The State of Hydroinformatics Prior to Generative AI: Establishing a Quantitative Baseline (2018–2023)

Carlos Erazo Ramirez[1,2*], Kevin Song[3], Ibrahim Demir[1,2]

[1] River-Coastal Science and Engineering, Tulane University, New Orleans, LA
[2] ByWater Institute, Tulane University, New Orleans, LA
[3] Computer Science, University of Pennsylvania, Philadelphia, PA, USA

[*] Corresponding Author, cerazoramirez@tulane.edu

Abstract
The rapid advancement of web applications and machine learning has fundamentally reshaped hydrogeological sciences. While the recent emergence of Large Language Models (LLMs) dominates current discourse, understanding the trajectory of this shift requires quantifying the foundational digitization trends that preceded it. This study presents an automated web-mining framework designed to extract and classify technological keywords from the full text of scientific literature, overcoming the limitations of abstract-only bibliometrics. We applied this framework to 3,701 manuscripts published between 2018 and mid-2023 to establish a quantitative baseline for the hydrological digital landscape immediately prior to the Generative AI disruption. Utilizing the Elsevier Text Mining API and Latent Dirichlet Allocation, we identified a mature integration of predictive machine learning and web technologies. Our findings characterize the infrastructure phase of hydroinformatics, highlighting the critical consolidation of data-driven modeling that now serves as the backbone for emerging agentic AI workflows. Moreover, we aim to establish a reproducible technological baseline against which post-2023 LLM-driven transformations in hydrology can be quantitatively evaluated.

Keywords: hydroinformatics**,** text mining, machine learning, scientometrics, web technologies

1. Introduction

The fields of environmental and hydrological sciences have significantly benefited from decades of research in information and communication technologies (ICT) and hydroinformatics, enhancing the analysis of spatially and temporally distributed data (Gourbesville et al., 2023). Coupled with advancements in techniques that employ statistically based methods and physically driven processes (Bayar et al., 2009), researchers have gained nuanced insights into water-related applications (Illian et al., 2008). Hydrology, as the study of the water cycle and its related processes, incorporates the distribution of water on Earth and its interactions with the atmosphere, biosphere, and geosphere. Its subfields include hydrogeology, hydrometeorology, surface water hydrology, engineering hydrology, environmental hydrology, and water resources management (Dingman, 2015; Alabbad and Demir, 2022). This complex and interdisciplinary field is crucial for comprehending Earth's water resources and ensuring sustainable management, especially amid the escalating challenges of climate change and global warming, which have emphasized the criticality of water as a resource requiring understanding and protection (Teutschbein & Seibert, 2012).

Hydroinformatics, a relatively new field, involves applying information technologies to the water domain, merging advancements in data visualization and comprehension with cutting-edge technology (Abbott, 1991). It integrates established procedures and algorithms from earth sciences into the water sector (Erazo et al., 2022). Hydroinformatics branches into areas such as geospatial technologies, hydrological modeling and simulation, data analysis and AI, and virtual and augmented reality, often exhibiting significant overlap (Ramirez et al., 2024; Erazo et al., 2023a; 2023b). This field represents a cross-domain of knowledge between environmental sciences and technology (Demir and Galelli, 2022), seeking comprehensive uses for societal benefit.

Recent technological advancements including artificial intelligence, machine learning, big data-driven modeling, predictive analysis, data analytics (Sit et al., 2021), and communication technologies like virtual reality (Sermet and Demir, 2022) and the Internet of Things (IoT) have pushed progress in various fields, including hydrology and environmental sciences (McCabe et al., 2017; Ward & Trimble, 2003). Precision mathematical methods using extensive training datasets sourced from satellite imagery (Li et al., 2023), land characteristics, and rainfall/runoff patterns have enabled novel approaches to modeling, visualization, and data democratization (Nagaraj et al., 2020; Li and Demir, 2024). Given the extensive use of these tools globally by researchers and educators, it is imperative to understand the focal points of interest within the field and identify potential trends and connections by employing bibliometric analytical tools.

Bibliometric analysis involves utilizing mathematical and statistical methods for qualitative and quantitative assessment of scientific documents within a specific field (Donthu et al., 2021; Yesilkoy et al., 2023). Its primary objective is to explore relationships among prevalent topics in that field and identify emerging trends by employing metrics like journal impact, collaboration patterns, and research interests (Baydaroglu et al., 2023). Within this domain, science mapping and performance analysis are crucial. Performance analysis involves assessing impact groups to understand how various actors, such as countries, institutions, and researchers, influence scientific outlets (Sivertsen, 2010). On the other hand, scientific mapping facilitates comprehension of knowledge structures and trends within a field, revealing connections between papers, authors, and other elements. In academic research, literature reviews and bibliometric analyses are essential for gaining current insights and evaluating the utilization and treatment of specific topics within a given sphere. They aid researchers in gathering adequate information before starting a study, allowing them to identify gaps and trends that require comprehensive exploration. Additionally, fostering collaboration among researchers and institutions worldwide is crucial, as it paves the way for further analytical exploration across domains. In the realm of water science, the incorporation of technological advancements and domain knowledge has significantly impacted visualization, knowledge democratization, and analysis used daily.

Examining the recent tools and techniques developed in water sciences alongside technological advancements over the last decade, this study investigates various technologies utilized by researchers during the five-year period (2018–2023) and their application in specific water research, particularly focusing on the intersection of hydrology. This study highlights past trends in hydrology research and identifies the technological trajectories that established the foundation for the current AI era. Moreover, it aims to identify the top affiliations and countries with the highest publication and citation rates, as well as the largest collaborative efforts.

We deliberately delimit our analysis to the period between 2018 and mid-2023. This timeframe captures the rapid maturity of Classical AI (predictive machine learning) and web-based infrastructure immediately prior to the distorting effects of the Generative AI explosion. By establishing this baseline, the study provides a clean, noise-free dataset against which the impact of post-2023 LLM adoption can be rigorously measured in future longitudinal studies.

The rest of the paper aims to respond to the previously stated objectives and is structured as follows: a methodology section that includes the data collection and preliminary analysis on the clean dataset, a result section that highlights all the findings on the clean corpus as well as the LDA analysis performed in the data. The discussion section reveals the different challenges found in the data, possible trends moving forward in the next years, and new avenues of research that can be combined, finalizing with a summary of what the study did and what did not work.

2. Methodology

The methods employed during this study were done considering a collection of scientific topics that will identify the trends that technology has shown and will possibly continue in the future. Specifically, this study aimed to understand how different technological applications and approaches developed in the latest decade have been used in research literature throughout the environmental and hydrological domain, in which aspects of these fields, as well as which are the likely combinations of this field of interest that will show a higher correlation in the following years. For this study, an automated text mining pipeline (Zhao, 2017) was developed to query the web for abstract, metadata, additional information, and full text for all the papers that fall within the research question 1. The information obtained was afterwards cleansed using the metrics described in Table 1.

2.1. Data Retrieval and Cleaning

The models and data collection were done on a MacBook Pro with 1.4 GHz Quad-Core Intel Core i5 with 8 GB DDR3 RAM and 1TB HD disk. The research scope was limited by searching in the Elsevier's database for papers from January 2018 through June 2023, with projections done based on the linear trend shown in the first three years of retrieval. Unlike standard bibliometric analyses that rely on metadata indexing services restricted to abstracts, this study leveraged the Elsevier Text Mining API (Elsevier, 2023) using the Selenium Web Driver (Selenium, 2023) to access the full text of manuscripts. This methodological choice was critical: technical implementation details—such as specific software libraries, web frameworks, and coding patterns—are frequently omitted from abstracts but are essential for accurately mapping technological trends. The dataset thus represents a high-fidelity proxy for technological adoption within high-impact hydrological literature. We selected a list of 28 journals related to the fields of hydrology and environmental science, shown in Table S1 in the annex. Using the Elsevier API, the metadata of the articles (citations, authors, etc.) were obtained, as well as the full text of the articles to search for the buzzwords, found Table S2 in the annex. The data was then prepared for analysis, visualization, and classification.

The variables of interest for the analysis included the affiliation citations, countries of publication, metadata including information about the authors and their affiliations, scope of the article found, and other accessible information from the API. The research yielded 30,681 articles from 20 journals. These articles were a mix of open access and subscription-based journals. From this initial step, a categorization was done to filter and analyze the articles that fall in the scope explained in Table 1.

Table 1. Criteria for inclusion and exclusion of papers.

Inclusion Criteria	Exclusion Criteria
Papers published between 2018 through first half 2023	Papers with no author(s) names or little information about affiliation
Full research papers	Papers that were in "press"
Papers with publication status "final"	Papers in another language other than English
Papers containing any of the keywords representing a technological topic	Papers that contained little to no usage of the research technological topics
Papers published in journals	
Papers with full author information	

After an initial screening using filtering criteria for keywords found in both special keywords within each of the papers and the abstract section, papers containing specific keywords related to the technological category described in Table S2 were identified. These papers contained a combination of keywords that might describe one or multiple technological topics.

Consequently, another filtration step was implemented to remove any papers that contained false topic misclassification. Further classification of papers was performed using the following criteria based on the technological keywords: a) Step 1: Retain all papers that cover more than one category; b) Step 2: Retain all papers that belong to at least two categories or have a buzzword count greater than 5; and c) Step 3: Apply frequency analysis to assess the count of keywords and topics in the papers.

For step 3, after conducting exploratory analysis on at least 100 articles, definitions for tangential topics and core technological indicators were established. Tangential topics are the ones where buzzwords that, while technological, lacked specific hydrological implementation context within the manuscript's full text (e.g., purely financial applications). Moreover, these were often found in isolation and did not connect within the overall scope of the papers. These categories included “Insuretech”, “Regtech”, part of “Predictive Analysis”, “Nanotech”, “Biotech”, and part of “Cybersecurity”. Core technological indicators included topics more prevalent in the technological landscape within the scope of this research and always found combined with another set of topics. These included: “AI and machine learning”, “Big Data”, “Data Analytics”, and “Web Applications”.

Similarly, categorization was done for journal articles falling under specific journals. Core technological topic journals are more likely to contain articles that use technology as the primary approach to solve a particular problem. These articles included Advances in Water Resources, Environmental Modelling and Software, Ocean Engineering, and Ocean Modelling. Tangential topics included journals likely to contain articles with buzzwords that resonate with specific topics but fall outside the scope of this research. These included Ecohydrology and Hydrobiology, Contaminant Hydrology, and Process Engineering. Any other journal was categorized using Part A of Step 3.

After the filtering process, the total count of articles used for the analysis was 3701, with all relevant information found in Table 2. Subsequently, the articles were obtained, sanitized to remove formatting artifacts and encoding errors, and subjected to a two-way analysis: a cluster of all the articles into a single corpus and a separation of the articles for bibliometric purposes. The clustered corpus was converted to lowercase, and special words that did not contribute content to the overall analysis were removed.

2.2. Bibliometric Analysis

Indicators for bibliometric analysis including number of publications, countries, authors, keywords, citations, and frequency of citations were used to detect statistical research features on the specific topics found within the papers. Given the number of papers and the short time span of the analysis, the growth in number of articles were best fitted into a regression linear model. The collaborations were established as the connection of multiple coauthors from different countries publishing articles together, and these relationships were used to create cooperation networks between countries. Moreover, co-word and keyword analysis has been used to evaluate which are the main topics, both technological and special topics, found within the papers.

2.2.1. Network Analysis

To analyze the collaborations and potential connections between countries, their productivity and trends towards the most productive neighborhoods, we built two different graph networks. The first graph aims to present the connectivity between different countries based on the number of coauthors in the papers, and the second analysis encompassed the cooccurrence of words through frequency analysis, abstracted from the approach explained in the results section.

To identify key nodes within the networks, coefficients of determination from clustering analysis were used, specifically the degree centrality, closeness centrality, betweenness centrality, and fragmentation centrality. The degree centrality of a node is the fraction of nodes it is connected to, with high degree centrality indicating high connectivity within the network (Freeman, 1978). Closeness centrality measures how close a node is to all other nodes within a graph, with nodes of high closeness centrality representing proximity to other nodes in the network (Freeman, 1978). Betweenness centrality measures the extent to which a node lies on the shortest paths between other nodes in the network, with high values acting as bridges to other parts of the network (Brandes, 2001). Fragmentation centrality shows the percentage of isolated nodes after a particular node is removed from a network.

3. Results and Discussion

3.1. Scientific Level Analysis

The analysis includes 3,701 papers that centered on the utilization of keywords within specific technologies, with important information highlighted in Table 2. These papers were predominantly found in periodical articles, accounting for 100% of the publications and were uniformly published in English. The comprehensive data examined in the analysis involved 14,539 authors across 3,335 affiliations. Remarkably, the research spanned 20 diverse journals and covered 25 technological topics along with 13 specific subtopics. The overall impact of these publications was evident in the cumulative 62,985 citations garnered. Notably, the scholarly contributions were composed of 122 countries, reflecting the global relevance and reach of the research findings. The number of articles produced per year are shown in Figure 1. Considering the number of papers and the time span of the analysis, we analyzed the linear growth trend characteristic of this pre-LLM period.

Table 2. Summary of most relevant results for selected metrics.

Summary Metric	**Quantity**
Total number of papers	3,701
Total number of authors	14,539
Total number of journals used for the articles	20
Total number of affiliations	3,335*
Total number of subject areas	25 tech topics, 13 specific topics
Total number of citations	62,985
Total number of countries	122

**Affiliations were abstracted as unique institutional connection per author.*

3.2. Journal Level Analysis

The most relevant and active journal was found to be Journal of Hydrology representing 37.39% of all the publications in this study between 2018 through 2023, as shown in Table 3. The journal has a broad scope of research, including many subfields of hydrological sciences including water-based management and policy. Technological applications specifically applied machine and deep learning techniques as well as IoT have been pivotal in the journal's output. Most relevant and active journals also include Agricultural Water Management, Environmental Modelling & Software, Water Research, and Ocean Engineering. Figure 2 shows the yearly article output per the top 5 most producing journals.

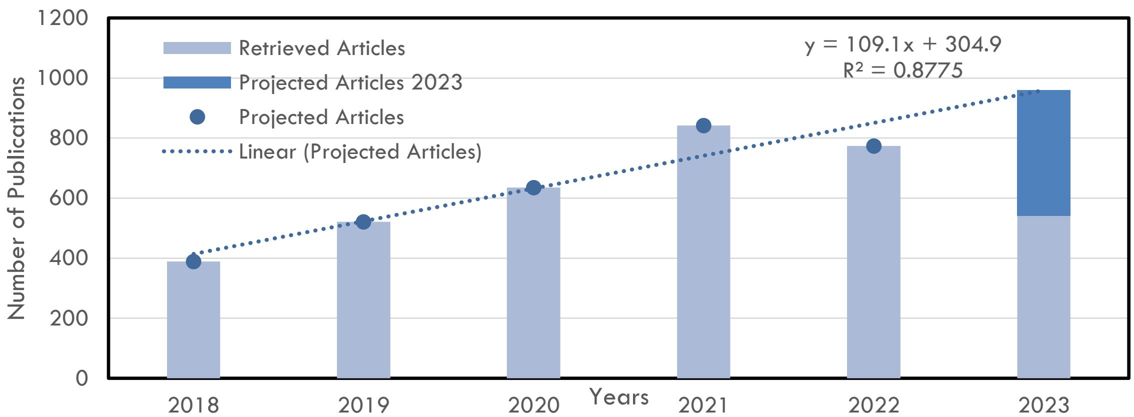


Figure 1. Number of retrieved articles from January 2018 through August 2023, along with the linear trend estimation for the final year of the study period.

Table 3. Number of publications per the selected journals from Jan 1, 2018, through Aug 1, 2023

Journal Name	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Total**
Journal of Hydrology	136	188	223	281	309	247	1,384
Agricultural Water Management	31	50	65	83	96	73	398
Environmental Modelling & Software	53	72	62	76	79	48	390
Water Research	37	37	61	83	84	31	333
Ocean Engineering	60	62	81	127	0	0	330
Journal of Hydrology: Regional Studies	9	10	23	46	70	53	211
Ecological Modelling	20	37	34	35	35	23	184
Advances in Water Resources	19	22	30	21	22	8	122
Groundwater for Sustainable Development	6	16	13	27	19	12	93
Journal of Water Process Engineering	4	9	15	20	19	14	81
Journal of Contaminant Hydrology	4	3	5	20	7	6	45
Ecohydrology & Hydrobiology	5	4	7	6	6	4	32
Ocean Modelling	2	1	7	4	8	9	31
Water Resources and Economics	3	4	2	3	7	5	24
Journal of Hydrology X	0	4	5	4	7	1	21
Water Resources and Industry	0	1	1	2	0	4	8

Journal Name	2018	2019	2020	2021	2022	2023	Total
Watershed Ecology and the Environment	0	0	0	0	5	1	6
Journal of Hydro-environment Research	0	0	1	1	1	0	3
Water Research X	0	1	0	1	0	1	3
Water Security	0	0	0	2	0	0	2

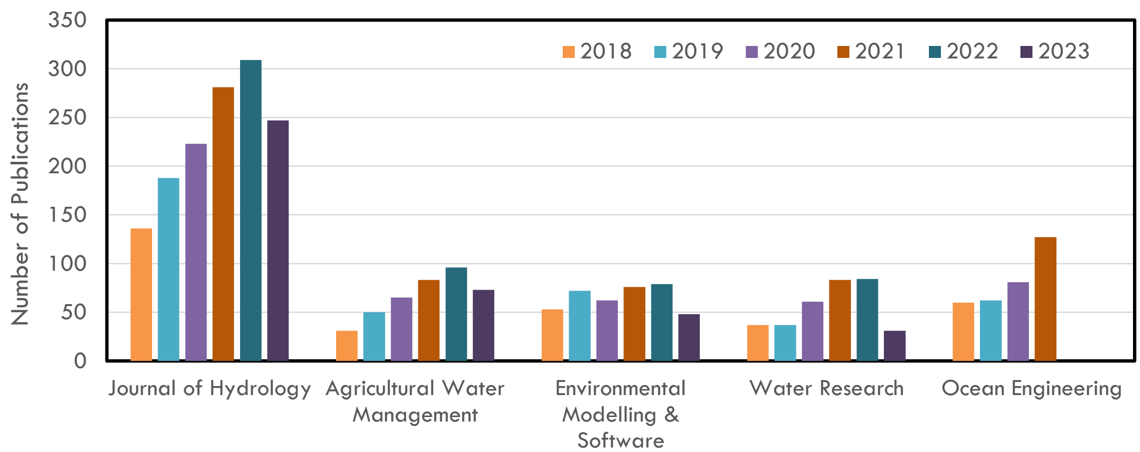


Figure 2. Top 5 most relevant and active journals per year.

3.3. National and Institutional Analysis

A total of 14,539 authors from across 3,345 institutions and 122 countries were found as contributors in the retrieved articles. The number of contributions per country is defined as the number of authors from institutions working as collaborators in the same research. Figure 3 shows the top 20 country contributions throughout the analyzed timeframe, and Figure 4 shows the cumulative percentage of research articles per year per the top 10 contributing countries. China and the United States are the top contributors within the selected articles. The cumulative outputs show a surge in research outputs from 2020 onwards for China and the United States, and a steady output percentage for the rest of countries.

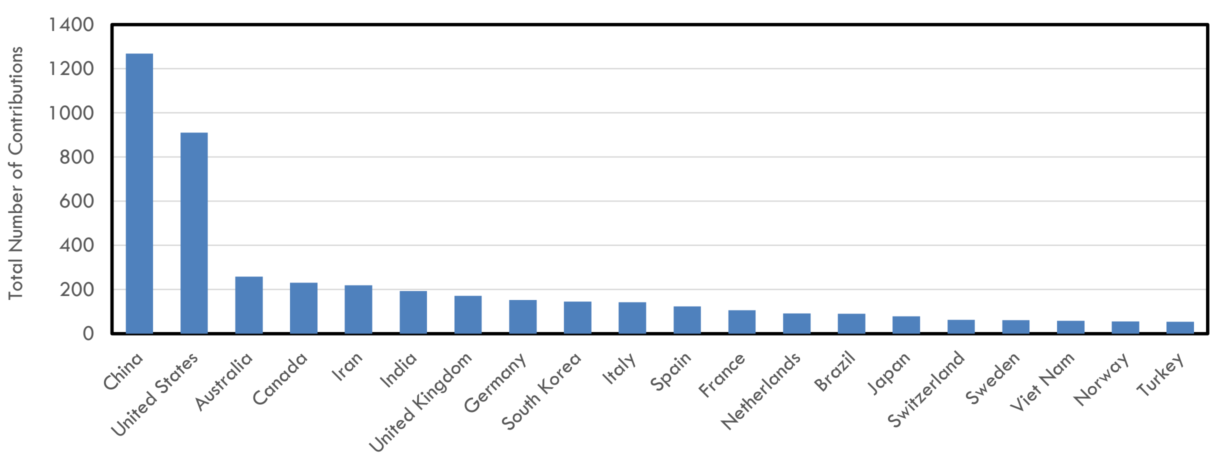


Figure 3. Research contribution per country throughout the span of 2018 through first half 2023.

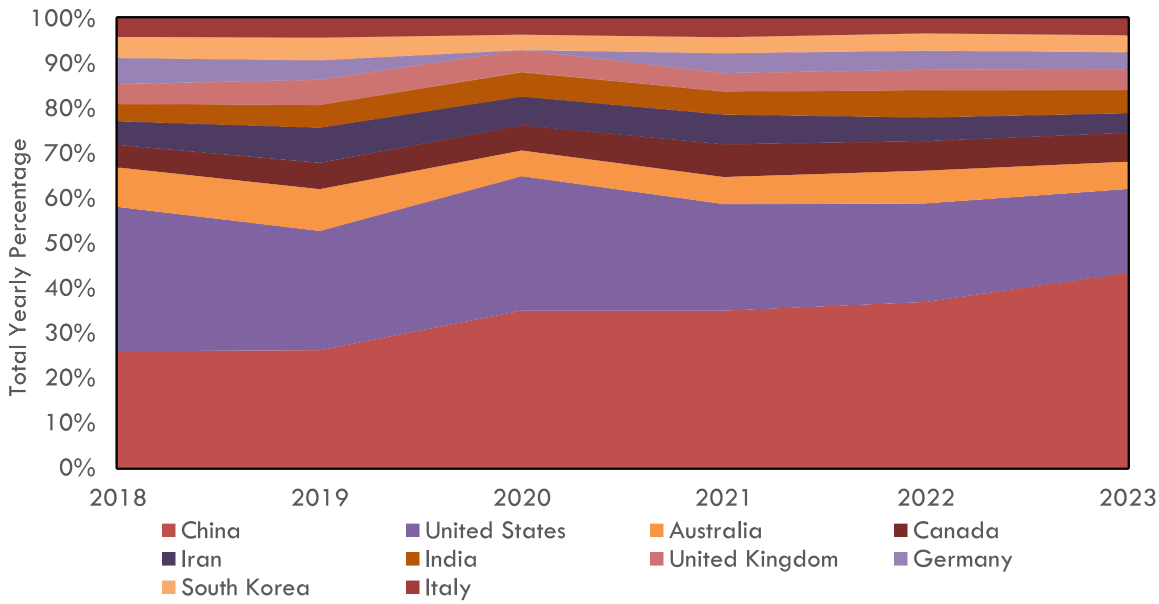


Figure 4. Percentage of publications per country per year.

4. Collaboration Networks

From the list of selected articles, a total of 122 countries collaborated in research within a broad scope of hydrology and beyond. This collaboration network emphasizes the increasing importance of collaboration across different regions or locations. Furthermore, a country cooperation network reflects a specific status and importance in the field. Figure 5 shows the collaboration network between the top 30 countries from the research scope. Cooperation among countries was observed in a wide variety of regions and countries, with the United States, China, Germany, and the United Kingdom playing pivotal roles as main hubs for research. The most extensive collaboration occurred between China and the United States, with both countries having hubs in European countries where research on hydrology, hydraulics structures, and physics has been prevalent.

A country's position in the cooperation network reflects its status and function in the field, with key country nodes exerting significant influences (Leclerc & Gagné, 1994). Table 5 shows the centrality analysis performed based on the contribution networks. The United States emerged as the key node in all three centrality indicators, demonstrating dominance in the international cooperation network. China, Germany, and the United Kingdom established prevalence as part of large networks, underscoring their importance within the global collaboration network, promoting a sustained and impactful contribution to international collaboration in hydrological research. These key country nodes not only demonstrate their prominence but also play a crucial role in shaping the direction and advancements within the field. As central participants, the country nodes serve as driving forces in keeping a collaborative environment that transcends geographical boundaries.

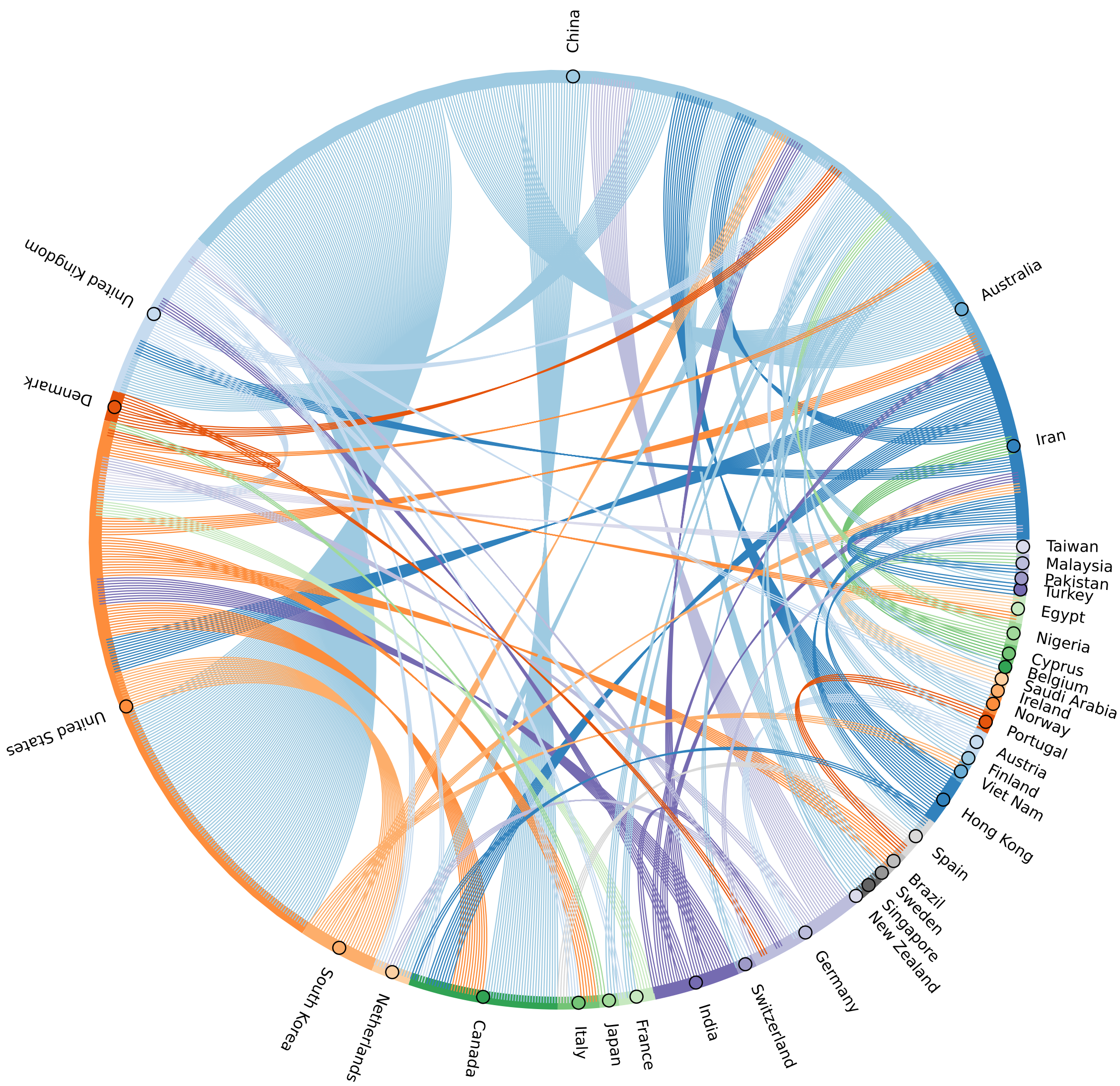


Figure 5. Top 30 most productive countries during the period 2018-2023. Arc lengths represent the total number of articles published in collaboration with other countries, while the strands of connections indicate the number of articles published together.

Table 4. Top 3 countries for degree centrality, weighted centrality, betweenness centrality, and fragmentation centrality from the collaboration network.

Degree Centrality	Country	Closeness Centrality	Country	Betweenness Centrality	Country	Fragmentation Centrality	Country
0.4474	United States	0.6046	United States	0.1913	United States	4.160%	China
0.4386	China	0.5980	China	0.1752	China	3.375%	Canda
0.3246	Germany	0.5586	Germany	0.1107	United Kingdom	3.233%	Iran

4.1. Technological Topic Analysis

The number of topics used for the analysis covered a variety of research interests closely related to the main topics in technological development. The analysis reveals that the predominant areas of research within the papers primarily revolve around data-driven applications, including AI and Machine Learning, Data Mining, Data Analytics, among others. Figure 6 illustrates the top 10 technological topics and their outputs per year.

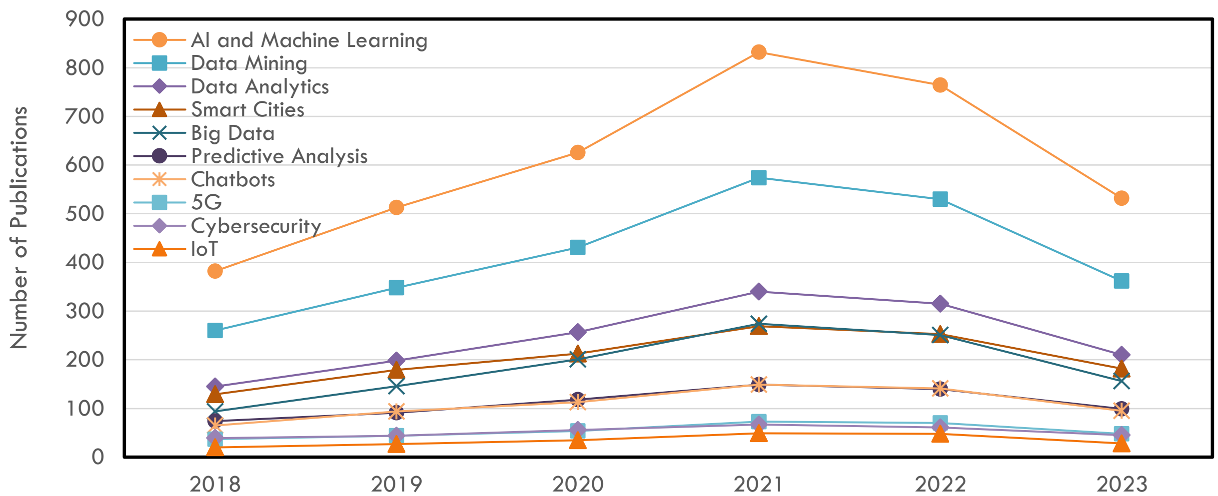


Figure 6. Number of publications per year per the top 10 most used technologies.

4.2. Word Frequency Analysis

The analysis of buzzword frequencies within the obtained articles revealed that most technology buzzwords were related to Data Analytics and Machine Learning. These categories accounted for 97% of the total buzzwords identified, with the remaining 3% distributed among 18 other categories. This information is summarized in Table 6 and visually represented in Figure 7. Table 5 presents the top 50 technology terms, with "regression" emerging as the most frequently occurring buzzword, accounting for 29.18% of all the identified terms. This is followed by "classification" at 12.71%, "neural network" at 11.34%, "machine learning" at 9.45%, and "random forest" at 3.66%.

Table 5. Top 50 words as per their frequency with the technological topics, ordered in descending order, left to right.

Sub-Word	Category	Count	Frequency	Sub-Word	Category	Count	Frequency
regression	AI & Machine Learning	28225	29.18%	java	Web Applications	540	0.56%
classification	AI & Machine Learning	12296	12.71%	gradient descent	AI & Machine Learning	497	0.51%
neural network	AI & Machine Learning	10972	11.34%	supervised learning	AI & Machine Learning	482	0.50%
machine	AI & Machine	9145	9.45%	backpropagati	AI & Machine	454	0.47%

Sub-Word	Category	Count	Frequency	Sub-Word	Category	Count	Frequency
learning	Learning			on	Learning		
random forest	AI & Machine Learning	3536	3.66%	data mining	Data Mining	439	0.45%
deep learning	Data Mining	2478	2.56%	sustainable development	Smart Cities	420	0.43%
decision tree	AI & Machine Learning	2282	2.36%	energy efficiency	IoT	419	0.43%
water management	Smart Cities	1793	1.85%	user interface	Web Applications	419	0.43%
machine learning models	Chatbots	1649	1.70%	risk assessment	Predictive Analysis	413	0.43%
clustering	Data Mining	1647	1.70%	reinforcement learning	AI & Machine Learning	392	0.41%
overfitting	Data Mining	1619	1.67%	ensemble learning	AI & Machine Learning	380	0.39%
support vector machine	AI & Machine Learning	1501	1.55%	k means	Data Mining	372	0.38%
statistical analysis	Data Analytics	1428	1.48%	attention mechanism	AI & Machine Learning	355	0.37%
data analysis	Data Analytics	1232	1.27%	data science	Data Analytics	347	0.36%
artificial intelligence	AI & Machine Learning	1080	1.12%	transfer learning	AI & Machine Learning	339	0.35%
data processing	Big Data	933	0.96%	data preprocessing	Data Mining	334	0.35%
logistic regression	Data Mining	868	0.90%	data management	Big Data	314	0.32%
long short term memory	AI & Machine Learning	786	0.81%	network architecture	5G	306	0.32%
nearest neighbor	AI & Machine Learning	734	0.76%	web application	Web Applications	287	0.30%
big data	Big Data	665	0.69%	risk management	Predictive Analysis	249	0.26%
feature selection	Data Mining	663	0.69%	cloud computing	Infrastructure as a Service / Cloud Computing	247	0.26%
principal component analysis	Data Mining	639	0.66%	time series analysis	Data Mining	235	0.24%
model evaluation	Data Mining	625	0.65%	data transformation	Big Data	199	0.21%
data quality	Big Data	580	0.60%	data storage	Big Data	180	0.19%
support vector regression	Data Mining	564	0.58%	automation	Automation	174	0.18%

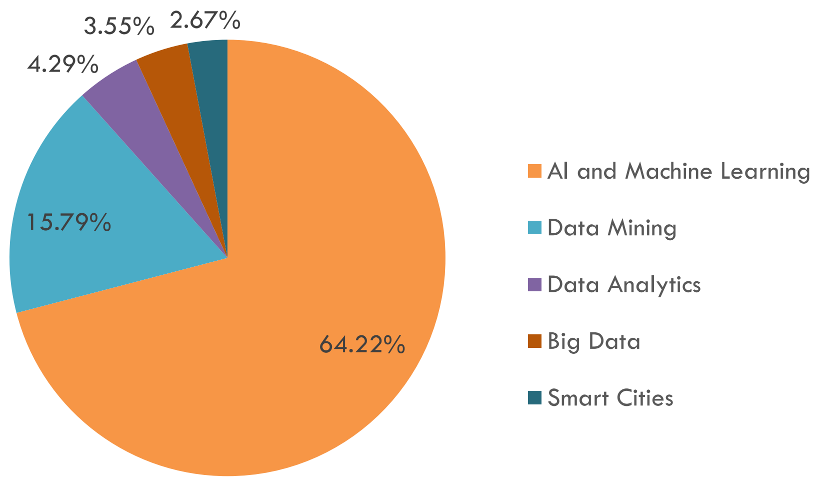


Figure 7. Percentage of the top 5 co-word frequencies per technological topic.

4.2.1. Citation Analysis

Citation analysis plays a crucial role in evaluating the impact and significance of scholarly publications in the realm of technological advancements (Nicolaisen, 2007). Within the sphere of water resources management, hydrology, and environmental engineering, high citation counts for top journals signify their role in disseminating knowledge and driving research progress. Researchers rely on these reputable journals such as the Journal of Hydrology, Water Research, Ocean Engineering, Agricultural Water Management, and Environmental Modelling & Software to gain valuable insights, foster innovation, and promote sustainable practices in water resource utilization. In this context, Table 6 presents the citation output per the journal's outputs.

Table 6. Number of citations per journal along with the citation score, and impact factor. N/D indicates there was no information available for the journal.

Journal Name	Citations	Cite Score	Impact Factor
Journal of Hydrology	25,838	10.4	6.4
Water Research	8,644	19.8	12.8
Ocean Engineering	7,643	6.6	5
Agricultural Water Management	6,139	10.7	6.7
Environmental Modelling & Software	5,450	9.9	4.9
HydroResearch	2,249	N/D	N/D
Ecological Modelling	2,189	5.9	3.1
Journal of Hydrology: Regional Studies	1,353	5.8	4.7
Groundwater for Sustainable Development	1,177	10.4	5.9
Journal of Water Process Engineering	826	9.7	7
Journal of Contaminant Hydrology	421	6.4	3.6
Journal of Hydrology X	302	8.5	4
Ocean Modelling	250	5.8	3.2
Ecohydrology & Hydrobiology	211	5.9	2.6

Journal Name	Citations	Cite Score	Impact Factor
Water Resources and Economics	96	5	2.2
Water Resources and Industry	86	8	5.1
Journal of Hydro-environment Research	56	4.7	2.8
Water Security	29	7.1	N/D
Water Research X	17	14.3	7.5
Watershed Ecology and the Environment	9	N/D	N/D

The most highly cited publications revolve around the development and application of machine learning and artificial intelligence (AI) technologies to analyze various topics within the hydrological domain. Table 7 displays the top publications in this field. With the advent of new AI and Machine Learning methodologies, such as large language models and novel architectures, the most cited articles primarily focus on the latter, showcasing significant potential applications. The utilization of powerful computational resources and AI signifies a promising direction for research, particularly in exploring large-scale applications that analyze climatology data to address climate change within the hydrological context. The automation of information analysis during this period signaled the imminent shift toward the autonomous workflows observed today.

Table 7. Top 10 most cited publications.

No	Publication Name	Year	# of Citations	Reference	Journal Name
1	Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas	2018	407	(J. Zhang et al., 2018)	Journal of Hydrology
2	An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction	2019	406	(Yaseen et al., 2019)	Journal of Hydrology
3	A comparative assessment of flood susceptibility modeling using Multi-Criteria Decision-Making Analysis and Machine Learning Methods	2019	324	(Khosravi et al., 2019)	Journal of Hydrology
4	A survey on river water quality modelling using artificial intelligence models: 2000–2020	2020	278	(Tiyasha et al., 2020)	Journal of Hydrology
5	Machine learning methods for better water quality prediction	2019	228	(Najah Ahmed et al., 2019)	Journal of Hydrology
6	Advancements in the field of autonomous underwater vehicle	2019	217	(Sahoo et al., 2019)	Ocean Engineering
7	Evaluation of CatBoost method for prediction of reference evapotranspiration in humid regions	2019	215	(Huang et al., 2019)	Journal of Hydrology
8	Tools and methods in participatory modeling:	2018	213	(Voinov et	Env. Mod.

No	Publication Name	Year	# of Citations	Reference	Journal Name
	Selecting the right tool for the job			al., 2018)	& Software
9	Modeling and simulating of reservoir operation using the artificial neural network, support vector regression, deep learning algorithm	2018	201	(D. Zhang et al., 2018)	Journal of Hydrology
10	Short-term runoff prediction with GRU and LSTM networks without requiring time step optimization during sample generation	2020	197	(Gao et al., 2020)	Journal of Hydrology

4.3. Specific Topic Analysis

To understand and summarize the content of each paper and explore specific topics within the refined dataset, a Latent Dirichlet Allocation (LDA) analysis was conducted. LDA is an unsupervised machine learning model that effectively summarizes large collections of documents by identifying conceptual connections among them through topics and themes (Blei et al., 2003), (Grimmer & Stewart, 2013). Each topic is represented as a statistical distribution across a set of topics, which in turn represents a distribution across words. Topics within the corpus are depicted as weights describing the probabilities associated with specific topics. These topic distributions enable an assessment of the significance of each topic in the corpus using measures like coherence and exclusivity, as explained by (Airoldi & Bischof, 2012) and (Röder et al., 2015). To perform the analysis, the Gensim Python package (Rehvek, 2010) with the appropriate word lemmatization and coherence scoring was used. The coherence scores for each of the selected topics is shown in Figure 9, highlighting that after the 13th topic, the coherence of the topics does not vary and the abstracted topic becomes irrelevant.

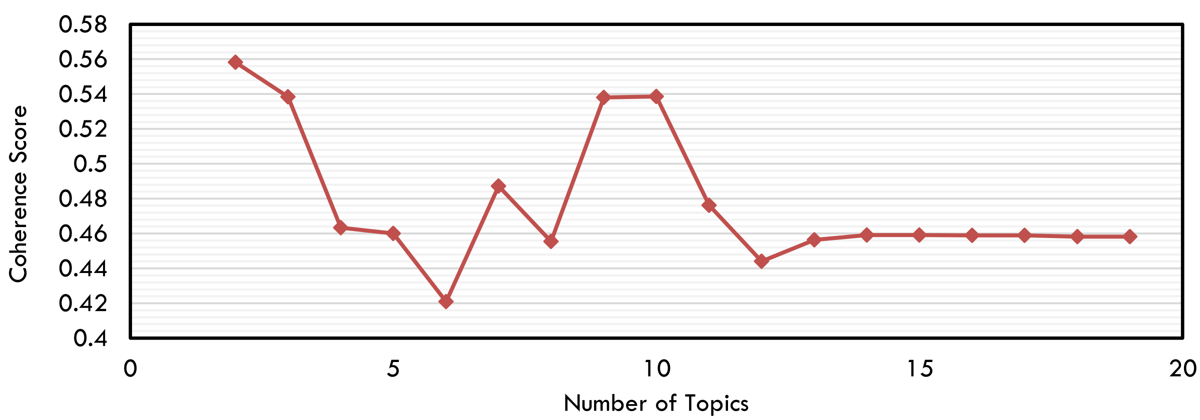
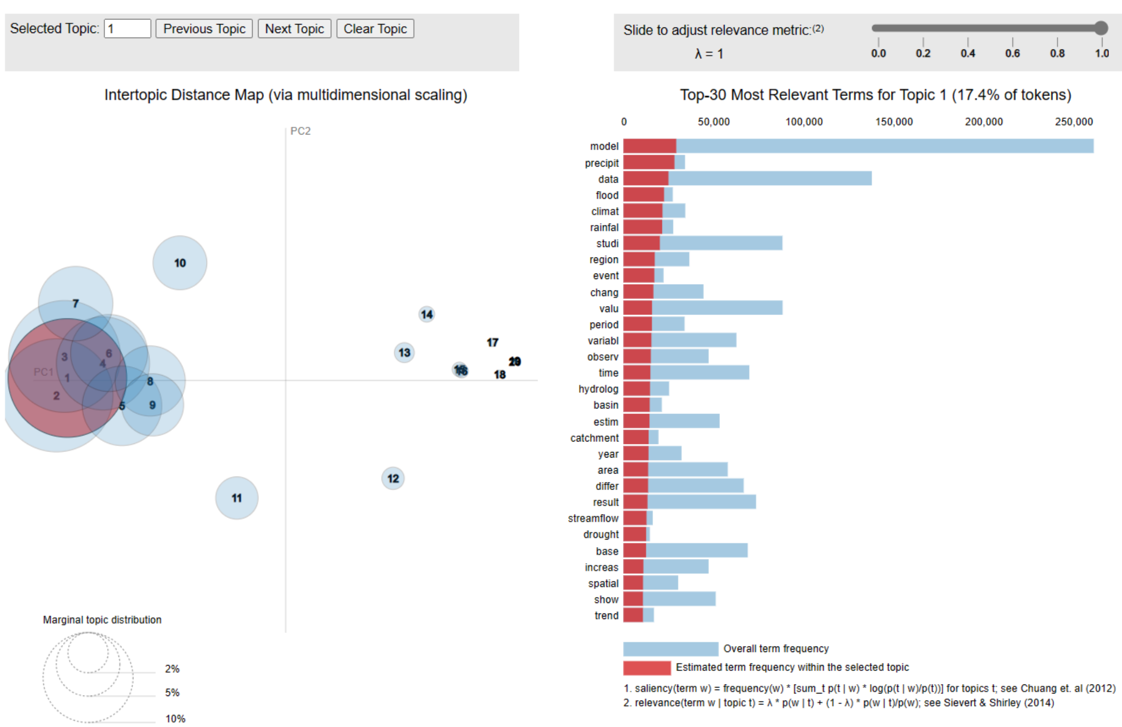


Figure 8. Coherence score analysis from the LDA outputs. The highest the correlation value, the more prevalent a topic in the co-word analysis.

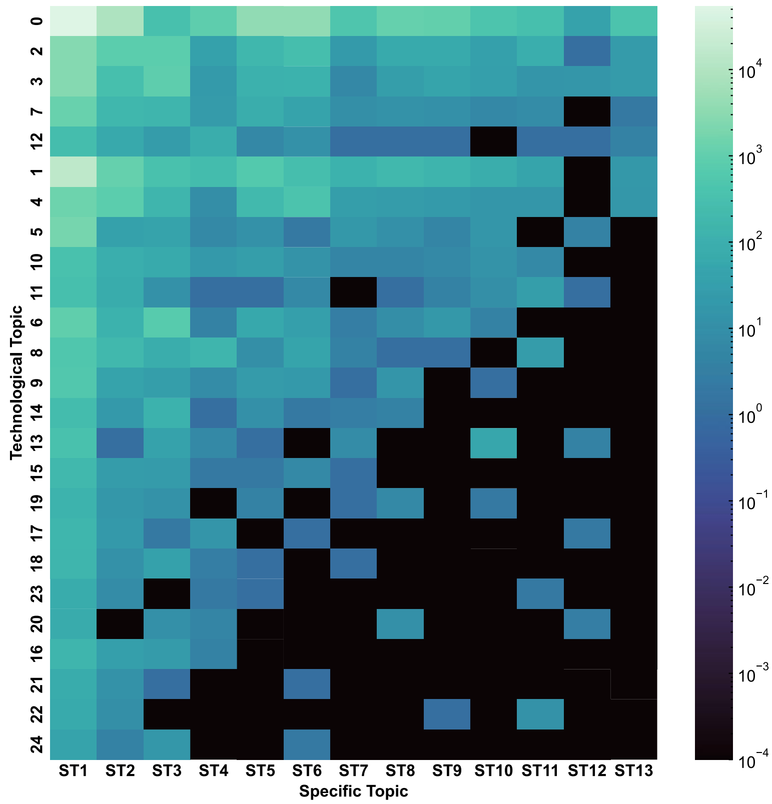
The analysis identified 13 specific topics, as detailed in Table 8. These topics are characterized by recurring keywords, chosen based on their saliency and relevance. Manual selection of these topics was guided by metrics that reflect their significance within the hydrological and environmental domain. Noteworthy themes include data-driven modeling in hydrology and hydraulics, assessments of water quality in diverse aquatic environments, and explorations of coastal and maritime interactions. Figure 9(a) presents the term frequency for the first identified topic. With varying distributions and rankings, the 13 topics exhibit different degrees of correlation with the 28 technical topics used for data retrieval as shown in Figure 9(b).

Table 8. Specific topics found using the LDA analysis with the percentage % tokens representing the overall number of repetitions per topic.

Topic	Description	% Tokens
ST1	Data driven modelling and prediction	17.4
ST2	Groundwater and surface water quality analysis	15.8
ST3	Hydrological modelling for flood estimation	15.4
ST4	Climate change impacts on agriculture	10.7
ST5	Simulation-Based Analysis and Uncertainty Estimation	7.8
ST6	Tools for hydrological data analysis and visualization	7.3
ST7	Coastal wave and wind interactions	6.8
ST8	Sediment transport and erosion modelling	6.1
ST9	Remote sensing and image processing for geospatial analysis	4.8
ST10	Multi-agent decision making for reservoir systems	3.6
ST11	Wastewater treatment and contaminant removal	2.2
ST12	Soil moisture estimation and vegetation cover	0.6
ST13	Hydrodynamic analysis on maritime structures	0.5



(a)



(b)

Figure 9. (a) Correlation and topic co-word abstraction using LDA visualization tools from Gensim (Rehvek, 2010), with the estimated term frequency within a selected topic along with saliency and relevance used as metrics for topic selection and (b) correlation heatmap between technological topics and specific topics from the LDA analysis in a log-normal scale; highest values represent higher correlation between each specific and technological subtopic. The list of technical subtopics and their definitions can be found in the supplementary material, Table S2.

4.3.1. Co-word Frequency Analysis

The results from the LDA analysis show that terms such as "data," "model," "precipitation" "flood," "user," "time," and "climate" had a high frequency throughout the entire corpus in topics. Moreover, the top 5 topics identified using these and the rest of the terms and frequencies are “Data-Driven Modeling and Prediction,” “Groundwater and Surface Water Quality and Analysis,” “Hydrological Modeling for Flood Estimation,” “Climate Change Impacts on Agriculture,” and “Simulation-Based Analysis and Uncertainty Estimation.” Table 9 displays the top 15 terms for each of the top 5 topics found in the main corpus. The topic outline aligns closely with the primary themes of the journals. Furthermore, given the significant prevalence of the mentioned terms, it is evident that there will be a higher adoption of technology for improving data analysis across a broad spectrum of topics within the field of hydrology.

Table 9. Co-word frequency analysis per the top 5 topics.

Data Driven Modelling and Prediction		Groundwater and Surface Water Quality and Analysis		Hydrological Modelling for Flood Estimation		Climate Change Impacts on Agriculture		Simulation-Based Analysis & Uncertainty Estimation	
Term	**Frequency**	**Term**	**Frequency**	**Term**	**Frequency**	**Term**	**Frequency**	**Term**	**Frequency**
data	0.03	water	0.045	model	0.013	soil	0.024	model	0.013
model	0.026	groundwat	0.017	precipit	0.012	water	0.02	precipit	0.012
process	0.008	lake	0.013	data	0.011	irrig	0.017	data	0.011
user	0.008	studi	0.009	flood	0.01	crop	0.016	flood	0.01
time	0.007	area	0.009	climat	0.009	land	0.014	climat	0.009
develop	0.007	river	0.009	rainfal	0.009	area	0.011	rainfal	0.009
provid	0.007	concentr	0.009	studi	0.009	yield	0.01	studi	0.009
base	0.006	level	0.009	region	0.008	model	0.009	region	0.008
inform	0.005	qualiti	0.007	event	0.007	chang	0.008	event	0.007
includ	0.005	data	0.006	chang	0.007	valu	0.008	chang	0.007
applic	0.005	increas	0.006	valu	0.007	studi	0.008	valu	0.007
requir	0.004	aquif	0.006	period	0.007	increas	0.008	period	0.007
differ	0.004	sampl	0.005	variabl	0.007	agricultur	0.007	variabl	0.007
research	0.004	valu	0.005	observ	0.007	differ	0.006	observ	0.007
servic	0.004	model	0.005	time	0.006	climat	0.004	time	0.006

4.4. Dominant Technological Trends

The rapidly evolving landscape of technology and water sciences has brought to the forefront several key topics in the last 5 years. Among the most prominent are AI and Machine Learning, Data Mining, Data Analytics, Big Data, and Smart Cities. These topics intersect with specific areas such as Flood Estimation Modelling, Simulation-Based Analysis, and Data-Driven prediction, indicating a shift towards more data-centric approaches in water-related studies.

There is a strong correlation between AI, Machine Learning, Data Analytics, and data-driven modelling across various water domains including groundwater, surface water, and water quality studies. The use of statistical and probabilistic methods within these domains allows researchers to explore a broader range of features beyond local events, leveraging tools such as web technologies to facilitate analysis and integration (Katz et al., 2002).

There is a clear trend towards merging data-driven and physically-driven models, facilitating a more comprehensive understanding of complex water systems and addressing challenges such as saltwater intrusion and rainfall analysis (Bhasme et al., 2022). The increasing reliance on data analytics underscores the importance of data-driven solutions in advancing water science and management practices (Vitolo et al., 2015).

These emerging trends signify a harmonious confluence of technology and water science, paving the way for innovative methodologies and cutting-edge technologies to drive transformative advancements in the field. As researchers continue to harness the power of AI, Machine Learning, and data analytics, the potential for unlocking new insights and improving water resource management capabilities remains promising.

4.5. Emerging or Niche Applications

The analysis of emerging applications from the research sheds light on key areas of interest for future exploration, leveraging the technological approaches discussed in the paper. These include multi-agent decision making, wastewater treatment and removal, soil moisture estimation, vegetation cover analysis, and hydrodynamic analysis on maritime structures. These topics exhibit a strong correlation with AI, Machine Learning, IoT, Big Data, and Automation, emphasizing the integration of advanced technologies with physical models and environmental interactions.

The application of these technological approaches is primarily centered around sensor deployment, data management, decision-making systems powered by data analytics, and aid on the design of hydraulic structures. This focus distinguishes these topics from more specific technological applications such as augmented reality or natural language processing. As we enter the era of AI driven models, these approaches are expected to evolve towards more comprehensive and integrated systems. Predictive technologies that enable sequential decision-making have the potential to enhance system integration in these specialized areas of study.

While these specific topics may not exhibit high correlation, ongoing collaborations are already underway to explore their potential. These collaborations leverage a range of technological approaches highlighted in the paper, even if they are not directly related to technologies such as web development or related ventures. For instance, Mohammed (2016) studied the utilization of 3D printing in hydrodynamic analysis of maritime structures has gained traction in research, showcasing how diverse technologies can converge for innovative solutions, despite not being a direct focus of the identified technology topics.

These topics present promising avenues for integrated research, highlighting the interdisciplinary nature of technological advancements in the field. Despite their limited direct connection to several of the technological topics used as main scope, the ongoing collaborations across varied domains underscore the broad impact and potential knowledge exchange in this dynamic and ever-evolving landscape.

5. Discussions

Our analysis characterizes the infrastructure phase of modern hydroinformatics. The dominance of regression and classification algorithms we identified (Table 5) confirms that prior to 2024, the field was focused on predictive accuracy rather than generative capabilities. While our data cutoff precludes the analysis of ChatGPT's immediate impact, recent work by Sajja et al. (2025) confirms that the core technological indicators identified here—specifically web data analytics and cloud infrastructure—served as the necessary retrieval backbones for the current generation of LLM applications. The overarching trends identified in the analysis point towards a significant shift towards the adoption of new technologies, innovative approaches, and evolving standards in the field of hydrology and the environmental domain. This shift is shown by the increasing integration of cutting-edge technologies like machine learning, AI, and the widespread adoption of new applications. The analysis highlights several key themes:

Enhancing decision support systems. There is a growing emphasis on leveraging various types of decision support systems to develop tools tailored for hydrological applications, utilizing information systems effectively.

Embracing AI and machine learning. The widespread adoption of machine learning, AI, and smart systems is transforming the hydrological domain, particularly in areas like remote sensing and data analysis.

Utilizing autonomous systems and advanced deployment environments. There is a notable increase in the use of new hardware and software technologies to facilitate analysis and exploration in fields such as oceanography and water quality monitoring.

Integrating technological approaches with physically driven modelling and error estimation. There is a movement towards combining data-driven methodologies for model correction with physically driven modeling, integrating both approaches seamlessly.

Real-time data analysis. With the exponential growth in data volume from sensor-based data retrieval systems, there is an increasing need for real-time analysis supported by predictive systems to make informed decisions efficiently.

These findings showcase the impact of technology on the hydrological and environmental sectors, shaping the way data is utilized, models are developed, and decisions are made. The convergence of advanced technologies with traditional methodologies signifies a shift towards more efficient, accurate, and insightful practices in these critical domains.

6. Conclusions

The findings of this study show the transformative impact of technology on environmental and hydrological research. By embracing new methods and cutting-edge research, new insights can be taken in decision-making processes, driving towards more sustainable water resources management. The integration of technological tools is pivotal for advancing research in the sciences. The increasing utilization of tools such as Machine Learning, predictive analysis, and innovative hardware/software solutions, alongside the deployment of information-driven sensors, signals a promising direction for future developments in these fields. By embracing new approaches and technologies, researchers can unlock new possibilities and drive progress towards more sophisticated and insightful insights in hydrological and environmental research.

The study focused on a subset of papers from selected journals in the field of environmental and hydrological studies, which may not capture the full spectrum of technological trends influencing analytical tools in these domains. The restriction to English-language publications also limited the diversity of perspectives included in the analysis. While these limitations could potentially impact the breadth of topics covered and their relationships within the study, it is worth noting that the predominant use of technologies such as Artificial Intelligence and Machine Learning suggests a consistent trend across the analyzed literature. Moreover, as the corpus is derived from high-impact Elsevier journals, this baseline should be interpreted as the technological frontier of hydroinformatics rather than the global median state of practice.

The convergence between data-driven and physically driven models, as shown by the increase of statistical and probabilistic methods, offers a promising avenue for achieving more comprehensive understanding and applications for water systems. This will enable researchers to dig deeper in the upcoming years in issues exacerbated by climate change, such as saltwater intrusion, flood inundation systems, and integration with intelligent data driven decision making.

The emerging topics identified, though not directly aligned with the main technological themes, offer avenues for further exploration. From multi-agent decision making to wastewater treatment exhibit strong correlation with advanced technologies such as AI, IoT, and Big Data. Collaborations through multiple domains like in 3D printing applications for hydrodynamic analysis showcase the potential for innovative solutions through interdisciplinary approaches.

This study confirms that the 2018–2023 period was not merely a time of incremental growth, but the structural consolidation phase where the data pipelines (Big Data) and predictive engines (Machine Learning) were integrated, effectively creating the necessary infrastructure for the Generative AI revolution that followed.

Credit Statement

Carlos Erazo: Conceptualization, Methodology, Software, Investigation, Writing – Original Draft **Kevin Song:** Software, Investigation **Ibrahim Demir:** Conceptualization, Supervision, Writing – Review and Editing, Funding acquisition

Acknowledgements

We would like to thank Dr. Yusuf Sermet for his contributions to data curation, guidance, and evaluation of the manuscript.

7. References

Abbott, M. B. (1991). *Hydroinformatics: information technology and the aquatic environment*. Avebury Technical.

Alabbad, Y., & Demir, I. (2022). Comprehensive flood vulnerability analysis in urban communities: Iowa case study. *International Journal Of Disaster Risk Reduction*, 74, 102955.

Airoldi, E. M., & Bischof, J. (2012). A Poisson convolution model for characterizing topical content with word frequency and exclusivity. *arXiv: Learning*.

Bayar, S., Demir, I., & Engin, G. O. (2009). Modeling leaching behavior of solidified wastes using back-propagation neural networks. *Ecotoxicology and Environmental Safety*, 72(3), 843-850.

Baydaroğlu, Ö., Yeşilköy, S., Sermet, Y., & Demir, I. (2023). A comprehensive review of ontologies in the hydrology towards guiding next generation artificial intelligence applications. *Journal of Environmental Informatics*, 42(2), 90-107.

Bhasme, P., Vagadiya, J., & Bhatia, U. (2022). Enhancing predictive skills in physically-consistent way: Physics Informed Machine Learning for hydrological processes. *Journal of Hydrology*, *615*, 128618. https://doi.org/https://doi.org/10.1016/j.jhydrol.2022.128618

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, *3*(Jan), 993-1022.

Brandes, U. (2001). A faster algorithm for betweenness centrality*. *The Journal of Mathematical Sociology*, *25*(2), 163-177. https://doi.org/10.1080/0022250X.2001.9990249

Demir, I., & Galelli, S. (2022). Next Generation Hydroinformatics Applications in Water Resources Research and Education. In ICWRER 2022 9th *International Conference on Water Resources and Environment Research*.

Dingman, S. L. (2015). *Physical hydrology*. Waveland press.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285-296. https://doi.org/https://doi.org/10.1016/j.jbusres.2021.04.070

Elsevier. (2023). *Elsevier API* https://dev.elsevier.com/

Erazo Ramirez, C., Sermet, Y., & Demir, I. (2023a). Hydrocompute: An Open-Source Web-Based Computational Library for Hydrology and Environmental Sciences. *EarthArxiv*. https://doi.org/10.31223/X5FM2D

Erazo Ramirez, C., Sermet, Y., & Demir, I. (2023b). HydroLang Markup Language: Community-driven web components for hydrological analyses. *Journal of Hydroinformatics*, *25*(4), 1171-1187. https://doi.org/10.2166/hydro.2023.149

Erazo Ramirez, C., Sermet, Y., Molkenthin, F., & Demir, I. (2022). HydroLang: An open-source web-based programming framework for hydrological sciences. *Environmental Modelling & Software*, *157*, 105525. https://doi.org/https://doi.org/10.1016/j.envsoft.2022.105525

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks*, *1*(3), 215-239. https://doi.org/https://doi.org/10.1016/0378-8733(78)90021-7

Gao, S., Huang, Y., Zhang, S., Han, J., Wang, G., Zhang, M., & Lin, Q. (2020). Short-term runoff prediction with GRU and LSTM networks without requiring time step optimization during sample generation. *Journal of Hydrology*, *589*, 125188. https://doi.org/https://doi.org/10.1016/j.jhydrol.2020.125188

Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political analysis*, *21*(3), 267-297.

Gourbesville, P., Freni, G., Demir, I., García Navarro, P., Lin, G.F., Boxall, J., Brentan, B.M., Nguyen, V.T.V., Tassi, P., Hinkelman, R. and Di Cristo, C., (2023). Why digital water–knowledge application and hydroinformatics?. *Digital Water*, 1(1), p.2321312.

Huang, G., Wu, L., Ma, X., Zhang, W., Fan, J., Yu, X., Zeng, W., & Zhou, H. (2019). Evaluation of CatBoost method for prediction of reference evapotranspiration in humid regions. *Journal of Hydrology*, *574*, 1029-1041. https://doi.org/https://doi.org/10.1016/j.jhydrol.2019.04.085

Illian, J., Penttinen, A., Stoyan, H., & Stoyan, D. (2008). *Statistical analysis and modelling of spatial point patterns*. John Wiley & Sons.

Katz, R. W., Parlange, M. B., & Naveau, P. (2002). Statistics of extremes in hydrology. *Advances in Water Resources*, *25*(8), 1287-1304. https://doi.org/https://doi.org/10.1016/S0309-1708(02)00056-8

Khosravi, K., Shahabi, H., Pham, B. T., Adamowski, J., Shirzadi, A., Pradhan, B., Dou, J., Ly, H.-B., Gróf, G., Ho, H. L., Hong, H., Chapi, K., & Prakash, I. (2019). A comparative assessment of flood susceptibility modeling using Multi-Criteria Decision-Making Analysis and Machine Learning Methods. *Journal of Hydrology*, *573*, 311-323. https://doi.org/https://doi.org/10.1016/j.jhydrol.2019.03.073

Leclerc, M., & Gagné, J. (1994). International scientific cooperation: The continentalization of science. *Scientometrics*, *31*(3), 261-292.

Li, Z., & Demir, I. (2024). Better localized predictions with Out-of-Scope information and Explainable AI: One-Shot SAR backscatter nowcast framework with data from neighboring region. *ISPRS Journal of Photogrammetry and Remote Sensing*, 207, 92-103.

Li, Z., Xiang, Z., Demiray, B. Z., Sit, M., & Demir, I. (2023). MA-SARNet: A one-shot nowcasting framework for SAR image prediction with physical driving forces. *ISPRS Journal of Photogrammetry and Remote Sensing*, 205, 176-190.

McCabe, M. F., Rodell, M., Alsdorf, D. E., Miralles, D. G., Uijlenhoet, R., Wagner, W., Lucieer, A., Houborg, R., Verhoest, N. E., & Franz, T. E. (2017). The future of Earth observation in hydrology. *Hydrology and earth system sciences*, *21*(7), 3879-3914.

Mohammed, J. S. (2016). Applications of 3D printing technologies in oceanography. *Methods in Oceanography*, *17*, 97-117. https://doi.org/https://doi.org/10.1016/j.mio.2016.08.001

Nagaraj, A., Shears, E., & de Vaan, M. (2020). Improving data access democratizes and diversifies science. *Proceedings of the National Academy of Sciences*, *117*(38), 23490-23498.

Najah Ahmed, A., Binti Othman, F., Abdulmohsin Afan, H., Khaleel Ibrahim, R., Ming Fai, C., Shabbir Hossain, M., Ehteram, M., & Elshafie, A. (2019). Machine learning methods for better water quality prediction. *Journal of Hydrology*, *578*, 124084. https://doi.org/https://doi.org/10.1016/j.jhydrol.2019.124084

Nicolaisen, J. (2007). Citation analysis. *Annual review of information science and technology*, *41*(1), 609-641.

Ramirez, C. E., Sermet, Y., Shahid, M., & Demir, I. (2024). HydroRTC: A Web-Based Data Transfer and Communication Library for Collaborative Data Processing and Sharing in the Hydrological Domain. *Environmental Modelling & Software*, 106068.

Rehvek, R. S., Petr. (2010). Software Framework for Topic Modelling with Large Corpora. Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks, Malta.

Röder, M., Both, A., & Hinneburg, A. (2015). *Exploring the Space of Topic Coherence Measures* Proceedings of the Eighth ACM International Conference on Web Search and Data Mining, Shanghai, China. https://doi.org/10.1145/2684822.2685324

Sahoo, A., Dwivedy, S. K., & Robi, P. S. (2019). Advancements in the field of autonomous underwater vehicle. *Ocean Engineering*, *181*, 145-160. https://doi.org/https://doi.org/10.1016/j.oceaneng.2019.04.011

Sajja, R., Xiong, S., Mermer, O., Sermet, M. Y., & Demir, I. (2025). A Comprehensive Bibliometric Analysis of Large Language Models in Hydrology and Environmental Sciences. *EarthArXiv*. https://doi.org/10.31223/X5SM61

Selenium. (2023). *Selenium Web Driver*. In https://www.selenium.dev/documentation/about/

Sermet, Y., & Demir, I. (2022). GeospatialVR: A web-based virtual reality framework for collaborative environmental simulations. *Computers & Geosciences*, 159, 105010.

Sit, M., Langel, R. J., Thompson, D., Cwiertny, D. M., & Demir, I. (2021). Web-based data analytics framework for well forecasting and groundwater quality. *Science of the Total Environment*, 761, 144121.

Sivertsen, G. (2010). A performance indicator based on complete data for the scientific publication output at research institutions. *ISSI newsletter*, *6*(1), 22-28.

Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of Hydrology*, *456*, 12-29.

Tiyasha, Tung, T. M., & Yaseen, Z. M. (2020). A survey on river water quality modelling using artificial intelligence models: 2000–2020. *Journal of Hydrology*, *585*, 124670. https://doi.org/https://doi.org/10.1016/j.jhydrol.2020.124670

Vitolo, C., Elkhatib, Y., Reusser, D., Macleod, C. J. A., & Buytaert, W. (2015). Web technologies for environmental Big Data. *Environmental Modelling & Software*, *63*, 185-198. https://doi.org/https://doi.org/10.1016/j.envsoft.2014.10.007

Voinov, A., Jenni, K., Gray, S., Kolagani, N., Glynn, P. D., Bommel, P., Prell, C., Zellner, M., Paolisso, M., Jordan, R., Sterling, E., Schmitt Olabisi, L., Giabbanelli, P. J., Sun, Z., Le Page, C., Elsawah, S., BenDor, T. K., Hubacek, K., Laursen, B. K., . . . Smajgl, A. (2018). Tools and methods in participatory modeling: Selecting the right tool for the job. *Environmental Modelling & Software*, *109*, 232-255. https://doi.org/https://doi.org/10.1016/j.envsoft.2018.08.028

Ward, A. D., & Trimble, S. W. (2003). *Environmental hydrology*. Crc Press.

Yaseen, Z. M., Sulaiman, S. O., Deo, R. C., & Chau, K.-W. (2019). An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction. *Journal of Hydrology*, *569*, 387-408. https://doi.org/https://doi.org/10.1016/j.jhydrol.2018.11.069

Yeşilköy, S., Baydaroğlu, Ö., Singh, N., Sermet, Y., & Demir, I. (2023). A Contemporary Systematic Review of Cyberinfrastructure Systems and Applications for Flood and Drought Data Analytics and Communication. *EarthArxiv*, 5814. https://doi.org/10.31223/X5937W

Zhang, D., Lin, J., Peng, Q., Wang, D., Yang, T., Sorooshian, S., Liu, X., & Zhuang, J. (2018). Modeling and simulating of reservoir operation using the artificial neural network, support vector regression, deep learning algorithm. *Journal of Hydrology*, *565*, 720-736. https://doi.org/https://doi.org/10.1016/j.jhydrol.2018.08.050

Zhang, J., Zhu, Y., Zhang, X., Ye, M., & Yang, J. (2018). Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas. *Journal of Hydrology*, *561*, 918-929. https://doi.org/https://doi.org/10.1016/j.jhydrol.2018.04.065
Zhao, B. (2017). Web Scraping. In (pp. 1-3). https://doi.org/10.1007/978-3-319-32001-4_483-1

Supplementary Materials

Table S1. Research journals used for the study.

Journal Name	**Scope**
HydroResearch	Hydrology and water resources management,
Advances in Water Resources	Innovative research on hydrology, hydrogeology, and water management
Ecohydrology & Hydrobiology	Ecosystem and hydrology interactions in ecological and biological processes
Journal of Contaminant Hydrology	Movement and remediation of contaminants in surface and groundwater systems
Journal of Hydrodynamics, Ser. B	Fluid dynamics and applications in hydrology
Journal of Hydro-environment Research	Environmental aspects of hydrology and impact on aquatic ecosystems and water quality
Journal of Hydrology	Wide range of hydrology topics including modeling, resource assessment, watershed management
Journal of Hydrology: Regional Studies	Region-specific hydrology and water resource issue
Journal of Hydrology X	Innovative and experimental studies on various hydrological aspects
Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere	Physical and chemical dynamics of hydrological, oceanic, and atmospheric systems
Water Resources and Economics	Economic aspects of water resource management
Water Resources and Industry	Intersection between water and industrial processes, including water use efficiency and sustainability
Water Resources and Rural Development	Rural water resource management and community-based approaches
Agricultural Water Management	Efficient and sustainable water allocation for agricultural practices
Groundwater for Sustainable Development	Groundwater-related research focused on sustainability and management
Journal of Water Process Engineering	Processes-related water treatment, purification, and distribution
Water Research	Wide range of water-related research for water quality and quantity
Sustainability of Water Quality and Ecology	Sustainable water quality and impact on ecological systems
Water Research X	Innovative and experimental studies on water related research
Watershed Ecology and the Environment	Watershed management from the perspective of ecological impacts and environmental protection
Water Security	Security and sustainability practices on water resources considering population growth
Water Science	Research on fundamental water science topics including hydrological processes and water quality

Journal of Ocean Engineering and Science	Ocean engineering research and oceanic systems
Ocean Engineering	Oceanography and marine environments research
Ocean Modelling	Mathematical and computational modelling of oceanic processes and systems
Ecological Modelling	Research on ecological modeling including aquatic ecosystems and their dynamics
Environmental Modelling & Software	Development and application of software for environmental and water modeling and simulation

Table S2. Technological topics and related keywords used for the analysis.

No	Description	Related Keywords
1	AI and Machine Learning	Artificial Intelligence, Machine Learning, Supervised Learning, Classification, Unsupervised Learning, Reinforcement Learning, Decision Tree, Random Forest, Support Vector Machine, Nearest Neighbor, Naive Bayes, …
2	Big Data	Hadoop, NoSQL, Apache Flink, Apache Kafka, Big Data, Distributed Computing, Data Processing, Data Storage, Data Warehousing, Data Pipeline, …
3	Blockchain and Cryptocurrency	Blockchain, Cryptocurrency, Bitcoin, Ethereum, Smart Contract, Decentralization, Distributed Ledger, Consensus Mechanism, Proof-of-Work, Proof-of-Stake, Decentralized Finance, …
4	IoT	Smart Medical Device, Industrial IoT, Home Automation, Internet of Things, Connected Devices, Sensor Network, Machine-to-Machine Communication, Smart Sensor, IoT Platform, IoT Security, IoT Application, …
5	AR and VR	Augmented Reality, Virtual Reality, Mixed Reality, Holography, Head-Mounted Display, Simultaneous Localization and Mapping, Hand Tracking, Spatial Computing, Haptic Feedback, Augmented World, …
6	Cybersecurity	Cybersecurity, SQL Injection, Ethical Hacking, Intrusion Detection System, Cryptography, Network Security, Information Security, Cyber Threats, Vulnerability Assessment, Penetration Testing, …
7	Automation	Automation, Industrial Automation, Home Automation, Test Automation, Robotics, Process Automation, Robotic Process Automation, Automated Systems, Machine Automation, Factory Automation, Industrial Internet of Things, …
8	NLP	NLP, Natural Language Processing, Sentiment Analysis, Text Mining, Chatbots, Language Understanding, Text Classification, Named Entity Recognition, Part-of-Speech Tagging, Text Summarization, Topic Modeling, …
9	Quantum Computing	Quantum Computing, Quantum Algorithm, Quantum Cryptography, Qubit, Entanglement, Quantum Gate, Quantum Circuit, Quantum Simulation, Quantum Annealing, Quantum Supremacy, …
10	5G	Massive MIMO, Beamforming, Network Slicing, Next-generation Networks, Wireless Communication, Mobile Networks, Cellular Networks, Internet of

		Things, Ultra-Reliable Low-Latency Communication, URLLC, Millimeter Wave, …
11	Edge Computing	Edge Computing, Fog Computing, Mobile Edge Computing, Internet of Things, Low Latency, Edge Device, Edge Server, Edge Analytic, Edge AI, Edge Storage, …
12	Data Analytics	Data Analytics, Data Analysis, Business Intelligence, Data Visualization, Data Warehousing, Data Integration, Data Governance, Data Quality, Data Science, Prescriptive Analytics, Descriptive Analytics, …
13	Biotechnology	Biotechnology, Genetic Engineering, Bioinformatics, Biomechatronics, Biopharmaceuticals, Genomics, Proteomics, Metagenomics, Synthetic Biology, Molecular Biology, …
14	Nanotechnology	Nanotechnology, Graphene Research, Quantum Dot, Nano-Medicine, Nanomaterials, Nanoparticle, Nanofabrication, Nanoscale, Nanorobot, Nanosensor, …
15	Wearable Technology	Wearable Technology, Fitness Tracker, Smartwatch, Virtual Reality Headset, Activity Tracker, Health Monitor, Smart Clothing, Augmented Reality Glass, Biometric Sensor, Sleep Track, GPS Tracking Device, …
16	Voice User Interface (VUI)	Voice User Interface, VUI, Amazon Alexa, Google Assistant, Apple Siri, Voice Recognition, Speech Recognition, Natural Language Processing, Voice Commands, Voice Assistants, …
17	FinTech	FinTech, Mobile Payments, Cryptocurrency, Robo-Advising, Peer-to-Peer Lending, Digital Banking, Online Payments, E-Wallets, Blockchain Technology, Cryptocurrency Exchanges, …
18	Data Mining	Data Mining, Association Rule Learning, Clustering, Decision Trees, Random Forests, Support Vector Machines, Naive Bayes, K-Means, DBSCAN, Hierarchical Clustering, Principal Component Analysis, …
19	Predictive Analysis	Predictive Analysis, Fraud Detection, Risk Assessment, Customer Retention, Predictive Modeling, Anomaly Detection, Credit Scoring, Predictive Analytics, Decision Support Systems, Pattern Recognition, …
20	Chatbots	Chatbots, Customer Service Bots, Virtual Health Assistants, Personal Shopping Bots, NLP, Conversational AI, Natural Language Processing, NLP Algorithms, Text Generation, Intent Recognition, …
21	3D Printing	3D Printing, 3-D Printing Additive Manufacturing, Rapid Prototyping, Digital Fabrication, Layer-by-Layer Printing, Stereolithography, Fused Deposition Modeling, Selective Laser Sintering, Powder Bed Fusion, …
22	Smart Cities	Smart Cities, Smart City, Intelligent Traffic Management, Smart Grid, Waste Management, Urban Planning, Sustainable Development, Renewable Energy, Electric Vehicle Infrastructure, Smart Lighting, …
23	Regtech	Regtech, Regulatory Technology, Regulatory Framework, Regulatory Standards, Regulatory Compliance Software, Compliance Automation, Regulatory Compliance Management Systems, Compliance Policies, Compliance Controls, Compliance Training, Regulatory Intelligence, …
24	Insurtech	Insurtech, Peer-To-Peer Insurance, On-Demand Insurance, Micro-Insurance,

		Digital Insurance, Insurance Technology, Insurance Innovation, Insurance Disruption, Insurtech Startups, Insurtech Solutions, …
25	E-Commerce	E-Commerce, Mobile Commerce, Social Commerce, Influencer Marketing, Online Shopping, Digital Payments, Virtual Stores, Online Marketplaces, Customer Experience, Omnichannel Retailing, …
26	Serverless Computing	Serverless Computing, AWS Lambda, Google Cloud, Microsoft Azure, Function as a Service, Event-driven Architecture, Pay-per-Use, Stateless Functions, Microservices, Serverless Frameworks, …
27	Software / Platform / Infrastructure as a Service / Cloud Computing	Software as a Service, Platform as a Service, Infrastructure as a Service, Cloud Computing, Cloud Storage, Virtual Machines, Multitenancy, Pay-as-you-go, On-demand Resources, Public Cloud, Private Cloud, …
28	Web Applications	Web Application, Front-end, Back-end, Client-side, Server-side, User Interface, User Experience, Responsive Design, Single-Page Application, Progressive Web App, …