A Comprehensive Bibliometric Analysis of Large Language Models in Hydrology and Environmental Sciences

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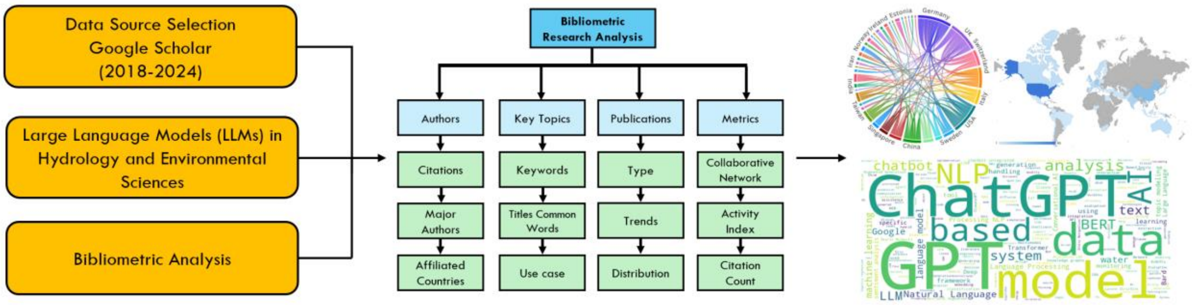
Abstract
The application of large language models (LLMs) in hydrology and environmental sciences is expanding rapidly, but a comprehensive understanding of their potential, best practices and application areas are studied extensively. This study conducts a bibliometric analysis of recent scientific literature to evaluate publication trends, citation impact, and the key contributors in LLM-related research within these fields and offers insights and suggestions for best practices. We focus on extracting and analyzing critical metadata, including citations, publication dates, journals, authors, affiliated countries, impact factors, cite scores, research types, domains, and keywords. Additionally, we assess the purpose, use cases, and applications of LLMs, as well as the ethical considerations surrounding cost, scalability, data privacy, transparency, and sustainability. Our findings indicate significant growth in LLM-based studies, especially in hydrological modeling, climate forecasting, and environmental monitoring. We also highlight key challenges related to scalability and ethical concerns, such as data privacy and transparency, that need further exploration. This study provides a detailed understanding for the landscape of LLM adoption in environmental sciences, offering valuable insights for future research and policy development in these critical areas.

Keywords: Hydrology; ChatGPT; Large Language Models (LLMs); Artificial Intelligence (AI); Environmental Sciences; Machine Learning (ML); Bibliometric Analysis

Highlights:

- Performed bibliometric analysis of LLMs in hydrology and environmental sciences (2018–2024).
- Identified trends, key authors, and collaborative networks in environmental applications.
- Analyzed citations, publication trends, keywords, domains, and geographic patterns.
- Highlighted LLM applications in prediction, monitoring, and policy.

Graphical Abstract:



1. Introduction

Large Language Models (LLMs) represent a significant advancement in artificial intelligence (AI), enabling machines to process, understand, and generate human-like text. Models like GPT-3 and GPT-4 utilize deep neural networks with billions of parameters, trained on vast datasets from diverse online sources (Klang et al., 2024). Built on the Transformer architecture, LLMs employ attention mechanisms that allow for efficient language processing (Klang et al., 2024). These capabilities enable LLMs to excel in tasks such as text generation, translation, and question answering, significantly impacting fields like radiology, robotics, and scientific research (Kim et al., 2024; Zhang et al., 2024; Sajja et al., 2024a). Despite these advancements, challenges such as bias, hallucinations, and data quality limitations persist, raising ethical concerns about the use of LLMs, particularly in sensitive areas like healthcare and environmental science (Fan et al., 2024; Sreerakuvandana et al., 2024).

AI has long been a critical tool in hydrology, especially in streamflow modeling (Demiray et al., 2024), offering innovative solutions to complex challenges. Machine learning (ML) and deep learning techniques have improved the accuracy and efficiency of streamflow predictions (Sit et al., 2021) and environmental pollution (Bayar et al., 2009), particularly in regions with limited data availability. Among the most widely used AI models in hydrology are Artificial Neural Networks (ANNs), which appear in over 25,000 instances in the literature and have proven effective in simulating river flows in data-scarce regions (Özdoğan-Sarıkoç, 2024; Mugume et al., 2024; Krajewski et al., 2021). Long Short-Term Memory (LSTM) models, another popular AI approach, excel at handling time-series data, capturing key factors like soil moisture dynamics that drive streamflow generation (Ley et al., 2024; Casper, 2023).

Recent advancements in Explainable AI (XAI) have aimed to make AI models more interpretable and transparent (Li and Demir, 2024). XAI techniques, such as gradient-based and perturbation-based methods, have been applied to LSTM models to highlight the importance of input data, including seasonal patterns, water quality (Mermer et al., 2024) and soil moisture dynamics (Ley et al., 2024; Casper, 2023). Additionally, Generative Adversarial Networks (GANs) have been employed to augment environmental data (Demiray et al., 2021) and predict streamflow in ungauged basins, excelling at extreme event prediction through interpretable models like Local Interpretable Model-Agnostic Explanations (LIME) (Perera et al., 2024).

AI-based hybrid models, which combine traditional hydrological models (e.g., HEC-HMS) with ANNs, have also shown superior performance in simulating future streamflow under climate change scenarios. These hybrid models offer greater computational efficiency and accuracy, projecting significant increases in future streamflow (Mugume et al., 2024). Despite these advancements, challenges remain, particularly in model interpretability and the integration of diverse data sources. Ensuring that AI models are effectively applied in practical water resource management is a critical area for future research.

Building on the success of AI models in hydrology, LLMs are now transforming scientific research, particularly in hydrology and environmental science. These fields often involve vast amounts of complex and unstructured data, making LLMs a valuable tool. For example, LLMs are being applied in flood management, water quality monitoring, and pollution control, enabling more informed decision-making in real-time systems (Kadiyala et al., 2024). In water engineering, LLMs have been benchmarked for tasks such as wastewater treatment and environmental restoration, generating precise research gaps and titles for scientific papers (Xu et al., 2024). Furthermore, the integration of LLMs with multimodal systems, such as GPT-4 Vision, enhances their ability to analyze visual data, broadening their applications in hydrology (Samuel et al., 2024).

AI, including ML, deep learning (DL), and LLMs, plays a transformative role in hydrology and environmental science. These technologies enhance data-driven insights, improve predictive accuracy, and support decision-making in water resource management. Applications of AI in these domains include data-driven modeling, such as using ML tools to process datasets like satellite imagery and meteorological data to predict streamflow, groundwater levels, and water availability, supporting water allocation, infrastructure planning, and operational decision-making (Guariso & Sangiorgio, 2024). In groundwater modeling, ANNS and DL methods improve predictions by recognizing complex patterns and non-linear relationships. Hybrid algorithms enhance these capabilities by integrating various AI techniques (Pourmorad et al., 2024). Furthermore, LLMs integrated into multimodal systems demonstrate proficiency in real-time hydrological applications, such as flood risk management (Yildirim et al., 2022) and water pollution monitoring, by combining textual and visual data.

To address the challenges of data uncertainty, data assimilation techniques are employed to propagate uncertainty and improve model generalization, thus reducing overfitting risks (Martin & White, 2024). Additionally, the integration of AI with mechanistic models fosters process-based understanding, aiding in the development of new theories and addressing the complexity of hydrological systems (Muñoz-Carpena et al., 2023).

Beyond specific applications, LLMs are playing a critical role in fostering interdisciplinary research. By facilitating knowledge transfer between fields, they bridge the gap between hydrology, ecology, and other environmental sciences, significantly reducing the costs of such collaborations (Mammides & Papadopoulos, 2024; Sajja et al., 2024b). Additionally, LLMs are being integrated into multi-agent systems, enhancing problem-solving capabilities by allowing multiple models to collaborate in complex environments (Guo et al., 2024).

While the benefits of LLMs are substantial, they are not without limitations. Challenges such as hallucinations, bias, and dependence on training data quality remain significant hurdles (Fan et al., 2024; Sajja et al., 2023). Ethical concerns surrounding misinformation, data privacy, and transparency are critical areas of ongoing research, especially as LLMs are increasingly applied to environmental science and hydrology (Sreerakuvandana et al., 2024; Mammides & Papadopoulos, 2024). Additionally, balancing the scalability and costs of deploying LLMs in large-scale environmental systems presents further challenges (Zhang et al., 2024; Ma et al., 2024; Sajja et al., 2024c).

With the rapid expansion of LLM applications in hydrology and environmental sciences, a systematic evaluation of the research landscape is crucial. Bibliometric analysis is essential for assessing key trends, citation impacts, author contributions, and collaboration networks in the field (Sreerakuvandana et al., 2024). It is particularly timely given the integration of LLMs with other technologies, such as multimodal systems, and their growing role in scientific discovery across disciplines (Zhang et al., 2024). Understanding the current state of LLMs research in hydrology and environmental science will enable researchers to better leverage these tools to address pressing environmental challenges while navigating the ethical and technical limitations of their use (Ma et al., 2024; Mammides & Papadopoulos, 2024).

The primary objective of this paper is to conduct a comprehensive bibliometric analysis of the current research landscape surrounding LLMs in the fields of hydrology and environmental science. By identifying key trends, collaboration networks, prominent authors, and emerging directions, this study seeks to provide valuable insights into how LLMs are being applied and how the field is evolving. A bibliometric approach allows for a systematic examination of the most influential works, identifying patterns in publication output, citation impacts, and the geographic distribution of research efforts.

One of the aims of this analysis is to highlight the most productive authors, institutions, and countries contributing to LLM research in environmental science. Furthermore, this study will explore the extent of interdisciplinary collaboration and identify key research hubs that are leading the way in the integration of AI technologies like LLMs into environmental applications. By mapping these networks, the paper seeks to shed light on how different regions and institutions are collaborating and sharing knowledge, thus fostering more effective global partnerships. Moreover, this analysis will help understand how LLMs are being applied to address critical environmental challenges such as flood prediction, water quality management, and pollution control, helping to guide future research efforts and foster interdisciplinary collaboration (ref; Foroumandi et al., 2023).

Additionally, this paper will address the following key research questions (RQ):

a) What are the dominant trends in the publication of LLM-related research within hydrology and environmental science over the past decade?
b) Who are the most influential authors and institutions, and how are they collaborating globally?
c) What are the primary research themes, applications, and methodologies being explored in LLM research within these fields?
d) What gaps or under-researched areas exist that present opportunities for future exploration?
e) How are ethical concerns, such as bias, reliability, and transparency, being addressed in the existing literature on LLM applications in environmental science?

By answering these questions, the paper aims to provide a detailed landscape of the current state of LLM research in environmental science, while also guiding future research directions and collaborations. This bibliometric analysis will serve as a resource for researchers and policymakers seeking to understand the potential and limitations of LLMs in addressing environmental challenges.

2. Methodology

2.1. Bibliometric Analysis Approach

Bibliometric studies follow a systematic approach to quantitatively analyze scientific literature, typically involving several key steps. First, researchers select a comprehensive database, such as Web of Science or Scopus, to gather relevant articles based on specific keywords or topics of interest (Büyükkıdık, 2022; Passas, 2024). Data is then processed through techniques like multidimensional scaling (MDS) and cluster analysis to calculate co-citation similarities between articles (Kilubi, 2017). Visualizations such as maps and graphs help in interpreting the results and identifying key trends (Kilubi, 2017). Finally, the findings are documented and shared with the scientific community, contributing to the broader knowledge base (Passas, 2024; Sousa et al., 2024). Bibliometric studies involve a systematic approach to quantitatively analyzing scientific literature. The procedure helps researchers map scientific information, identify trends, and evaluate the impact of research within a specific field. In this study, we followed a five-step approach (Figure 1), which is detailed below:

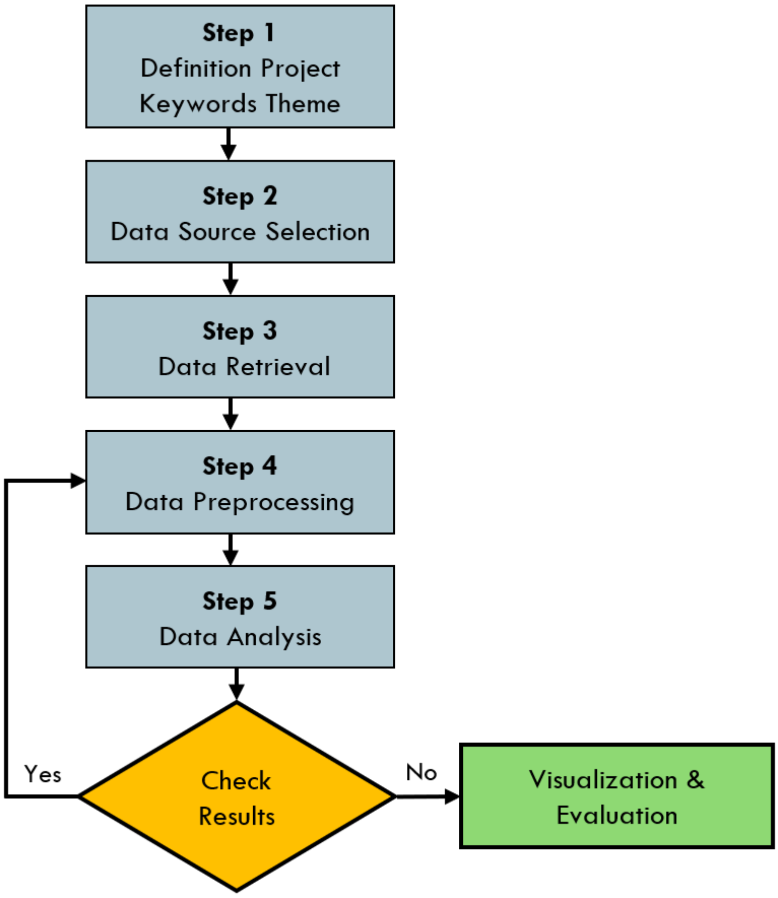


Figure 1. The workflow diagram of the bibliometric analysis process

Step 1 – Definition of Project Keywords and Theme: The first step involves defining the project's keywords and themes. This includes identifying relevant keywords, topics, and themes related to LLM applications in environmental science and hydrology. The boundaries of the research are clarified to ensure the study remains focused and aligned with its objectives.

Step 2 – Data Source Selection: The next step involves selecting a suitable database. This includes choosing a database that provides comprehensive coverage of peer-reviewed scientific outputs. to retrieve comprehensive bibliometric data. For this study, Google Scholar was selected due to its extensive coverage, citation tracking features, and relevance to the study's objectives.

Step 3 – Data Retrieval: In this step, data retrieval is conducted using the predefined keywords and thematic parameters identified in the earlier steps. Search is applied to titles, abstracts, and keywords to extract relevant publications. Metadata such as publication dates, authors, affiliations, and references are collected for further analysis.

Step 4 – Data Preprocessing: The next step involves preprocessing the retrieved data. This step includes removing duplicates, filtering out irrelevant publications, and ensuring that the dataset aligns with the research focus. Outliers and data not meeting the study criteria are excluded at this stage.

Step 5 – Data Analysis: In this step, preprocessed data is analyzed using bibliometric indicators, statistical methods, and keyword frequency analysis. Co-citation matrices and cluster analyses are created to identify influential works, key authors, and collaboration networks. After analyzing the data, a critical step involved checking the underlying results. If discrepancies or irrelevant results were found, the process looped back to the preprocessing stage to ensure data accuracy. Once all checks were complete, the data moved to the visualization phase.

Visualization and Evaluation: Visual tools like maps, graphs, and network diagrams are created to represent the analyzed data. These visual tools helped in interpreting the results, identifying trends, and drawing insights into the research landscape of LLMs in hydrology and environmental science. The results were then evaluated to ensure they aligned with the initial research questions and objectives, providing a foundation for further discussion and dissemination.

This structured approach ensures that bibliometric analysis is both comprehensive and reliable, helping to uncover valuable insights into LLM applications in environmental science and hydrology.

2.2. Keywords and Search Strategies

To ensure a comprehensive collection of relevant publications for the bibliometric analysis, we developed a structured search strategy that combined targeted domains with specific keywords related to LLMs and AI agents. The domains represent key areas of interest where AI technologies are being applied, such as environmental science, water, earth science, hydrology, water resources, and civil engineering. These domains were chosen to capture a broad spectrum of research in the environmental and hydrological fields, ensuring that we cover various subfields where LLMs are increasingly being utilized.

The search queries for each domain were structured around specific AI-related keywords, including "AI Agents," "Large Language Model," "GPT," and "LLM." These keywords were selected because they represent the most prominent AI technologies and methodologies relevant to our study, particularly in the context of their application to environmental science and hydrology. By focusing on these terms, we aimed to capture publications that specifically explored the use of advanced AI systems in these fields.

Our search strategy involved pairing each domain with all the selected keywords. For example, in the domain of Hydrology, we ran searches like "Hydrology AND AI Agents," "Hydrology AND Large Language Model," "Hydrology AND GPT," and "Hydrology AND LLM." Similarly, in the domain of Civil Engineering, search queries included combinations like "Civil Engineering AND Large Language Model" and "Civil Engineering AND LLM." This approach ensured that the search was broad enough to capture the intersection of AI advancements with various scientific and engineering fields, while maintaining a focus on LLMs and their applications. By systematically applying this strategy, we were able to retrieve a diverse and comprehensive set of publications relevant to the study's objectives. This method also allowed us to identify key trends, authors, and institutions at the forefront of integrating AI technologies with environmental science, hydrology, and other related disciplines.

2.3. Data Source Selection

For this bibliometric analysis, Google Scholar was selected as the primary source for retrieving relevant scientific literature. Google Scholar offers a comprehensive and freely accessible database, covering a wide range of disciplines and providing citations for peer-reviewed journals, conference papers, theses, books, and technical reports. Its extensive coverage made it ideal for capturing a broad spectrum of research publications related to LLMs in environmental science and hydrology.

Google Scholar is a valuable tool for bibliometric analysis due to its comprehensive coverage, ability to track citations, and capacity to provide insights into research trends across various disciplines. Unlike traditional databases such as Web of Science and Scopus, Google Scholar indexes a wide range of academic materials, including journal articles, conference papers, theses, and even patents (Chertow et al., 2021). This inclusivity allows for a more comprehensive bibliometric analysis. Additionally, it captures publications from non-Anglophone countries and regions, such as Latin America, offering a broader perspective on global research trends (Mugnaini, 2023).

A key strength of Google Scholar is its ability to track citations across diverse sources, enabling a deeper evaluation of the impact and reach of individual research publications. It also provides valuable metrics such as the h-index and i10-index, which are useful for assessing the influence of both authors and their publications (Mugnaini, 2023). These metrics enhance the ability to quantitatively assess the contributions of key researchers in the field.

In addition to citation tracking, Google Scholar can be used in conjunction with various data visualization and analysis tools. Tools like Publish or Perish and VOSviewer can be employed to perform detailed bibliometric analyses, including the identification of co-occurrence patterns and the mapping of research networks (Kartakusumah et al., 2023; Ariyanto, 2023). These tools are instrumental in uncovering research trends and visualizing scholarly collaborations, thus enhancing the overall understanding of research dynamics (Subagja et al., 2022).

Furthermore, Google Scholar's ability to search the full text of documents, rather than just metadata, provides additional value for discovering interdisciplinary research and emerging fields. This capability is particularly useful in identifying topics like industrial symbiosis, which might be overlooked by more traditional databases focused on specific disciplines (Chertow et al., 2021). As LLM applications in environmental science often intersect with other fields, this feature facilitates a more holistic understanding of the research landscape.

While Google Scholar offers extensive coverage and valuable metrics, it is important to acknowledge its limitations. The open-access nature of the platform can lead to inconsistencies in data quality and indexing. Some publications might lack the same level of rigor in their peer-review process compared to those in more traditional databases. Therefore, it is essential for researchers to cross-verify the data retrieved from Google Scholar with other databases to ensure accuracy and maintain the reliability of their bibliometric analyses. By utilizing Google Scholar, we were able to ensure a rich dataset for analysis, encompassing both well-established research and cutting-edge studies, which provided a strong foundation for the bibliometric analysis of LLM research in environmental science and hydrology.

2.4. Time Range Selection

The time range selected for this bibliometric analysis spans from 2018 to 2024. This period was specifically chosen to capture the significant advancements and widespread adoption in LLMs and their application to environmental science, hydrology, and civil engineering. Starting in 2018, the development of advanced LLMs such as GPT (Generative Pre-trained Transformer) models began to gain significant attention, particularly with the release of GPT-2 (OpenAI, 2019) in 2019, followed by GPT-3 (Brown, 2020) in 2020, which brought major advancements in natural language processing and AI capabilities. These models demonstrated unprecedented potential for generating human-like text, understanding complex language, and providing sophisticated insights from vast datasets.

The period from 2020 onwards saw transformative developments in LLMs. GPT-3, released in 2020, introduced 175 billion parameters, offering unprecedented performance in tasks like text completion, question answering, and predictive modeling. The introduction of ELECTRA further improved training efficiency, while conversational models such as Google's Meena and Facebook's BlenderBot showcased advancements in dialogue systems. In 2021, the Megatron model by NVIDIA further scaled LLM capabilities, and the BLOOM project from the BigScience Consortium provided an open-access LLM, democratizing AI research.

By 2022, the advent of GPT-4, Falcon LLM, and domain-specific models like Med-PaLM highlighted the growing specialization and multimodal integration of LLMs. These advancements were accompanied by a surge in their application to environmental sciences, including tasks such as climate modeling, flood prediction, and water quality monitoring. The final year of the analysis, 2024, reflects the maturity of LLM applications in hydrology and environmental science. OpenAI's and Meta's multimodal LLMs pushed the boundaries by integrating text with other data forms like images and audio, facilitating real-time decision-making and environmental monitoring.

These key developments are summarized in Table 1, which provides a timeline of the evolution of LLMs from 2018 to 2024. This period encapsulates the transition from early innovations to the widespread adoption and interdisciplinary application of LLMs in hydrology and environmental sciences, capturing their transformative impact on research and decision-making.

2.5. Bibliometric Indicators and Data Collection

Bibliometric indicators and data collection form a critical component of this study, enabling a systematic evaluation of the research landscape surrounding LLMs in hydrology and environmental sciences. The selection and organization of these indicators allow for the identification of key trends, influential authors, and collaborative networks, while also highlighting the broader impact of LLM applications across various domains. The elements of data collection and bibliometric analysis are shown in Figure 2, which highlights the systematic approach used to organize and refine the dataset, ensuring its suitability for in-depth bibliometric analysis.

Table 1. Timeline of the development of Large Language Models.

Year	Developments
2018	• BERT (Bidirectional Encoder Representations from Transformers) from Google introduced bidirectional training, improving contextual understanding in NLP. • ULMFiT (Universal Language Model Fine-tuning) demonstrated faster and efficient transfer learning in NLP tasks.
2019	• GPT-2, introduced by OpenAI, launched with 1.5 billion parameters, demonstrating advanced text generation capabilities but raising ethical concerns. • RoBERTa, developed by Facebook AI, enhanced BERT by improving pretraining strategies and achieving higher accuracy on NLP benchmarks. • XLM (Cross-Lingual Language Model) launched by Facebook AI, making a significant impact on translation tasks and multilingual understanding.
2020	• GPT-3 released by OpenAI, with 175 billion parameters, offering unprecedented capabilities in text completion, question answering, and natural language understanding. • ELECTRA by Google introduced a faster, more efficient pretraining NLP method, enhancing training accuracy. • The rise of large-scale conversational AI models like Google's Meena and Facebook's BlenderBot, demonstrating advancements in chatbot interactions, dialogue generation, and contextual understanding.
2021	• Megatron by NVIDIA further scaled LLMs, to handle vast datasets, making it possible to train LLMs like GPT-3 more efficiently. • BLOOM, developed by The BigScience consortium, became an open-access multilanguage model (including 46 languages and 13 programming languages), democratizing LLM research.
2022	• GPT-4 was launched by OpenAI, with improved performance (reasoning, safety and multimodal capabilities) over GPT-3. • Falcon LLM, released by the Technology Innovation Institute, offered the first open-source models for research and industry, making it explore LLMs without proprietary restrictions.
2023	• Med-PaLM and Med-PaLM2 launched by Google Research, specializing in healthcare applications, providing expert-level performance on medical tasks. • LLaMA and LLaMA2 released by Meta, open-source LLMs aimed at enhancing accessibility for researchers and developers.
2024	• Multimodal LLMs from OpenAI and Meta integrated text with images and audio, enabling advanced real-time decision-making and environmental monitoring. These models set new benchmarks for cross-disciplinary applications.

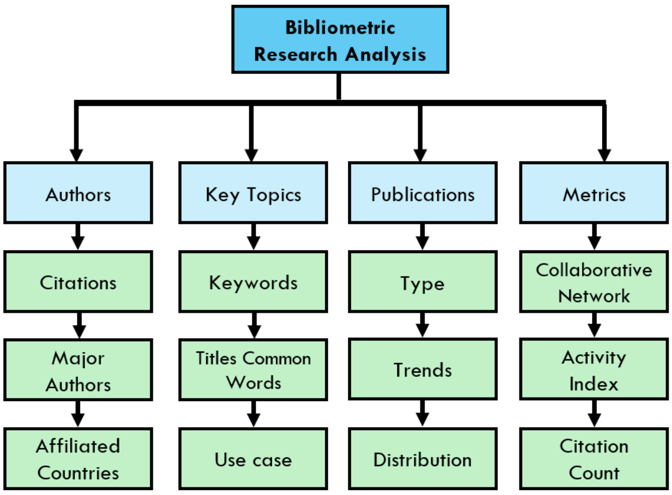


Figure 2. Elements of Bibliometric Data Collection and Analysis

To quantify the influence and scope of research contributions, several bibliometric indicators shown in Figure 2 were collected and analyzed for each publication:

Citations: The number of times each paper has been cited, providing a metric of its influence and reach within the scientific community.

Publication Date: The year or specific date when the paper was published, helping to track the evolution of research over time.

Journal: The journal in which the paper was published, offering insights into the publication outlets most frequently chosen for LLM research.

Authors: A record of the authors involved, which will help analyze co-authorship networks and determine key contributors to the field.

Affiliated Countries: The countries affiliated with the authors, allowing us to map global collaboration and identify leading research hubs.

Impact Factor and Cite Score: The impact factor and cite score of the journal, providing a measure of the journal's prominence and the potential influence of the published research.

Origin of the Article: Whether the paper is the result of original research, review, or another type of contribution.

Publication Type: Whether the publication is published as peer-reviewed journal, or conference preceding or preprint or book/book chapter.

Domain: The scientific domain or fields to which the research contributes, such as environmental science, hydrology, or AI technologies.

Keywords: Keywords used by the authors to describe the paper, which will aid in identifying research trends and thematic areas.

Use Case and Application: Specific applications or use cases of LLMs mentioned in the paper, such as environmental monitoring, climate modeling, or water resource management.

By gathering these bibliometric indicators, we aim to build a comprehensive dataset that not only tracks the growth and impact of LLM research but also explores the collaboration patterns, research focus, and ethical considerations in this rapidly evolving field. This dataset will form the foundation of our bibliometric analysis and help identify key trends and areas for future research.

2.6. Inclusion and Exclusion Criteria

The selection of articles for this bibliometric analysis followed a rigorous process to ensure relevance to the research questions and quality of the data. This stage of methodology aimed to focus on the most significant contributions in the field of LLMs as applied to environmental science and hydrology, while excluding irrelevant or low-quality studies.

The inclusion process is illustrated in Figure 3 using a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram, which provides a visual summary of the screening and selection strategy. The initial step in the inclusion process involved keyword filtering. A broad search was conducted using predefined keywords such as "Large Language Models," "LLM," "AI Agents," and related terms, with the aim of retrieving articles that applied these AI technologies within the domains of environmental science, hydrology, and related fields. Although this search captured a large number of papers, it also resulted in irrelevant publications that, while containing the keywords, did not align with the specific focus of LLM applications in environmental contexts. To address this, a detailed manual review of titles, abstracts, and keywords was conducted to exclude publications that were not directly related to hydrology, environmental monitoring, or the intended applications of LLMs.

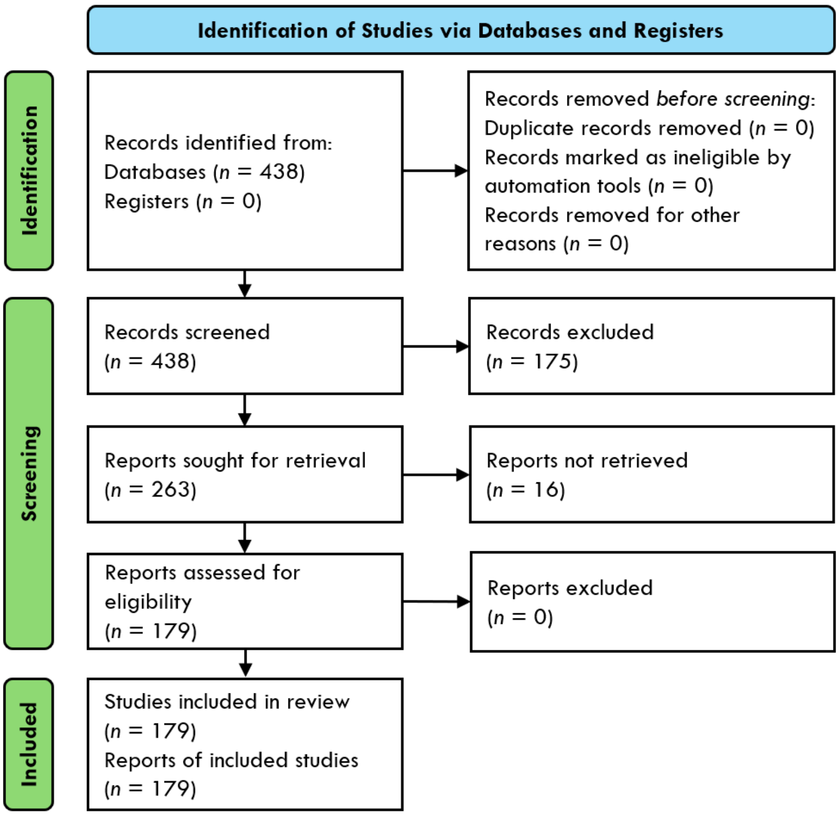


Figure 3. Screening strategy for included articles using PRISMA diagram

Another critical criterion for exclusion was the time frame of publication. This analysis focused on articles published between 2018 and 2024, a period that marks the rapid rise of LLMs and their increasing application in environmental research. Articles published outside this window were excluded, as the advancements in LLM technology prior to 2018 did not have the same level of relevance to the current developments and applications in the environmental sciences. By focusing on this six-year period, the analysis captured the most recent and impactful research in the field.

To ensure the accuracy and quality of the dataset, duplicate article removal was an essential part of the data cleaning process. Duplicate entries can occur when the same paper is indexed multiple times in different databases or when both preprint and peer-reviewed versions of the same article are retrieved. All duplicates were filtered out, ensuring that each paper was only represented once in the dataset, avoiding any bias or overrepresentation of certain studies.

Additionally, a key exclusion criterion was relevance to the specific focus of environmental science and hydrology. Papers that focused primarily on the technical development of LLMs or AI without any clear application to environmental monitoring, hydrology, or water resource management were removed. This helped maintain the study's focus on the intersection between LLMs and environmental applications, ensuring that only the most pertinent research was included. By applying these inclusion and exclusion criteria, the dataset was refined to include only high-quality, relevant publications, allowing for a focused and accurate bibliometric analysis. These steps helped ensure that the analysis reflected the most significant and impactful research in the application of LLMs to environmental science and hydrology.

2.7. Activity Index

The Activity Index is a valuable bibliometric tool used to measure and compare research activity across different entities, such as countries or institutions. By normalizing publication numbers relative to the size of the entity, the activity index allows for a more accurate comparison of research output, making it particularly useful for identifying emerging trends, patterns, and areas of specialization within specific research fields. It can be applied across various databases, including the Web of Science, and has been widely used to assess research activity in fields like data science, big data analytics, and AI (Nageye et al., 2024).

In this study, the activity index was used to evaluate the research performance of countries in the domain of LLMs within environmental science and hydrology. Originally proposed by Frame (1977) and further developed by Schubert and Braun (1986), it has become a standard tool for assessing research contributions at both institutional and national levels. The equation (Eq. 1) for the activity index was most recently updated by Hu and Rousseau (2009), making it a reliable measure of how different countries contribute to specific areas of scientific research (Chen & Guan, 2011).

It is calculated as the ratio of a country's share of publications in a specific field to its share of publications across all fields. This can be expressed mathematically as:

$$Activity\ Index = \frac{P_t^i/P_P}{P_t^T/P_{TP}} \qquad \text{Eq. 1}$$

where P_t^i and P_P are the number of publications in the specific field by the i-th country in the year *t* and the total publications by the i-th country during the study period, respectively. P_t^T is the total publications in the specific field for the world in year t and P_{TP} is the total publications in the specific field for the world during the study period.

The activity index serves as a relative performance indicator. A value of 1 suggests that a country's research activity in the specific field is on par with the global average. When a country's activity index is greater than 1, it indicates a high level of specialization in the field, with the country contributing more than the global average of publications. In contrast, an activity index below 1 indicates that the country is underperforming relative to the global average in that area of research (Chen & Guan, 2011).

For example, in fields like Graph Neural Networks (GNNs) and tourism, the activity index has been used to detect leading contributors and emerging areas of focus across countries, helping to highlight specialized research activity (Alavi et al., 2024; Asif & Fazel, 2024). Similarly, in this study, the activity index helps to identify which countries are leading the research efforts in LLM applications in environmental science and hydrology. By evaluating the activity index in this context, it becomes possible to pinpoint areas of high research concentration, emerging trends, and potential leaders in global research.

The practical implications of the activity index are significant, as it provides stakeholders with a clearer understanding of where research efforts are being concentrated. This can guide decisions about resource allocation, policymaking, and collaborations to foster innovation in emerging fields (Asif & Fazel, 2024). However, it is important to recognize that while the activity index is an effective tool for measuring publication activity, it primarily focuses on quantity. Therefore, it should be complemented by other bibliometric indicators to gain a more holistic understanding of research quality and impact (Nageye et al., 2024).

3. Results

3.1. Publication Types and Trends

The numbers and percentages of publication types according to the database of the study are summarized in Table 2. Among the references selected for the study, the majority belong to journal articles, comprising 48.0% of the total publications, followed by conference proceedings at 27.4%. Preprints account for 21.8%, while books and book chapters, along with dissertations, make up the remaining 2.8% (1.1% and 1.7%, respectively).

Table 2. Types, numbers, and percentages of publications on the subject of LLMs in hydrology and environmental sciences.

Reference Type	Number	Percentage (%)
Journal	86	48.0
Preprint	39	21.8
Conference Proceedings	49	27.4
Books / Book Chapters	2	1.1
Dissertation	3	1.7

During the study period, the number of publications began with three papers in 2018 and reached a peak of 82 publications in 2024. Early publications provided foundational insights into the field, with works such as Mostaco et al. (2018), who introduced AgronomoBot, a chatbot for agricultural sensor networks, and Kumar (2018), who developed the TRS Tool leveraging natural language processing for TMDL assessment. Juanals and Minel (2018) also contributed with a methodology for analyzing Twitter information flows on air quality using deep learning. The research output showed steady growth over the years, with nine papers selected in 2019, six in 2020, and 13 in 2021. A gradual increase was noted in 2022 with 14 papers, followed by a sharp rise to 52 in 2023 and a remarkable peak of 82 in 2024 (Figure 4).

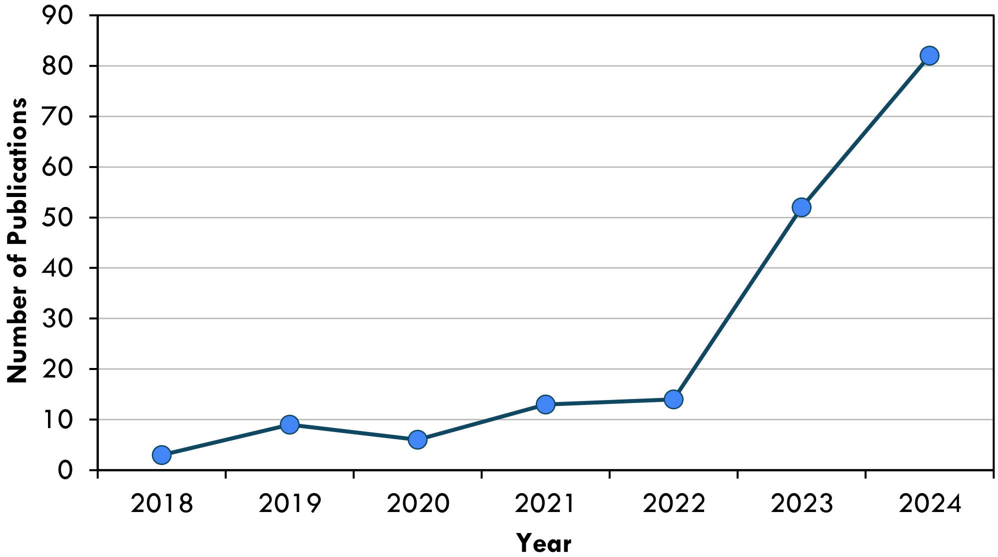


Figure 4. Publication trends for LLMs in hydrology and environmental sciences by year (2018–2024).

Additionally, in terms of publication categorization by type, research papers dominate the field with 161 papers (89.9%), while reviews (15 papers, 8.4%) and other publication types (3 papers, 1.4%) form a much smaller proportion. This reflects a strong emphasis on original contributions and novel methodologies in applying LLMs to hydrology and environmental sciences.

3.2. Citation Analysis

The most cited publications, their citation numbers, and applications reveal their significant contributions to advancing LLMs in hydrology and environmental sciences, as summarized in Table 3. These works highlight the interdisciplinary nature of the field, integrating AI, environmental science, and education. The most cited paper by Biswas (2023), with 292 citations, explores how ChatGPT can improve climate change awareness and mitigation strategies. Its exceptional citation count underscores the growing role of AI in addressing global environmental challenges.

Another impactful work by Hartmann et al. (2023), with 190 citations, investigates the political and environmental biases of conversational AI systems like ChatGPT and their implications for public opinion and policymaking. Its focus on the societal influence of AI resonates broadly with researchers and policymakers. Zhu et al. (2023), with 186 citations, demonstrates the utility of ChatGPT in synthesizing and analyzing complex environmental data, highlighting the growing importance of AI in complementing traditional research methods. Additionally, Rillig et al. (2023), with 151 citations, provides a balanced evaluation of LLMs' environmental risks, such as energy consumption, alongside their transformative potential in research, offering a critical resource for stakeholders. Another noteworthy study by Gosal et al. (2019), with 144 citations, applies natural language processing (NLP) and social media data analysis to evaluate recreational spaces, providing actionable insights for sustainable environmental planning and public health issues (Sermet and Demir, 2021). This foundational work continues to influence interdisciplinary research in environmental and social data applications.

Table 3. Top 10 most cited publications on LLMs in hydrology and environmental sciences

Title	Author (s)	Citations	Year
Potential Use of Chat GPT in Global Warming	Biswas	292	2023
The Political Ideology of Conversational AI: Converging Evidence on ChatGPT's Pro-Environmental, Left-Libertarian Orientation	Hartmann et. al.	190	2023
ChatGPT and environmental research	Zhu et. al.	186	2023
Risks and Benefits of Large Language Models for the Environment	Rillig et. al	151	2023
Using social media, machine learning and natural language processing to map multiple recreational beneficiaries	Gosal et. al.	144	2019
CLIMATEBERT: A Pretrained Language Model for Climate-Related Text	Webersinke et. al.	132	2021
kBot: Knowledge-Enabled Personalized Chatbot for Asthma Self-Management	Kadariya et. al.	114	2019
The Growth of Climate Change Misinformation in US Philanthropy: Evidence from Natural Language Processing	Farrell	109	2019
Which environmental features contribute to positive and negative perceptions of urban parks? A cross-cultural comparison using online reviews and Natural Language Processing methods	Huai & Van de Voorde	89	2021
Natural language processing for urban research: A systematic review	Cai	74	2021

Recent citation trends indicate rapid growth for papers published in 2023. For instance, Biswas (2023) garnered 292 citations within a year of publication, reflecting the increasing interest in integrating AI into climate change mitigation strategies. Similarly, Zhu et al. (2023) and Hartmann et al. (2023) both gained over 180 citations within a year, emphasizing the relevance of LLM applications in environmental research and policy domains. Earlier works, such as Gosal et al. (2019), maintain steady citations due to their foundational role in combining machine learning, NLP, and social data analysis for environmental purposes. The citation patterns highlight the transformative role of LLMs in hydrology and environmental sciences, with rapid growth in recent years and sustained impact from foundational studies. These highly cited papers showcase the field's dynamic evolution and underscore the critical role of LLMs in tackling global challenges and fostering interdisciplinary innovation.

3.3. Keyword Analysis

Keyword analysis reveals the dominant themes and focuses of research in LLMs applied to hydrology and environmental sciences. As illustrated in Figure 5, the most frequently occurring keywords include "water," "climate," and "environmental," each appearing in over 80 instances. These keywords underscore the central role of water resources and climate-related challenges in the field. Other prominent keywords such as "flood," "hydrology," and "pollution" further highlight the specific domains where LLMs are being utilized, including disaster management, water resource monitoring, and pollution analysis. Emerging areas such as "sustainability," "groundwater," and "drought" also feature prominently, reflecting a growing interest in addressing long-term environmental challenges through predictive modeling and data-driven insights. Keywords such as "agriculture" and "ecosystem" suggest that LLM applications extend beyond hydrology into broader environmental and agricultural systems, supporting interdisciplinary research.

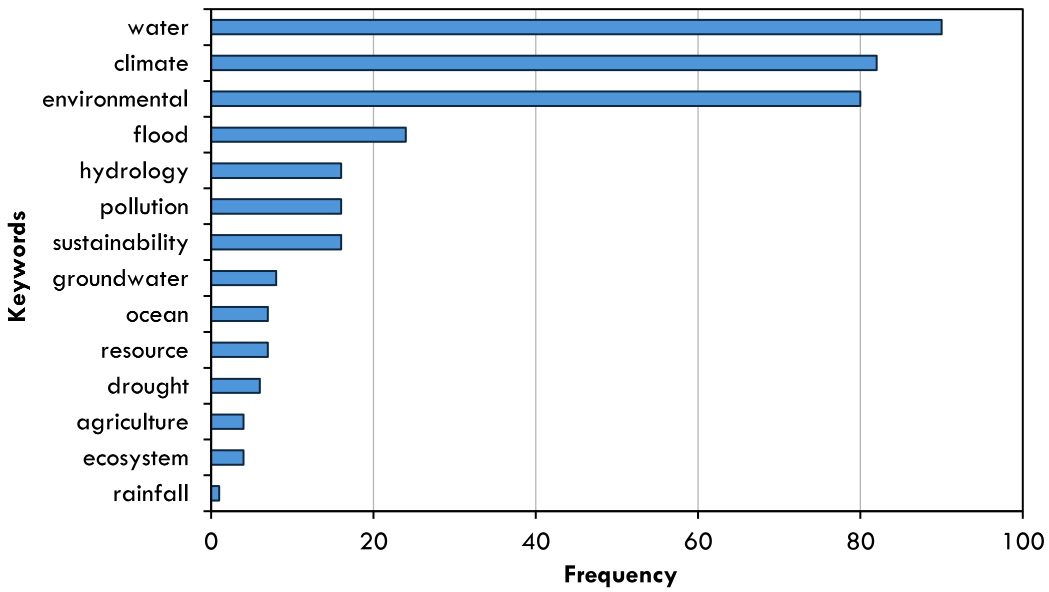


Figure 5. Frequency of popular keywords listed in LLM application in environmental science and hydrology

In addition, a title word frequency analysis was also conducted to identify recurring themes in publication titles highlighted by the authors. As shown in Figure 6, the most common words in publication titles include "Language," "Natural," "AI," "Processing," and "Water." The dominance of terms like "Language" and "AI" highlights the emphasis on the core technologies underpinning LLMs, while words like "Water" and "Climate" reflect the environmental and hydrological focus of these studies. Other recurring terms such as "ChatGPT," "Climate," "Environmental," "Data," and "Chatbot" indicate the widespread adoption of AI-driven tools and their integration into environmental monitoring, analysis, and communication workflows.

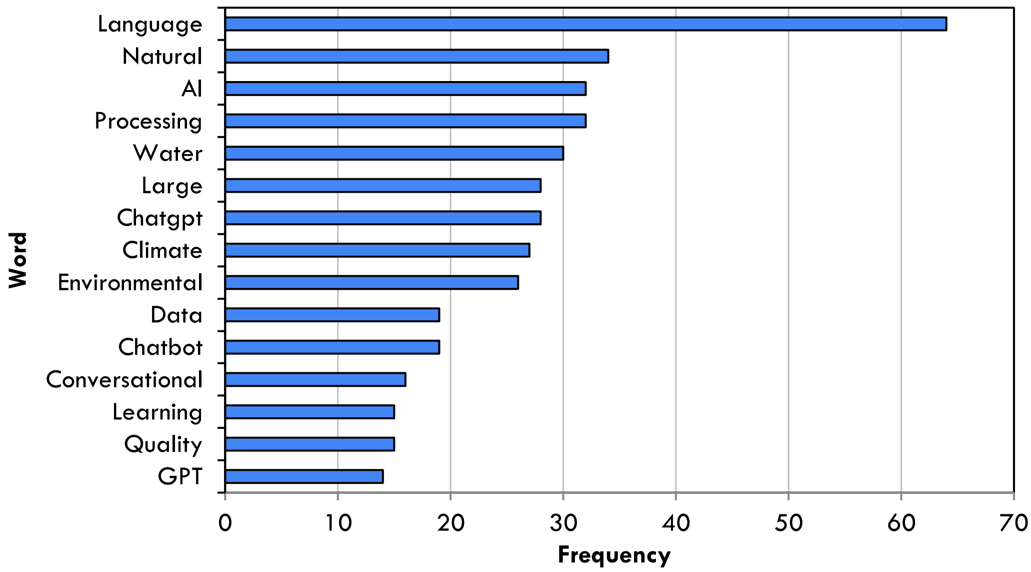


Figure 6. Frequency of popular title words used in the publications about LLM in environmental science and hydrology

Figure 7 complements this analysis with a word cloud of models and frameworks used in these studies. Terms like "ChatGPT," "GPT," "data," "model," and "AI" appear prominently, emphasizing the widespread adoption of generative AI models and machine learning frameworks in this field. Specific references to tools like "BERT," "LSTM," and "Natural Language Processing" indicate the diversity of approaches employed for tasks ranging from data analysis and prediction to conversational interfaces and educational tools.

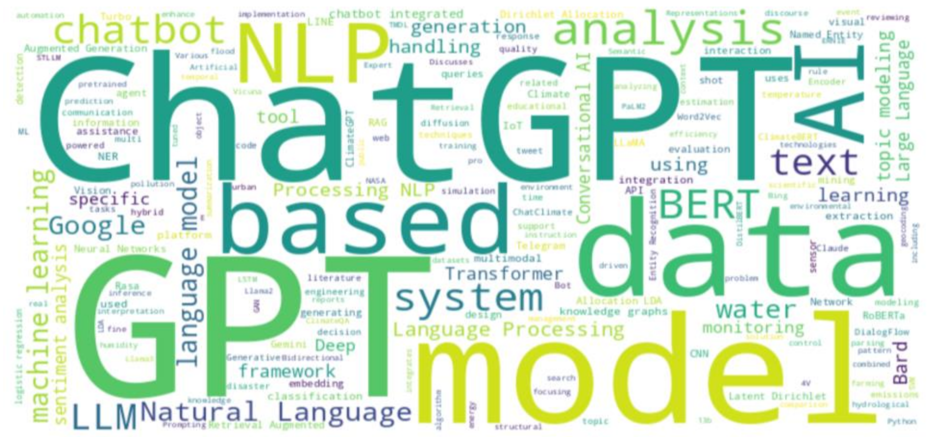


Figure 7. Number Word Cloud of Keywords

The keyword analysis highlights how LLMs are being integrated into various workflows, including flood forecasting, environmental monitoring, and educational platforms. For instance, terms like "chatbot" and "dialogue system" suggest the growing use of conversational AI for engaging stakeholders and disseminating environmental knowledge. Similarly, terms like "NLP," "framework," and "system" point to the methodological innovations driving this research. Together, the diagrams in Figures 5, 6, and 7 provide a comprehensive view of the thematic focus and technological tools shaping the application of LLMs in hydrology and environmental sciences. These insights demonstrate the versatility of LLMs and their potential to address complex environmental challenges through interdisciplinary approaches and advanced AI methodologies.

3.4. Collaborative Network

The collaborative networks in LLMs research for hydrology and environmental sciences demonstrate the significance of international and interdisciplinary collaboration. As visualized in Figure 8, the USA emerges as the dominant contributor, with 60 collaborations or publications, reflecting its leadership in AI research and environmental applications. China follows with 24 contributions, highlighting its growing influence in LLM research. Germany (17) and the United Kingdom (15) represent key players in Europe, supported by strong regional funding mechanisms and research programs. Other notable contributors include India (12), Switzerland (10), and France, South Korea, and Italy, each with 8 contributions, while Spain adds 7 to the global effort. This distribution underscores the combined efforts of both developed and emerging economies in addressing hydrological and environmental challenges through LLMs.

The geographic map in Figure 8 provides a clear visualization of this global research footprint. The USA serves as a central hub, engaging in collaborations with countries worldwide, including strong bilateral ties with China and key European nations like Germany and the UK. European countries demonstrate a dense network of interconnected collaborations, driven by their regional emphasis on interdisciplinary and multinational research. Meanwhile, countries such as India, South Korea, and Switzerland are increasingly contributing to the global conversation, leveraging their expertise in AI and environmental sciences to expand the application of LLMs.

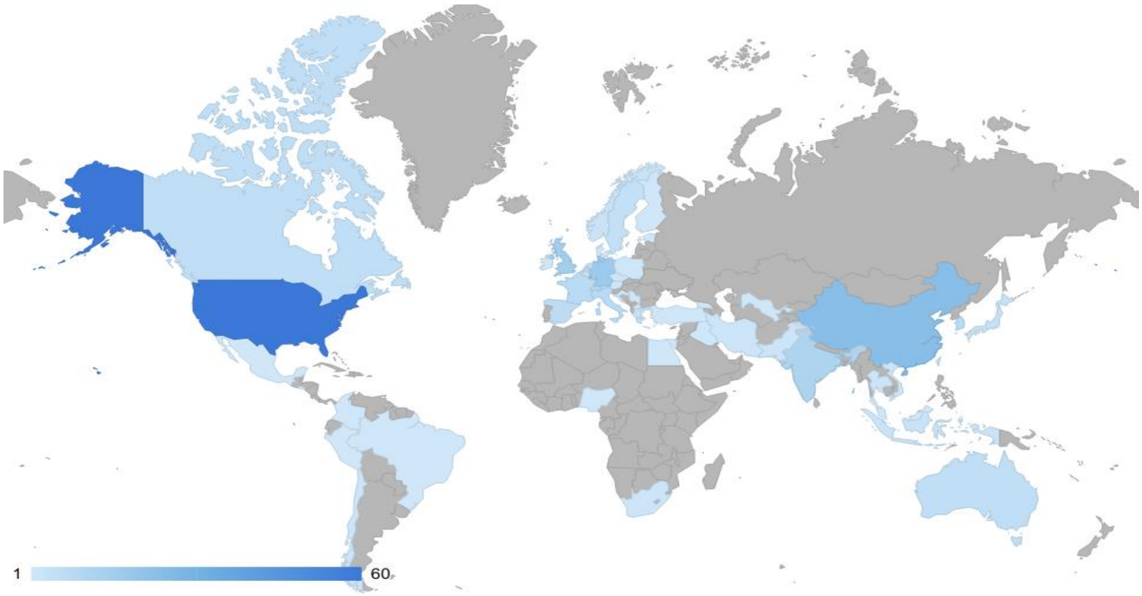


Figure 8. Distribution of publications published by country

As shown in Figure 9, the chord diagram illustrates the intricate co-authorship networks that underpin this research landscape. The USA-China connection is particularly prominent, reflecting robust academic and institutional partnerships between two global leaders in AI. European nations, including Germany, the UK, Switzerland, and Italy, demonstrate high interconnectivity, with frequent collaborations across borders that enhance the quality and breadth of research outputs. Asian countries such as India and South Korea are also notable contributors, establishing partnerships that bridge geographical and disciplinary boundaries.

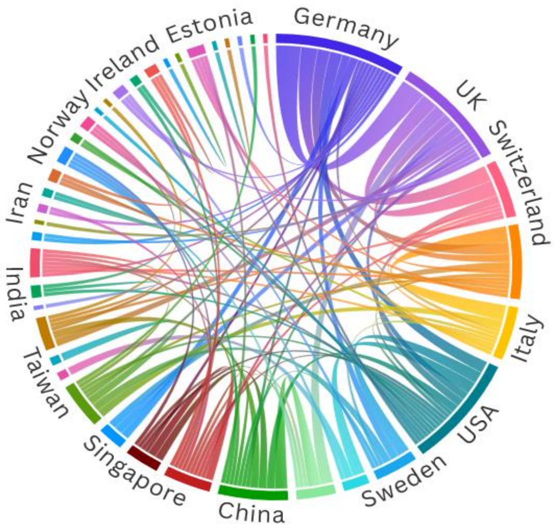


Figure 9. Global collaborative networks in hydrology and environmental science research

These collaborative efforts highlight the interdisciplinary nature of LLM research in hydrology and environmental sciences, requiring expertise in AI, environmental science, and hydrological modeling. The interconnectedness of these networks facilitates knowledge exchange, promotes innovation, and ensures that research findings are disseminated and applied globally. However, the visualizations also reveal gaps in contributions from regions such as Africa and South America, emphasizing the need to expand collaborative networks to underrepresented areas. Increasing participation from these regions would bring diverse perspectives and localized solutions to address global environmental challenges more comprehensively. The collaborative networks visualized in Figures 8 and 9 underscore the importance of fostering global partnerships to advance LLM research. These networks reflect the collective effort required to leverage AI effectively in addressing pressing environmental and hydrological issues.

3.5. Research Activity Index

The research activity index, summarized in Table 4, provides a quantitative assessment of the contributions of various countries to large language model (LLM) research in hydrology and environmental sciences across the study period (2018–2024). This index reflects relative productivity, adjusted to account for differences in overall publication trends.

In 2018, the USA showed the highest activity index at 1.92, dominating the early phase of LLM applications in hydrology. Contributions from other countries, including China, Germany, the United Kingdom, and India, were negligible during this period. By 2019, however, countries like India (1.66), the United Kingdom (1.42), and Germany (1.17) began to emerge as active contributors, with China's activity index reaching 0.83. During 2020, China overtook the USA in terms of relative productivity, achieving an activity index of 1.24, while the USA saw a significant decline to 0.48. This shift indicates a growing interest and capacity for LLM research in China. Other countries, such as Germany and the United Kingdom, showed no measurable activity during this year.

The year 2021 marked a resurgence in activity for the USA (1.33), while Germany (0.81) and India (1.15) maintained consistent contributions. By 2022, India reached its peak activity index of 2.13, leading global research efforts, with Germany (1.50) also seeing a substantial increase. This year highlights the growing involvement of countries outside traditional AI hubs in advancing LLM research. In 2023, activity indices across the top contributors became more balanced. The USA (1.05), China (0.72), and Germany (1.01) showed steady contributions, while India (1.15) maintained a strong presence. The United Kingdom (0.74) also continued its consistent involvement in LLM research. The year 2024 marked the maturity phase of this field, with China leading in relative activity at an index of 1.46. The USA (0.99), Germany (1.03), and the United Kingdom (1.25) followed closely, reflecting balanced global efforts. India’s activity index decreased to 0.73, but the country remained an active contributor.

This analysis underscores the dynamic evolution of LLM research activity across nations, highlighting the USA's initial dominance, China's steady rise, and India's significant contributions in recent years. The increasing global distribution of research efforts, as shown in Table 4, reflects the interdisciplinary and international nature of LLM applications in hydrology and environmental sciences.

Table 4. Activity index scores of the five countries with the highest number of relevant publications during 2018–2024.

Year	United States	China	Germany	United Kingdom	India
2018	1.92	0.00	0.00	0.00	0.00
2019	1.28	0.83	1.17	1.42	1.66
2020	0.48	1.24	0.00	0.00	0.00
2021	1.33	0.00	0.81	0.98	1.15
2022	0.41	0.53	1.50	0.91	2.13
2023	1.05	0.72	1.01	0.74	1.15
2024	0.99	1.46	1.03	1.25	0.73

3.6. Key Journal

The top journals publishing studies on LLMs in hydrology and environmental sciences are summarized in Table 5. These journals, with their impact factors, citation scores, and publication histories, provide critical platforms for disseminating research findings in the field.

The IEEE/CAA Journal of Automatica Sinica emerges as the leading journal, with the highest impact factor (15.3) and citation score (23.5), reflecting its significant influence on AI-related research since its inception in 2014. Following closely, Environmental Science & Technology (10.9 impact factor) and Environmental Science & Technology Letters (8.9 impact factor) highlight their roles as major contributors to research on environmental technologies and AI applications in environmental sciences. These journals have consistently maintained high citation scores, emphasizing their relevance and broad readership.

Other prominent journals include Desalination and Science of the Total Environment, which focus on environmental systems, sustainability, and climate studies. Both journals began publication in the late 20th century (1966 and 1972, respectively), making them long-standing contributors to the field. Notably, Communications Earth & Environment, a relatively new journal (2020), reflects emerging trends and rapid advancements in interdisciplinary environmental research involving AI.

The second half of the table features journals like Landscape and Urban Planning, Telematics and Informatics, and Engineering Applications of Artificial Intelligence, which provide insights into specialized applications of AI and LLMs across environmental and technological contexts. Despite comparatively lower impact factors, their high citation scores (ranging from 15.2 to 17.0) underscore their importance in advancing AI-driven solutions in hydrology, environmental management, and urban planning. The temporal trends observed among these journals indicate a consistent increase in publications involving LLMs and AI applications, particularly in recent years.

Established journals like Environmental Science & Technology and Science of the Total Environment continue to attract high-quality research, while newer platforms such as Communications Earth & Environment are fostering the rapid dissemination of cutting-edge advancements. Collectively, these journals represent key forums for interdisciplinary collaboration, enabling researchers to explore the applications, challenges, and opportunities of LLMs in addressing complex environmental and hydrological problems.

Table 5. Key journals publishing research on LLMs in hydrology and environmental sciences

Journal	**Impact Factor**	**Cite Score**	**Beginning Year**
IEEE/CAA Journal of Automatica Sinica	15.3	23.5	2014
Environmental Science & Technology	10.9	17.5	1967
Environmental Science & Technology Letters	8.9	17.9	2014
Desalination	8.4	14.6	1966
Science of the Total Environment	8.2	17.6	1972
Communications Earth & Environment	8.1	8.6	2020
Landscape and Urban Planning	7.9	15.2	1974
Telematics and Informatics	7.6	17.0	1984
Engineering Applications of Artificial Intelligence	7.5	9.6	1988
Information Processing & Management	7.4	17.0	1963

3.7. Applications of LLMs in Hydrology and Environmental Sciences

LLMs have emerged as transformative tools in hydrology and environmental sciences, revolutionizing how researchers, practitioners, and the public interact with data and address complex challenges. Their applications span diverse domains, leveraging advanced capabilities in natural language processing, machine learning, and AI, as outlined below:

Environmental Knowledge Evaluation: Open-source LLMs have been extensively tested for their ability to evaluate and synthesize knowledge in environmental sciences. These models are applied in educational and research contexts to identify knowledge gaps, generate actionable insights, and enhance understanding of critical environmental concepts. By evaluating zero-shot and few-shot learning capabilities, LLMs have proven instrumental in benchmarking environmental knowledge across various disciplines. The primary objective is to advance both formal education and public awareness campaigns, making environmental science more accessible.

Conversational Agents for Citizen Science and Data Literacy: Conversational AI agents designed using frameworks like Rasa enable laypersons to engage with environmental data effectively. These agents act as intermediaries, simplifying complex scientific information for the public and encouraging participation in citizen science projects. Such tools also improve data literacy, empowering users to analyze, interpret, and contribute to scientific datasets. They have been particularly impactful in projects involving environmental monitoring and community engagement.

Behavioral Influence in Environmental Protection and Eco-Tourism: AI chatbots equipped with LLMs are used to drive sustainable behaviors in environmental protection and tourism. By delivering tailored recommendations and engaging users through interactive dialogue, these systems influence eco-friendly decision-making. In tourism, they encourage practices such as waste reduction, wildlife conservation, and responsible travel, fostering a culture of sustainability.

Automation and Engineering Applications: LLMs are being integrated with engineering systems to automate complex tasks in energy, infrastructure, and environmental management. These applications aim to improve operational efficiency, reduce manual intervention, and enable data-driven decision-making. By coupling LLMs with AI and machine learning models, organizations can address challenges such as climate adaptation, resource optimization, and disaster mitigation.

Bibliometric Analysis and Emerging Technologies: In research, LLMs have proven invaluable for bibliometric analysis, enabling scientists to track advancements in emerging technologies and assess their impact. By leveraging LLMs to process vast amounts of scientific literature, researchers can identify trends, benchmark innovations, and guide future studies. These tools are particularly useful in evaluating interdisciplinary contributions in fields like hydrology, machine learning, and environmental modeling.

Environmental Monitoring and Decision Support: LLMs are also deployed in real-time monitoring systems for environmental parameters such as air quality, water levels, and climate data. By integrating with IoT sensors and visualization platforms, these models assist in making data actionable for decision-makers. They enable predictive analytics, early warning systems, and scenario planning to mitigate environmental risks.

Public Engagement and Sustainability Awareness: LLMs contribute to public engagement by generating content for educational campaigns and awareness drives. From summarizing complex environmental policies to creating interactive educational materials, these models enable better communication between scientists, policymakers, and the general public.

4. Discussions

The bibliometric analysis conducted in this study was structured around five key research questions (RQ1–RQ5) introduced in the introduction. These questions aimed to explore publication trends, key contributors, research themes, existing gaps, and ethical considerations surrounding the adoption of LLMs in hydrology and environmental sciences.

In response to RQ1, which examined dominant trends in LLM-related publications within hydrology and environmental sciences, our analysis identified a sharp increase in research activity after 2020, driven by the rapid adoption of advanced AI technologies. However, this growth is heavily concentrated in technologically advanced regions like the United States, China, and Germany. This geographical imbalance creates an issue directly tied to RQ4, which focuses on identifying under-researched areas and gaps. The limited contributions from regions such as Africa and South America highlight disparities in resource availability, computational infrastructure, and funding mechanisms, ultimately limiting the global applicability of LLM solutions in environmental management.

The exploration of RQ2, which addressed the identification of influential authors, institutions, and global collaboration networks, revealed significant international partnerships, particularly between the USA, China, and European nations like Germany and the UK. These nations benefit from access to advanced computational resources, robust funding mechanisms, and extensive research collaborations. For example, USA-affiliated publications often involve collaborations with leading institutions such as NASA, MIT, and other research centers, showing their infrastructure advantage and interdisciplinary research focus. Similarly, China's rapid rise in activity reflects its strategic investments in AI research, while Germany's consistent contributions highlight the effectiveness of regional funding mechanisms within Europe. International partnership, such as collaborations among Germany, Sweden, USA and China emphasize the global nature of environmental challenges. However, these collaborations often exclude low-resource regions, echoing the regional disparities highlighted in RQ4. Bridging this gap through capacity-building initiatives and more inclusive collaboration networks would not only address ethical considerations raised in RQ5 but also improve the overall impact of LLM research across diverse environmental contexts.

In addressing RQ3, which investigated primary research themes and methodologies, the study uncovered key focus areas such as flood prediction, water quality monitoring, and ecosystem modeling. Tools like OceanGPT and LITE exemplify the success of domain-specific LLMs in addressing specialized environmental challenges. However, these advancements also raised concerns tied to RQ5, particularly regarding transparency, data privacy, and environmental costs associated with training large-scale models. For example, while LLMs show great promise in predictive analytics and real-time environmental monitoring, the significant carbon footprint associated with their training remains an ethical dilemma that must be addressed through sustainable AI practices.

Furthermore, ethical concerns explored in RQ5 resonate across multiple findings from the analysis. Issues such as dataset bias, transparency in decision-making processes, and privacy risks were consistently highlighted as barriers to the equitable deployment of LLMs in hydrology and environmental sciences. These challenges align closely with the gaps discussed under RQ4, where ethical considerations remain underexplored in many environmental applications of LLMs. This interconnectedness emphasizes the need for a unified ethical framework tailored specifically for environmental applications of LLMs.

The insights from this bibliometric analysis reveal the interconnected nature of the five research questions (RQ1–RQ5), highlighting key trends, influential contributors, dominant research themes, existing gaps, and ethical challenges in LLM applications within hydrology and environmental sciences. Addressing these challenges requires coordinated efforts from researchers, institutions, and policymakers to develop domain-specific LLMs, promote inclusive and interdisciplinary collaborations, and establish sustainable AI practices. By aligning technical advancements with ethical and environmental considerations, LLMs can effectively contribute to solving global environmental challenges while fostering equitable and sustainable innovation.

4.1. Recommendations

To fully realize the potential of LLMs in hydrology and environmental sciences, a coordinated effort is required across researchers, institutions, and policymakers. Below are expanded recommendations to address challenges and capitalize on emerging opportunities.

For Researchers:

- Prioritize the development of domain-specific LLMs by fine-tuning general-purpose models on curated, high-quality datasets.
- Improve the availability and quality of environmental datasets with standardized formats, metadata, and documentation to facilitate better training and evaluation of LLMs.
- Emphasize explainability and transparency to build trust and enhance the usability of LLM-based predictions in environmental decision-making.
- Address bias and ethical concerns actively for the development and deployment of LLMs to produce fair, non-discriminatory, and contextually relevant outputs.

For Institutions:

- Invest in building interdisciplinary teams and dedicated research center that combine expertise in hydrology, environmental science, and AI to address complex challenges.
- Support open-source projects to promote equitable access to LLMs and foster collaboration across the research community.
- Invest in advanced computational infrastructure, including high-performance computing clusters and cloud-based AI platforms.

For Policymakers:

- Encourage the adoption of ethical AI frameworks for environmental monitoring and policy applications.
- Mandate sustainable AI practices, such as monitoring and reducing carbon footprints during LLM training and deployment.
- Promote funding for AI research, particularly in underrepresented regions to bridge existing disparities
- Prioritize investments in open-access projects, interdisciplinary research, and sustainable AI initiatives.

- Establish independent oversight bodies to monitor AI deployment in environmental applications, ensuring compliance with ethical guidelines, assessing environmental impacts, and addressing misuse of LLMs in critical domains.

By addressing these recommendations systematically and leveraging emerging trends, LLMs can become a transformative tool for hydrology and environmental sciences, enabling innovation, inclusivity, and sustainability across diverse regions and applications. Through collaborative efforts from researchers, institutions, and policymakers, the potential of LLMs can be fully harnessed to address pressing global environmental challenges effectively.

5. Conclusion

The bibliometric analysis highlights the growing application of LLMs in hydrology and environmental sciences, particularly depicting their transformative potential in prediction, monitoring, and data-driven decision making. LLMs have demonstrated significant advancements in improving predictive accuracy, enabling real-time environmental monitoring, and facilitating public engagement through conversational AI platforms. Ethical concerns, including carbon footprints, bias, and data transparency, remain pivotal areas requiring focused attention to ensure the responsible and equitable use of LLMs in environmental contexts.

The integration of LLMs with multimodal frameworks represents significant advancement, allowing the processing of diverse data types such as textual, numerical, and spatial information. This capability supports applications ranging from ecosystem modeling to disaster management, underscoring the versatility of LLMs in addressing complex global environmental challenges. The essential findings of this article can be summarized as follows:

- **Rapid Growth in Research Activity:** There has been a significant increase in research output on LLMs in hydrology and environmental sciences, particularly after 2020, reflecting growing global interest and investment in AI technologies.
- **Key Research Domains:** LLMs are primarily applied in environmental prediction, flood forecasting, water resource management, and pollution monitoring, with promising results in improving model accuracy and efficiency.
- **Leading Contributors and Collaborations:** The USA, China, and Germany lead in research contributions, with strong international collaborations shaping the global research landscape. However, underrepresentation from low-resource regions remains a persistent challenge.
- **Ethical and Environmental Concerns:** Ethical issues, including dataset bias, transparency, and misinformation, alongside environmental costs related to high energy consumption during model training, require immediate attention.
- **Emerging Trends:** The rise of domain-specific LLMs, multimodal integration frameworks, and sustainable AI practices are shaping future research directions in environmental sciences.

However, critical challenges persist, including regional disparities in research contributions, ethical concerns, and the environmental costs of deploying LLMs. Addressing these challenges requires a global, collaborative effort involving researchers, institutions, and policymakers to ensure responsible and sustainable AI practices. Strategic investments in computational infrastructure, ethical AI frameworks, and interdisciplinary collaborations will be key to overcoming these barriers.

Looking ahead, the focus needs to shift toward developing domain-specific LLMs, enhancing model interpretability, and democratizing access to AI technologies. Increased attention to equitable research representation, especially from underrepresented regions, will further expand the impact of LLMs in environmental sciences. By fostering innovation, promoting ethical governance, and prioritizing sustainability, LLMs can play a pivotal role in addressing global environmental challenges and supporting evidence-based decision-making for a more resilient and sustainable future.

5.1. Future Directions

The future of LLM research in hydrology and environmental sciences is shaped by several emerging trends and ongoing challenges. A significant direction is the development of domain-specific LLMs, such as OceanGPT, WaterGPT, tailored for environmental and hydrological applications like oceanography, hydrology, and ecosystem modeling. These specialized models promise improved performance with reduced computational resources compared to general-purpose models like GPT-4. Another growing trend is the integration of multimodal frameworks, which combine textual, numerical, and spatial data to improve prediction accuracy. Frameworks like LITE exemplify this approach, applying multimodal methodologies to ecosystem modeling, with potential extensions to hydrology and climate sciences. These advancements broaden the scope of LLM applications, enabling more comprehensive analyses of environmental systems.

Sustainability-oriented AI is also gaining prominence, with a focus on reducing the environmental footprint of training and deploying LLMs. Green AI initiatives and energy-efficient modeling practices are expected to become standard in the field. Concurrently, the ethical development and deployment of LLMs remain a priority. Addressing concerns related to data privacy, misinformation, and bias is essential to building trust in AI technologies and ensuring responsible use in critical environmental applications.

Interdisciplinary research and global collaboration are pivotal in overcoming the challenges posed by data scarcity, infrastructure limitations, and ethical dilemmas. Collaborative research initiatives, open-access frameworks, and shared datasets can democratize access to LLM technologies, fostering inclusive innovation across regions. Additionally, the rise of scalable LLMs designed for real-time applications in resource-constrained environments offers promising opportunities for broader adoption.

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Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this manuscript, the authors used ChatGPT, based on the GPT-4 model, to improve the flow of the text, correct grammatical errors, and enhance the clarity of the writing. The language model was not used to generate content, citations, or verify facts. After using this tool, the authors thoroughly reviewed and edited the content to ensure accuracy, validity, and originality, and take full responsibility for the final version of the manuscript.

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Credit Author Statement

Ramteja Sajja: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing - Original Draft, and Visualization. **Shirley Xiong:** Resources, Data Curation, and Investigation. **Omer Mermer:** Writing - Review & Editing**,** Visualization**,** Investigation, Conceptualization and Methodology. **Yusuf Sermet:** Writing - Review & Editing, Conceptualization, Funding acquisition, and Validation. **Ibrahim Demir:** Writing - Review & Editing, Supervision, Project administration, Funding acquisition, and Resources.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

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