analysis:** Analyzing time series of satellite data can help in understanding the phenological patterns of wetland vegetation and detecting changes over time [27, 28].
- Future studies could investigate the relationship between phenological trajectories and local environmental conditions [28].
- Long-term monitoring of wetlands, using time-series data, is important for assessing the impacts of climate change and human activities [19].
- Analyzing the spatial-temporal changes of aquaculture areas with historical Earth observation images can provide valuable insights [29].
- Utilizing cloud-computing platforms:** Cloud-computing platforms like GEE provide powerful tools for processing large amounts of satellite data, enabling large-scale wetland mapping and monitoring.
- Further research could explore the full potential of GEE for wetland mapping [22].
- Future studies should consider the use of GEE for operational mapping, particularly for areas with heterogeneous land cover [30].
- Improving classification methods:** More accurate classification methods still needed to be investigated, as there are issues with the misclassification of rivers or other features adjacent to wetlands [29].
- Studies should also focus on the spectral characteristics of salt marsh and saline wetlands [31].**
- Future research should focus on developing classification and change detection methods applicable at larger geographical scales [24].**
- Addressing specific wetland types and conditions:**
- Future studies should aim to map more specific aquaculture types.
- More research could be done on classifying open-water wetlands based on water occurrence [32].
- Future studies need to focus on the spectral separability of water hyacinth from other IAAP species [24].
- Creating comprehensive inventories:** There is a need for more comprehensive and up-to-date wetland inventories at local, provincial, and global scales [33].
- Future research could develop methods for global wetland mapping [22].
- Further efforts are needed to create a Canada-wide wetland inventory based on the specifications of the CWCS [24].
- Improving water quality monitoring:** Future studies could transform water quality prediction frameworks into online monitoring tools [34]:
- The use of machine learning methods can be used to predict water quality parameters that are not easily observed through remote sensing, such as total nitrogen [34].
- Studying the impacts of climate change:** More research is needed on how climate change impacts wetlands.

○ There is a need to study how wetlands may be able to mitigate changes to hydrology caused by variations in precipitation.

○ Future studies should investigate how climate change might affect tree regeneration following fire at northern latitudes, as well.

● **Developing management tools:** The creation of tools that allow users to track water and aquatic vegetation extent will be helpful in systematically evaluating the effectiveness of past and future management efforts.

● **Considering socioeconomic factors:** Future research should combine land change analysis with an in-depth understanding of socioeconomic factors to inform policy and decision-making.

● **Validating results with field data:** Future studies should include field surveys and aerial surveys to fully explain the discrepancies in the classification results.

By addressing these areas, future research can contribute to more accurate and comprehensive wetland mapping and monitoring, which is essential for effective conservation and management of these valuable ecosystems.

5. CONCLUSION

The bibliometric analysis of wetland monitoring using Google Earth Engine reveals a rapidly evolving and increasingly influential research field. The dramatic rise in publications from 2017 to 2024, particularly the surge after 2021, demonstrates the growing adoption of GEE as a crucial tool for wetland assessment. The geographic distribution of research highlights both the global reach of GEE applications and the concentration of expertise in specific regions, with China, the United States, and Canada leading in contributions. The analysis reveals a strong trend toward collaborative research, evidenced by the extensive international co-authorship networks and the high collaboration index of 5.67.

The methodological landscape shows a clear preference for machine learning approaches, particularly Random Forest classification, while emerging trends indicate growing interest in deep learning applications and multi-source data integration. The dominance of Remote Sensing journal publications underscores the technical nature of the field, while the high citation rates for recent publications reflect the immediate impact and relevance of GEE-based wetland research.

Key challenges and opportunities for future research include the need for improved integration of socio-ecological factors, enhanced biodiversity monitoring capabilities, and the development of more sophisticated classification methods. The field shows particular promise in areas such as time-series analysis, deep learning applications, and the development of automated training sample selection methods. As global environmental challenges continue to mount, the role of GEE in wetland monitoring and observation is likely to become increasingly critical, suggesting a bright future for this research domain.

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