

Physics-Informed Machine Learning in Hydrology and Water Resources: A Systematic Bibliometric Analysis

George Kwame Frimpong¹, Omer Mermer², Ibrahim Demir^{1,2}

¹ River-Coastal Science and Engineering, Tulane University, New Orleans, LA 70118, USA

² ByWater Institute, Tulane University, New Orleans, LA 70118, USA

* Corresponding Author: Omer Mermer, Email: omermer@tulane.edu

Abstract

This study presents a systematic bibliometric review of Physics-Informed Machine Learning (PIML) research in hydrology and water resources, examining the field's evolution in response to the limitations of traditional process-based models and data-driven approaches. Using a PRISMA-guided framework and a curated dataset from the Scopus database, the analysis evaluated publication trends, leading publication venues, national specialization patterns, international collaboration networks, and emerging research themes. The results reveal a rapidly expanding and increasingly collaborative field, led primarily by China and the United States, with applications concentrated in areas characterized by complex physical processes and limited data availability, particularly flood and disaster management and groundwater modeling and management. Citation patterns highlight the importance of physically consistent prediction and computationally efficient surrogate modeling as major drivers of the field's growth. Despite significant progress, challenges remain, including sensitivity to heterogeneous data, model transferability, and geographical disparities in research participation. Emerging advances in differentiable modeling, multimodal physics-informed frameworks, and domain-specific foundation models are expected to shape the next generation of hydrological intelligence systems. Overall, the findings demonstrate that PIML is becoming an increasingly important paradigm for developing physically consistent, interpretable, and scalable solutions to contemporary water resources and climate resilience challenges.

Keywords: Physics-Informed Machine Learning; Hydrology; Physics-Informed Neural Network; Bibliometric analysis; Water resource management;

This manuscript is an EarthArXiv preprint and has been submitted for possible publication in a peer reviewed journal. Please note that this has not been peer-reviewed before and is currently undergoing peer review for the first time. Subsequent versions of this manuscript may have slightly different content.

1. Introduction

The management of global water resources is increasingly complex, driven by the intensifying impacts of climate change, rapid urbanization, and the heightened frequency of extreme hydrological events like floods and droughts (Yang et al., 2021; Nydrioti et al., 2024; Rosińska et al., 2024). Historically, hydrological modeling has been dominated by process-based approaches grounded in physical laws (Blöschl et al., 2019). Traditional process-based models, rooted in the fundamental laws of physics, such as mass, momentum, and energy conservation, offer high interpretability and reliability in simulating complex hydrological phenomena (Devia et al., 2015). However, these models often face significant bottlenecks, including high computational costs for high-resolution simulations and the difficulty of characterizing the inherent heterogeneity of natural systems (Fatichi et al., 2016; Zhou et al., 2021; Li et al., 2023). Over the last decade, data-driven environmental planning and management have emerged as a complementary paradigm utilizing machine learning and cyber systems (Demir et al., 2015; Yesilkoy et al., 2024).

With the advent of the Big Data and monitoring techniques, novel ML and deep learning (DL) architectures, including ensemble learning, Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU) and transformer, have demonstrated remarkable predictive accuracy in runoff forecasting, groundwater mapping, and water quality assessment by identifying non-linear patterns within large datasets (Kratzert et al., 2018; Xiang & Demir, 2021; Mermer et al., 2025; Bahadori-Jahromi et al., 2025). Purely data-driven architectures, particularly LSTM-based frameworks, have demonstrated strong capabilities for rainfall-runoff modeling and prediction across both gauged and ungauged catchments (Xiang et al., 2021; Demiray et al., 2024;). Recent studies have shown that ML can generate realistic short-term hydrology predictions (Sit et al., 2024; Mermer & Demir, 2026) and significantly speed up the simulation of hydrodynamic processes (Vinuesa and Brunton, 2022). While standard deep learning frameworks excel at temporal sequencing, capturing the distributed spatial complexities of localized flash flooding requires explicit modeling of river network topology.

Despite their predictive capabilities, these pure data-driven models are often criticized for being "black-boxes," lacking transparency and failing to adhere to the fundamental physical laws that govern the water cycle (Zounemat-Kermani & Kheimi, 2026; Chukwu & Jibril, 2025). They suffer from a persistent gap between statistical performance and physical interpretability (Mermer & Demir, 2025). They frequently fail to generalize in data-scarce regions or out-of-distribution scenarios, occasionally producing physically impossible results, such as negative streamflow or non-conservative mass balances (Shen et al., 2023).

To overcome these dual limitations, a transformative third paradigm has emerged: Scientific Machine Learning (SciML), providing a transformative approach to advancing hydrological research and addressing the complex challenges of water systems (Adombi, 2025; Cuomo et al., 2022; Thiyaalingam et al., 2022). SciML integrates physical knowledge (e.g., physics based, process-based, conceptual models) with machine learning (ML) models. Several methodological families have emerged under the SciML umbrella, including physics-informed ML (Huang et al., 2023; Ji et al., 2024), explicit physics-ML coupling models (Okkan et al. 2021), physics-guided ML (Chen et al. 2022, 2023; Palmitessa et al., 2022), and data driven approaches for physics discovery (Brunton and Kutz 2019; Floryan and Graham 2022). Each reflects a different strategy for incorporating domain knowledge.

Physics-informed ML (PIML) designates a broad family of approaches that incorporate known physical laws (e.g., governing equation), and initial and boundary conditions as constraints within the training objective of ML models (Karniadakis et al., 2021; Raissi et al. 2019). Raissi et al., 2019 first introduced PIML by embedding partial differential equation (PDE) residuals into loss functions, thereby enabling physics-informed learning. This integration is intended to ensure that the learned model respects fundamental physical principles, improving generalization, interpretability, and robustness, especially when observational data are limited or noisy. Also, one key advantage of PIML is that it does not require the incorporated physical knowledge to be complete or fully specified (Rossi et al. 2023). Currently, PIML systems are considered an innovative approach that combines the robust predictive power of ML algorithms with the governing physical laws described by PDEs and ordinary differential equations (ODEs) (Meng et al., 2025). This synergy allows for the development of physics-aware or physics-guided models that maintain the efficiency of ML while adhering to the rigorous constraints of hydrological science (Raissi et al., 2019).

Architecturally, a PIML framework typically consists of a standard ML model augmented with a loss function that incorporates both data-driven components and physics-based constraints, and its development generally follows seven sequential steps. First, the governing physics of the problem is identified and formulated through the differential equations that represent the physical system. Second, the ML architecture is defined, including its structure, hyperparameters, and appropriate activation functions. Third, a multi-task loss function is constructed that balances a data loss, which measures accuracy on observed data points; a physics loss, which penalizes departures from the governing equations; and a boundary/initial condition loss, which enforces constraints at the edges and start of the domain. Fourth, the model is trained using optimization algorithms that minimize this composite loss. Fifth, the trained model is tested on unseen data to ensure generalization and checked to verify that its outputs are physically consistent. Sixth, the model is optimized by adjusting hyperparameters, modifying the loss weights, or refining the model topology. Finally, the model is finalized and deployed for real-world application.

The adoption of PIML in hydrology and geosciences is driven by several critical challenges that traditional ML fails to address. First, in many geoscientific applications, labeled data is expensive or challenging to obtain at scale, leading to data scarcity issues that degrade the performance of pure ML (Reichstein et al., 2019). Second, the computational burden of traditional numerical simulators limits their utility for real-time disaster management and long-term climate projections (Wibowo et al., 2025). Furthermore, as the demand for trustworthy and responsible AI grows within civil and environmental engineering, the lack of transparency in standard DL models becomes a liability (Maier et al., 2024). There is an urgent need to integrate prior physical knowledge to refine existing knowledge and discover new processes that are currently poorly understood or data-limited, such as 21st-century permafrost extent or subsurface multiphase flow (Huang et al., 2025). While individual studies have shown the potential of PIML to bridge this gap, a systematic, high-level evaluation of the field's evolution is necessary to understand how these disparate methodologies are converging into a unified community of practice (Jagtap et al., 2026; Sajja et al., 2025).

The rapid proliferation of PIML across sub-disciplines like groundwater modeling, rainfall-runoff processes, and flood risk assessment has created a fragmented research landscape

(Tartakovsky et al., 2020; Herath et al., 2021; Donnelly et al., 2024). To our knowledge, there is no systematic analysis or comprehensive bibliometric review of physics-informed ML specifically focused on the broad and integrated scope of hydrology and water resources. Existing reviews are primarily tailored to specialized sub-fields such as geo-energy, geotechnical engineering, or provide a general overview of hydrology. Davoodi et al. (2025) provides a comprehensive analysis of PIML within the geo-energy sector, focusing on how integrating physical laws with deep learning delivers reliable, computationally efficient predictions for reservoir modeling and subsurface multiphase flow. While Yuan et al. (2025) presents a direction-focused overview of PIML in geotechnical engineering, Habib et al. (2025) systematically examines the versatility of PINNs across the broader geosciences, highlighting their capacity to solve complex differential equations in seismology, geophysics, and atmospheric studies without the constraints of traditional numerical meshes. Xu et al. (2025) introduces a structured framework for physics-aware ML that bridges the gap between mechanistic models and data-driven in hydrology by integrating governing laws into model training and architecture.

To provide a coherent overview, this study conducts a detailed bibliometric analysis of the current research landscape surrounding PIML in the fields of hydrology and water resources. By identifying key trends, collaboration networks, prominent authors, and emerging directions, this study seeks to provide valuable insights into how PIML frameworks are being applied and how the field is evolving. A bibliometric approach allows for the 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 research teams, institutions, and countries contributing to PIML research in hydrology. Furthermore, this study will explore the extent of interdisciplinary collaboration and identify key research hubs that are leading the way in the integration of novel AI technologies like PIML into hydrological 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 PIML frameworks 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 (Chukwu & Jibril, 2025; Davoodi et al., 2025).

Specifically, this study addresses the following key research questions:

- RQ1: What are the dominant growth trajectories and publication trends of PIML-related research in hydrology from 2015 to 2026?
- RQ2: Which countries, institutions, and core journals define the global research output, and how collaborative networks are structured?
- RQ3: What are the primary thematic categories (e.g., subsurface flow, hydrodynamic processes, disaster management) and technical subject areas most influenced by PIML?
- RQ4: Which foundational publications have had the highest citation impact, and what core contributions do they represent?
- RQ5: What are the emerging research frontiers, and how is the community addressing persistent challenges like uncertainty quantification and model flexibility?

Through this analysis and answering these questions, we aim to provide a comprehensive roadmap for researchers and practitioners, highlighting how physics-informed ML is revolutionizing the scientific paradigm for hydrology and water related applications.

This paper is organized as follows: Section 2 provides the bibliometric methodologies, database protocols, and systematic screening criteria utilized to curate the literature search. Section 3 presents quantitative results, including publication trends, journal quality, national specialization metrics, and collaborative networks. Section 4 highlights a critical discussion of the findings by research question, practical applications and operational use cases, geographical challenges, and limitations. Finally, Section 5 concludes the manuscript with a synthesis of key insights and a roadmap for future research.

2. Methodology

2.1. Bibliometric Analysis Workflow

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 pipeline (Figure 1).

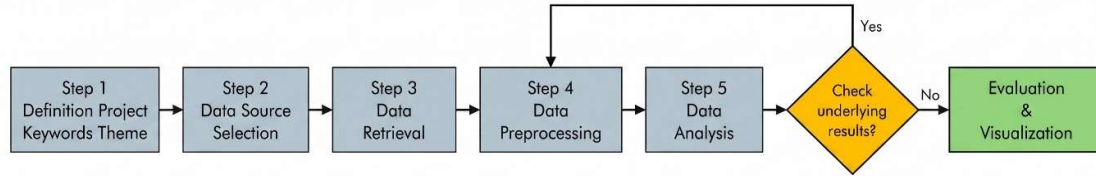


Figure 1. Workflow of the bibliometric analysis process

The process initiates with “Step 1: Definition of Project Keywords and Theme”, where the project keywords, themes, and research boundaries for physics-informed machine learning in hydrology and water resources are defined to identify the targeted literature. Next, “Step 2: Data Source Selection” identifies and anchors a comprehensive academic repository capable of tracking peer-reviewed scientific outputs across the domain. For this study, Scopus was selected due to its standardized bibliographic metadata, citation tracking features, and relevance to the study’s objectives. This transitions directly into “Step 3: Data Retrieval”, which executes the query parameters against titles, abstracts, and index terms to harvest comprehensive metadata, including author details, institutional affiliations, and citation metrics. The raw dataset then undergoes rigorous screening in “Step 4: Data Preprocessing”, filtering out irrelevant publications, eliminating duplicate records, and establishing quality-control verification.

Once data integrity is verified, “Step 5: Data Analysis” utilizes advanced statistical indicators, co-citation clustering matrices, and keyword frequency maps to systematically decode key research trends, prominent global collaboration networks, and influential intellectual hubs driving the PIML paradigm. At the end of this step, if discrepancies or outlying artifacts are detected during evaluation, the workflow dynamically loops back to refine the dataset rules before proceeding.

Finally, the pipeline culminates in the “Evaluation & Visualization” phase, where advanced network mapping tools, chord diagrams, and trend graphs are generated to visually interpret the data, evaluate compliance with the core research questions, and provide an intuitive, high-level abstract of the global PIML research landscape.

2.2. Data Source Selection

The bibliographic dataset for this analysis was retrieved exclusively from the Scopus database. While Google Scholar is widely utilized due to its comprehensive indexing capabilities, Scopus was selected for this study because of its superior data reliability, standardized bibliographic metadata, and rigorous journal indexing protocols, all of which are essential for high-quality bibliometric mapping (Mongeon & Paul-Hus, 2016). In contrast, Google Scholar frequently introduces algorithmic noise into bibliometric pipelines through the inclusion of non-peer-reviewed literature, preprints, and inconsistent citation tracking (Martín-Martín et al., 2018). Preprints indexed in Scopus (mainly from arXiv, SSRN, and Research Square) were nevertheless retained, as they went through the screening and expert review, and excluding them would omit the most recent methodological advances in this fast-moving, machine-learning-driven field, where formal publication often lags by a year or more.

Furthermore, data extraction from Scopus provides a highly structured and precise workflow compared to alternative repositories. Scopus accommodates complex, nested Boolean search strings, ensuring that the retrieved dataset remains strictly focused on the intersection of physics-informed machine learning and hydrology. Despite its acknowledged limitations, such as a potential underrepresentation of non-English literature and localized conference proceedings, Scopus remains the gold standard for rigorous, reproducible bibliometric research in engineering and the environmental sciences (Mongeon & Paul-Hus, 2016).

The selected keywords were not only chosen for their individual relevance but were strategically combined using advanced logical operators to target precise intersections of advanced ML and physical hydrology. Terms as "machine learning", "neural network", and "graph neural networks" were utilized to capture state-of-the-art computational implementations, while modifiers like "physics-informed," "physics-constrained," and "physics-guided" isolated their explicit interaction with hydrological principles. This specialized keyword strategy ensures that the finalized search strings encompass both foundational machine learning technologies and their domain-specific applications

This rigorous methodology enabled us to capture a diverse and interdisciplinary body of literature, spanning computer science, fluid mechanics, environmental engineering, and hydroinformatics, without diluting the dataset with unrelated engineering anomalies. It also supported the identification of key research trends, leading contributors, and emerging applications at the intersection of PIML development and hydrology.

2.3. Keyword Selection and Search Strategy

To capture the complete scope of literature at the intersection of advanced artificial intelligence and hydrology, this study implemented a highly structured domain–keyword pairing logic. The search query was systematically constructed by intersecting core terminology from the machine learning domain with specific parameters representing key hydrological and water-related sub-disciplines.

The first keyword cluster (Group 1: Technical PIML Core) was designed to isolate fundamental and state-of-the-art physics-informed computational paradigms. This group included phrases such as physics-informed machine learning, physics-informed neural network, physics-guided machine learning, and physics-aware machine learning. The second keyword cluster (Group 2: Hydrological and Water-related Domain) was defined to encompass varied operational scales within hydrological science. This group included terms such as hydrology, water resources, groundwater, flood, and rainfall. To execute data retrieval, these parameters were applied simultaneously across the Title, Abstract, and Indexed Keyword fields of the repository using standard Boolean operators.

The exact classification, inclusion terms, and logical grouping of this strategy are simplified and detailed in Table 1. Through an iterative optimization process executed via a custom Python script, we compiled and deployed 140 unique search string permutations derived from these two keyword matrices. This deliberate pairing strategy minimized under-coverage errors and ensured that the final dataset captured all the relevant literature of the field, ranging from early theoretical mathematical proofs of PIML to recent distributed, field-scale applications hydrology.

Table 1. Search strategy and keyword groups

Group #1	“Physics-informed machine learning” OR “physics-informed neural network” OR “physics-constrained machine learning” OR “physics-constrained neural network” OR “physics-guided machine learning” OR “physics-guided neural network” OR “physics-aware machine learning” OR “physics-aware neural network” OR “physics-informed graph neural networks” OR “physics-informed graph machine learning”
Group #2	“hydrology” OR “hydrogeology” OR “water resources” OR “surface water” OR “groundwater” OR “subsurface” OR “hydrological modeling” OR “flood” OR “watershed” OR “drought” OR “streamflow” OR “runoff” OR “rainfall” OR “fluvial”
Strategy	<i>TITLE-ABS-KEY ("Group 1 Terms" AND "Group 2 Terms")</i>

2.4. Time Range Selection

This bibliometric analysis spans a timeframe from 2015 to September 2026. This period was selected to capture the significant advancements and widespread adoption of PIML in hydrology from its earliest theoretical mathematics to its current status. Prior to 2015, AI applications in hydrology and water resources were heavily dominated by purely data-driven black-box statistical models (Solomatine & Ostfeld, 2008; Nourani et al., 2014; Yaseen et al., 2015). While these models exhibited high predictive accuracy under optimal conditions, they introduced significant uncertainty and structural instability due to their systemic inability to respect the physical laws governing the water cycle. Although initial concepts of physics-guided data mining began surfacing around 2014 to evaluate climate extremes (Ganguly et al., 2014), 2015 represents a distinct turning point. It marks the beginning of a deliberate shift toward overcoming the limitations of black-box models by designing algorithms that explicitly

respect the physical laws governing hydrological domains. This timeframe is categorized into three distinct developmental periods characterizing scientific literature:

Stage I: Foundations and Mathematical Proof of Concept (2015–2019): This initial phase was defined by groundbreaking theoretical breakthroughs in the broader computational and data sciences. Most notably, during this period, the foundational conceptual introduction of Physics-Informed Neural Networks (PINNs) was presented by Raissi and his colleagues, disseminated initially as widely circulated preprints in late 2017 (Raissi et al., 2017). These architectures proved that neural networks could be trained to solve supervised learning tasks while respecting physical laws described by nonlinear partial differential equations. While the intellectual genesis of PINNs occurred during this phase, their consolidated peer-reviewed publication appeared in the Journal of Computational Physics in 2019 (Raissi et al., 2019).

This lag between preprint and final publication means that bibliometric indexing engines capture the formal citation impact only in the subsequent era, a common characteristic of rapidly advancing, high-momentum computational fields. Parallel breakthroughs during this era, such as Neural Ordinary Differential Equations (Neural ODEs), established the mathematical frameworks necessary to embed physical constraints directly into loss functions (Chen et al., 2018). However, actual adoption within domain-specific hydrology before 2018 remained gradual and was heavily restricted by data scarcity and limitations in model interpretation (Shen, 2018).

Stage II: Domain Transition and Algorithmic Adaptation (2020–2022): This period was characterized by an aggressive migration of theoretical PIML frameworks into environmental science and hydroinformatics. Supported by the formal publication of foundational texts and accompanied by a rapid surge in peer-reviewed literature, the community shifted from general computational validation to domain-specific adaptation. Hydrologists successfully integrated PIML to construct hybrid models capable of solving complex inverse problems and parameter estimation challenges in porous media, leveraging physics-informed architectures to reliably solve the non-linear Richards equation under sparse observational conditions (Bandai & Ghezzehei, 2021; Kadeethum et al., 2020; He & Tartakovsky, 2021). Furthermore, significant efforts were also directed toward creating hybrid models that combine physics with machine learning to derive sophisticated solutions for subsurface transport and groundwater modeling (Depina et al., 2022; Tartakovsky et al., 2020; He et al., 2020).

Stage III: Operational Deployment, Explainable AI (XAI), and Digital Twins (2023–September 2026): The final period represents the transition of PIML from controlled validation datasets to real-world operational deployments and field-scale services. Recent literature demonstrates the direct integration of PIML into real-time flood forecasting systems, hazard mitigation, and complex water resources management (Taghizadeh et al., 2025; Chew et al., 2025; Song et al., 2025). Furthermore, this period is also characterized by the convergence of PIML with XAI frameworks, aiming to provide human-interpretable feature attributions while simultaneously ensuring physical consistency (Towfiqul Islam et al., 2026; Ye et al., 2026). Extending the bibliometric data through September 2026 ensures that the dataset captures these current and state-of-the-art methodological advancements, offering a comprehensive assessment of current research momentum and a robust foundation for projecting the future trajectory of hydrological modeling.

2.5. Prisma Framework and Inclusion/Exclusion Criteria

To establish a high-fidelity, reproducible dataset, this study implemented a rigorous, multi-layered screening protocol adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Page et al., 2021). The PRISMA methodology provides a structured workflow including identification, screening, eligibility, and inclusion/exclusion phases, to systematically filter bibliographic records while minimizing selection bias (Moher et al., 2009). The screening strategies (Figure 2) began with the identification phase, where the initial search process generated many records from Scopus using keyword combinations, as described in Section 2.3. These results were then subjected to several rounds of screening.

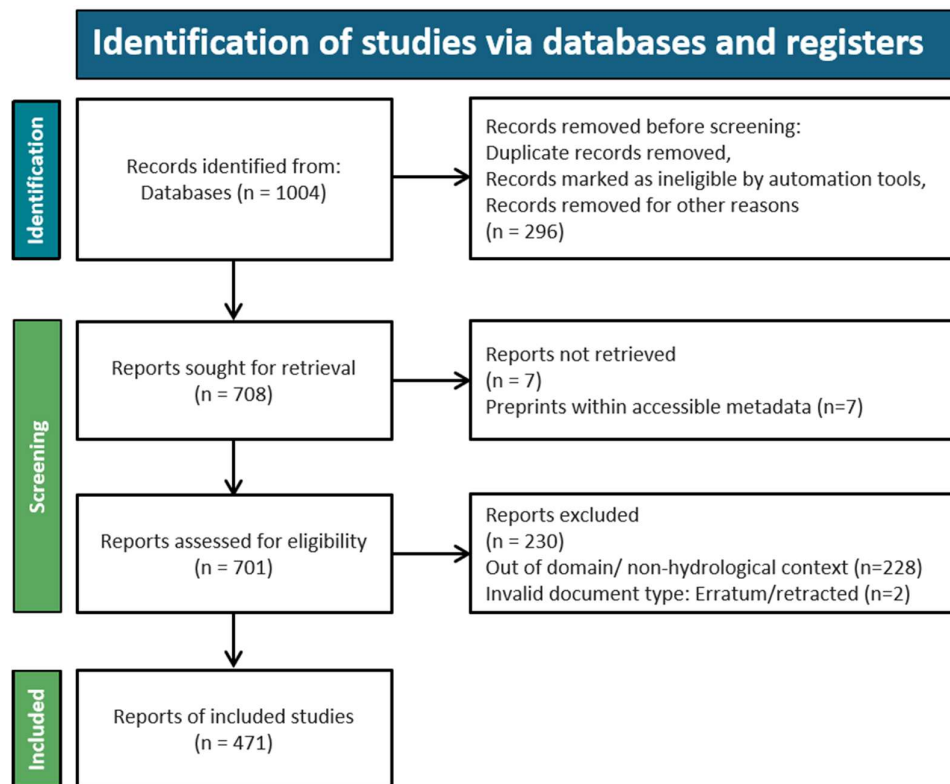


Figure 2. Screening strategy for included articles using PRISMA diagram.

This initial dataset comprised peer-reviewed journal articles, conference proceedings, book chapters, and preprints published within the 2015–2026 timeframe. In the first stage, all the records were filtered based on relevance to the core focus of PIML application in hydrology and water resources. To eliminate bibliographic redundancies and metadata overlaps, a custom Python script was deployed during the screening phase to perform automated deduplication. The algorithm prioritized matching Digital Object Identifiers (DOIs), utilizing a secondary text-matching fallback mechanism based on normalized titles where DOI metadata was absent. This automated phase successfully identified and removed 296 duplicate entries, compressing the dataset from 1004 to 708 unique records.

The remaining unique documents were then subjected to strict inclusion and exclusion criteria during the eligibility phase to ensure deep thematic alignment. To meet the inclusion

criteria, a study was required to explicitly deploy or evaluate a Physics-Informed Machine Learning (PIML) framework or a Physics-Informed Neural Network (PINN) architecture within an explicit water resource or hydroinformatics context. Conversely, strict exclusion criteria were applied to remove irrelevant literature; documents utilizing purely data-driven, black-box ML models without the structural integration of physical constraints, partial differential equations, or mass balance laws were permanently eliminated.

During the final eligibility and inclusion analysis, a total of 237 records were permanently excluded from the active dataset. First, 7 preprint documents were removed because they had transitioned to closed-review statuses, leaving their metadata completely inaccessible. Second, an additional 230 records were discarded following an analytical expert opinion phase. During this step, domain experts reviewed the screened articles to ensure the final dataset captured the most relevant and high-quality contributions to the field; 228 of these records lacked a definitive hydrological context, and 2 were flagged as invalid document types consisting of one erratum and one retracted paper.

Notably, a significant portion of these out-of-domain exclusions stemmed from the keyword "subsurface," which frequently captured unrelated advancements in materials engineering and semiconductor physics rather than groundwater hydrology. To resolve the remaining ambiguities within borderline metadata, a final expert domain-level review was conducted to manually audit the abstracts. This expert judgment helped to refine the dataset further by excluding marginally relevant or lower-quality publications that might not be evident through automated screening alone.

2.6. Bibliometric Indicators and Evaluative Metrics

To evaluate the rapidly evolving research landscape of PIML in hydrology, this analysis is structured around four primary bibliometric dimensions. This multi-faceted approach provides a comprehensive analytical framework necessary to deconstruct the complex intellectual architecture of the field, moving beyond publication counting to map the underlying socio-cognitive networks and knowledge transfer pathways driving scientific innovation.

Within this broader framework, specific metrics and indicators are fundamentally relied upon to quantify and interpret the evolutionary dynamics of the discipline. First, analyzing Publications evaluates the overall growth velocity, academic momentum, and historical scaling of PIML literature. Second, tracing Authors and their co-authorship networks maps out collaborative relationships between researchers, establishing central knowledge hubs and tracking how technical expertise is exchanged on a global scale. Third, parsing Key Topics through keyword co-occurrence and thematic trajectory decodes the cognitive evolution of the domain, tracking how physical constraints are integrated with data-driven models over time to reveal emerging applications and active research frontiers.

Finally, tracking Metrics serves as a primary proxy for quantifying intellectual influence, scholarly impact, and knowledge absorption within the academic community. The specific indicators within each category are summarized in Table 2, which highlights the approach used to organize and refine the dataset. By gathering these indicators, we aim to build a well-rounded dataset that tracks the growth and evolution of PIML research, uncovers collaboration patterns, identifies high-impact research, and highlights thematic and ethical considerations shaping the field.

Table 2: Categorization and rationale of primary bibliometric dimensions

Category	Sub-Category	Purpose/Explanation
Publications	Types, Trend, Core Publishers	Evaluates the growth velocity, academic momentum, and historical scaling of the field
Authors	Citations, Major Authors, Affiliated Countries	Evaluates research impact, identifies key contributors, and reveals global collaboration patterns.
Key Topics	Keywords, Title Words, Use Case	Highlights dominant research themes and practical applications.
Metrics	Collaborative Network, Activity Index, Citation Count	Analyzes co-authorship links, national specialization, and the total influence of individual works.

2.7. Activity Index

The Activity Index (AIndex) is a robust bibliometric metric designed to quantify and compare the research specialization of individual nations while controlling their total scientific output. First proposed by Frame (1977) and mathematically developed by Schubert and Braun (1986), the AIndex eliminates the systemic size bias inherent in raw publication counts, which naturally favor large research economies. By normalizing country output against global baselines, this tool effectively shows disproportionate research concentrations, uncovers strategic areas of country's specialization, and identifies emerging global leaders within rapidly evolving computational sub-disciplines (Nageye et al., 2024).

In this study, the AIndex is operationalized to evaluate country's research performance specifically at the intersection of PIML and hydrology. The metric calculates the ratio of a country's publication share in this specialized domain to its overall share across all scientific fields relative to the global average. Mathematically, the AIndex is defined as follows (Hu & Rousseau, 2009):

$$Activity\ Index = \frac{P_i^t / \sum P_i^t}{\sum P_i / \sum \sum P} \quad Eq. 1$$

where P_i^t represents the number of PIML-related hydrological publications by country i in year t and $\sum P_i^t$ is the total number of publications from country i across all scientific fields during the same period. The denominator represents the global baseline, where $\sum P_i$ is the total number of global publications in the specialized PIML-hydrology domain, and $\sum \sum P$ represents the total global publication output across all specific fields in year t .

The empirical interpretation of this metric is highly structured. An $AIndex > 1$ denotes a high level of research specialization, indicating an exceptional national focus and resource commitment to PIML frameworks compared to the global baseline (Chen & Guan, 2011; Stare & Kejřar, 2014). Conversely, an $AIndex < 1$ suggests an under-specialized focus, where a nation's research momentum in this specific sub-discipline lags the international average (Chen & Guan, 2011; Stare & Kejřar, 2014).

From a practical perspective, the AIndex provides stakeholders, funding bodies, and policymakers with a clear diagnostic mapping of where intellectual capital and research efforts are concentrated globally. These insights are critical for strategic resource allocation, targeted policymaking, and the formation of high-impact cross-border collaborations (Asif & Fazel, 2024). However, because the AIndex is primarily an indicator of thematic volume and specialization density rather than direct scholarly impact, it is paired with the citation performance and network metrics established in Section 2.6 to provide a holistic, multi-dimensional evaluation of research quality, structural impact, and paradigm evolution (Nageye et al., 2024).

3. Results

3.1. Publication Trends and Document Type

The annual production of literature at the intersection of PIML and hydrology exhibits a pronounced exponential growth trajectory as shown in Figure 3. The temporal distribution of the curated records reveals a distinct evolutionary pattern that precisely shows the developmental phases of scientific machine learning (SciML) outlined in the methodology.

During the initial theoretical phase (2015–2019), there was a notable absence of indexed publications directly deploying PINNs within the water sector. This latency represents the time required for the engineering community to translate pure theory-based calculations and computational algorithms into applied water sciences. Formal indexing of domain-specific PIML hydrology research emerged in 2019 with a recorded baseline of 3 publications.

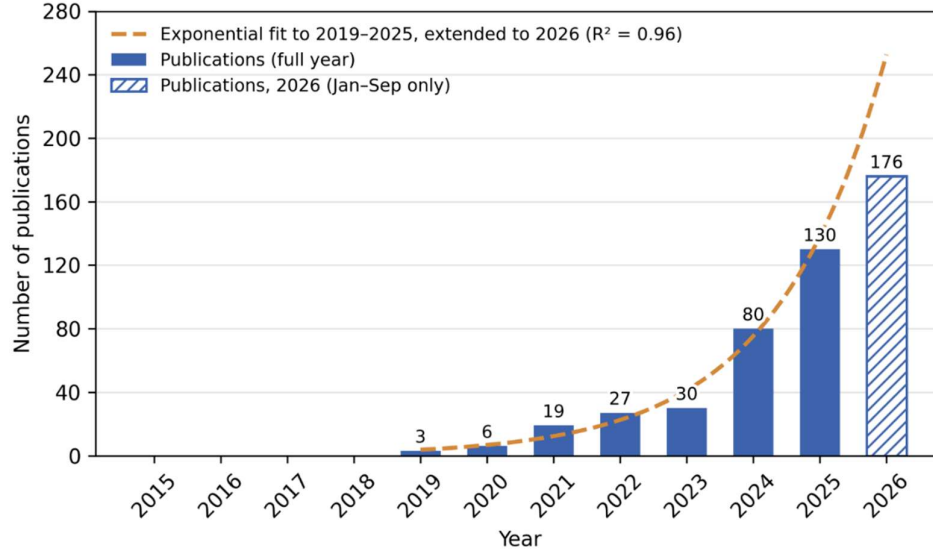


Figure 3. Publication trends for PIML in hydrology by year between 2015 – 2026 (up to September)

Subsequent era between 2020 and 2022 served as an extremely critical period, marked by the systematic adaptation of theoretical methodologies to existing hydroinformatics frameworks. During this period, scholarly output scaled significantly: 2020 recorded 6 publications, which surged by 216.7% to 19 publications in 2021, and expanded further to 27 papers in 2022. This early momentum signals the foundational acceptance of hybrid modeling

frameworks over purely data-driven alternatives within environmental disciplines (Willard et al. 2022).

The most striking feature of the temporal distribution is the explosive growth in publications characterizing the recent maturation phase (2023 and beyond). After a stable baseline of 30 publications in 2023, research output increased dramatically in 2024, rising by 166.7% to 80 articles. This upward trend continued into 2025, which recorded a peak of 130 publications. Notably, 2026 had already reached 176 publications at the time of data collection, this should be interpreted with caution, as the data collection period covered only January to September 2026. Achieving 176 publications within approximately nine months, already exceeding the 2025 total by 35.4%, indicates an exceptionally rapid pace of research activity. Based on the exponential trend fitted to complete years (2019-2025; $R^2=0.96$), the total for 2026 is projected to reach approximately 253 publications. The 176 publications recorded by September already represent about 70% of this estimate, underscoring the growing adoption of PIML architectures as a dominant framework in modern hydrological modeling (Slater et al., 2025).

An analysis of the structural typology of the 471 compiled records, as shown in Figure 4, provides important insights into the scholarly communication channels shaping this research domain. The dataset is dominated by peer-reviewed journal articles, which account for 62.6% ($n = 295$) of the total publications. This predominance reflects the strong emphasis within the applied hydrology and environmental sciences on rigorous peer review, detailed methodological transparency, and large-scale validation to establish scientific credibility. More importantly, it indicates that PIML has evolved beyond its origins as an experimental subfield of computer science and has become firmly integrated into mainstream hydrological research.

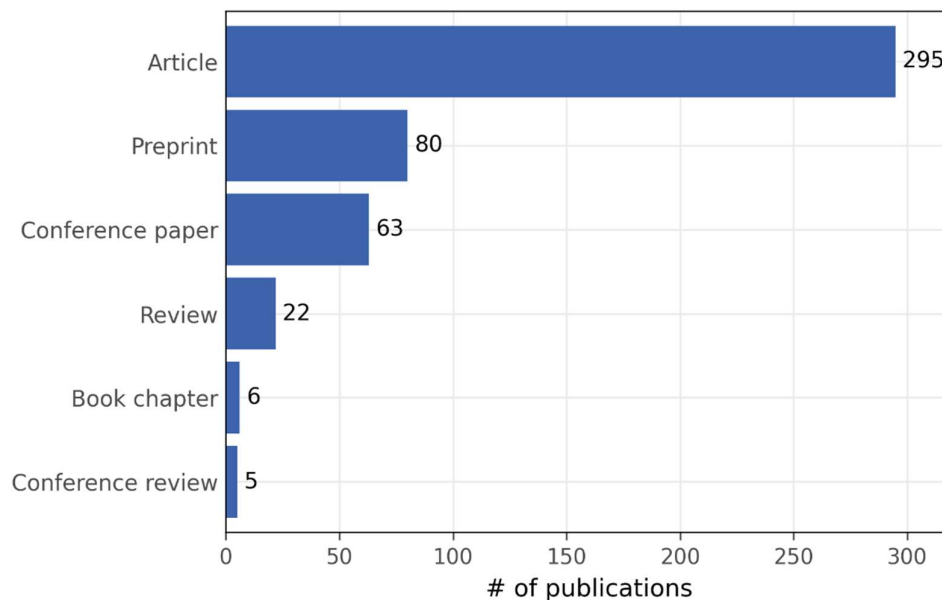


Figure 4. Typological distribution of the curated literature ($n = 471$) on PIML applications in applied hydrology, highlighting the relative prevalence of major scholarly publication formats

At the same time, the notable presence of Preprints (17.0%; $n = 80$) and Conference Papers (13.4%; $n = 63$) highlights the interdisciplinary nature of the field and its rapidly evolving publication culture. In traditional hydrological research, these publication types generally occupy a smaller share of literature; however, in artificial intelligence and computer science, they function as primary channels for the rapid dissemination of emerging methods and innovations (Maganur & Kejriwal, 2026; Chen et al., 2025). This hybrid publication structure suggests an accelerated research cycle in which novel neural network architectures are first shared through open-access preprints and conference proceedings before being further refined and formally published in specialized hydrological journals.

Review articles represent 4.7% ($n = 22$) of the dataset and serve as an additional indicator of field maturation. The emergence of such synthesis studies typically reflects a growing need to consolidate fragmented methodologies, establish standardized taxonomies, and identify persistent research gaps (Donthu et al., 2021). The remaining portion of the literature consists of supplementary scholarly formats, including Conference Reviews (1.1%; $n = 5$) and Book Chapters (1.3%; $n = 6$), which contribute to the pedagogical and integrative dimensions of the field.

3.2. Journal Impact and Quality

The top journals publishing studies on PIML in hydrology and water resources are summarized in Table 3. Evaluating the impact factors and overall prestige of the principal publication venues provides a quantitative perspective on the scientific acceptance of PIML frameworks within the broader research community. The distribution of journal impact factors exhibits a pronounced positive skew, with a strong average of 5.32 and a median value of 4.6. These metrics indicate that most PIML-related studies are being published in well-established, high-impact journals, predominantly within top-quartile (Q1) environmental science, hydrology, and computational research outlets rather than in lower-impact or peripheral venues. These journals, with their impact factors, citation scores, and publication histories, provide critical platforms for disseminating research findings in the field.

Table 3: Top 10 Leading Journals in PIML Hydrology Research.

Journal	Impact Factor	Cite Score	# of Publication	Beginning Year
Journal of Hydrology	6.3	11.1	45	1963
Water Resources Research	4.6	8.2	24	1965
Advances in Water Resources	4.2	7.8	14	1977
Water Research	12.4	21.2	8	1967
Journal of Hydrology: Regional Studies	5.0	7.4	8	2014
Scientific Reports	3.9	7.2	8	2011
IEEE Trans. on Geoscience & Remote Sens.	8.6	13.6	7	1980
Water	3.0	6.0	7	2009
Geoenery Science and Engineering	4.6	10.7	6	2023
Hydrology and Earth System Sciences	5.8	10.8	5	1997

The top three positions are occupied by hydrology's long-established flagship journals: the Journal of Hydrology (45 papers; IF: 6.3), Water Resources Research (24 papers; IF: 4.6), and Advances in Water Resources (14 papers; IF: 4.2). The strong representation of PIML research within these historically influential venues demonstrates that physics-informed computational approaches have gained broad acceptance as scientifically robust and methodologically reliable tools within the hydrological sciences. Given the longstanding reputations and rigorous publication standards of these journals, their adoption of PIML reflects the growing institutional recognition of physics-informed modeling as a mature research paradigm in water resources engineering.

Beyond the core hydrology literature, the top-ranked journals also reveal a substantial degree of interdisciplinary integration. High-impact engineering and environmental science journals, including Water Research (IF: 12.4) and IEEE Transactions on Geoscience and Remote Sensing (IF: 8.6), feature prominently among the leading publication venues. The appearance of Geoenergy Science and Engineering further illustrates the methodological overlap between hydrogeology and subsurface energy research. Porous-media flow and transport are governed by the same physical laws in groundwater and energy-related settings. So PIML techniques developed in one context transfer readily to the other. Similarly, the presence of specialized outlets such as Journal of Hydrology: Regional Studies and multidisciplinary venues such as Scientific Reports highlights the expanding reach of PIML across regional applications and broader scientific audiences. Together, this distribution suggests that researchers are increasingly leveraging physics-informed neural architectures to address complex, multi-scale hydrological and environmental challenges across a wide range of disciplinary domains.

3.3. Activity Index, Geographic Distribution and Collaborative Networks

The collaborative networks in PIML research for hydrology and water resources highlights the growing importance of both international and interdisciplinary collaboration. This section presents an integrated analysis of national research contributions, temporal trends in research activity, and the evolving patterns of international collaboration within the field.

The Activity Index (AIndex), summarized in Table 4, reveals distinct national trajectories in the adoption and specialization of PIML research within hydrology and water resources. The United States emerged as an early leader in the field, exhibiting a strong specialization profile that peaked at $AIndex = 3.69$ in 2020. In contrast, China's level of specialization remained below the global benchmark ($AIndex < 1.0$) during the early stages of development. However, beginning in 2025, China experienced a marked acceleration in research activity, with its AIndex rising above the global average to $AIndex = 1.15$ in 2025 and further increasing to $AIndex = 1.29$ by September 2026. This trend suggests that China's growing prominence in the field is driven not only by overall research expansion but also by a targeted emphasis on physics-informed and hybrid AI-based modeling approaches.

Other countries also display notable specialization patterns. India recorded a particularly high level of early engagement, reaching $AIndex = 2.89$ in 2020, while Canada exhibited a pronounced recent concentration of research activity, attaining $AIndex = 2.31$ in 2024. Collectively, these trends highlight the heterogeneous pathways through which different nations have contributed to the advancement of PIML applications in hydrology.

Table 4: Activity Index scores of the five countries with highest publications (2019-2026)

Year	China	United States	India	Canada	Germany
2019	0	2.59	0	0	0
2020	0.53	3.69	2.89	0	0
2021	0.15	2.69	2.43	0	2.13
2022	0.34	2.19	1.22	0	1.62
2023	0.63	1.51	0.99	1.25	0
2024	0.72	1.14	0.66	2.31	1.09
2025	1.15	0.94	0.61	0.78	0.54
2026	1.29	0.44	1.28	0.76	1.35

In terms of absolute research output, Table 5 shows the distribution of publications by country. China and the USA are the two largest contributors, with 181 and 129 publications, respectively. Other notable contributors include India (33), Canada (26), Germany (25), and United Kingdom (23). The GDP data presented in Table 5 are sourced from the International Monetary Fund (IMF), World Economic Outlook Database, April 2026 edition (IMF, 2026). Normalizing publication output against macroeconomic indicators provides additional insight into national research priorities and investment strategies. While China's economy is smaller than that of the United States in terms of total GDP, its cumulative publication output in the field exceeds that of the United States, reflecting a particularly strong research emphasis on PIML applications in hydrology and water resources.

Table 5: Distribution of publications published by countries and their GDP

Country	Number of Publications	GDP
China	181	20.85T USD
United States	129	32.38T USD
India	33	4.15T USD
Canada	26	2.51T USD
Germany	25	5.45T USD
United Kingdom	23	4.26T USD
Rest of the World	250	56.68T USD

Likewise, several countries demonstrate a level of scientific productivity that is disproportionately high relative to their economic scale. For example, Canada and India generate publication volumes comparable to or exceeding those of larger economies such as Germany, indicating a relatively high concentration of research effort and specialization in this emerging area. These patterns suggest that national commitment to PIML research is influenced not only by economic capacity but also by strategic research priorities and targeted investments in computational hydrology and related disciplines.

Although individual countries exhibit distinct research trajectories, the development of PIML in hydrology and water resources is fundamentally driven by international collaboration. Figure 5 shows international co-authorship network using a chord diagram to map how scientific knowledge is shared between countries. Co-authorship network analysis reveals a

highly interconnected global research community characterized by extensive cross-border exchanges of expertise, data, and methodological innovations. The strongest collaborative link in the network is observed between the United States and China, highlighting a particularly productive bilateral partnership. As indicated by collaboration trends over time, joint publications between these two countries have increased steadily alongside their respective national research outputs through 2025.

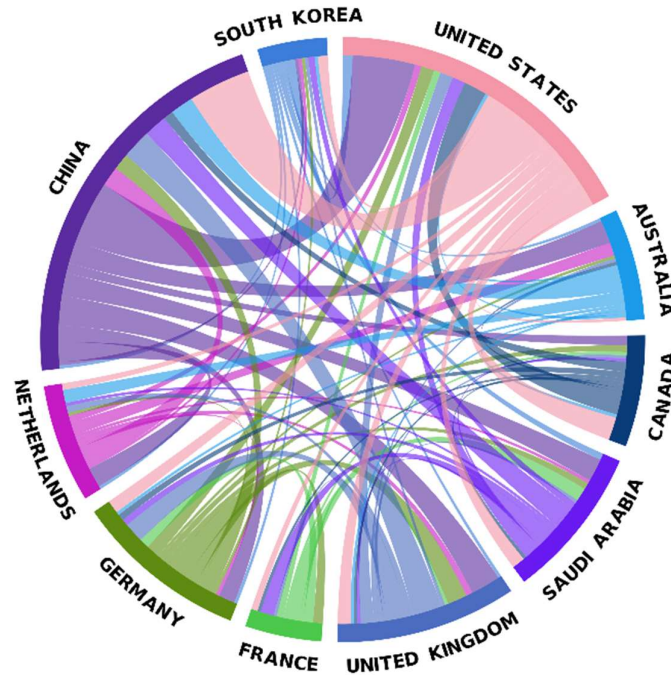


Figure 5: Chord diagram illustrating the top 10 global international collaboration network in PIML hydrological research.

Beyond this dominant partnership, the collaboration network displays a diverse and multipolar structure. The United States maintains broad connections across North America and Europe, particularly with the United Kingdom, Canada, and Germany, while China serves as a major hub linking researchers throughout the Asia-Pacific region, including Australia and Singapore. Within Europe, countries such as the United Kingdom, Germany, and Switzerland occupy strategically important positions in the network, acting as key intermediaries that facilitate the dissemination of emerging methodologies and advances across the global research community. Collectively, these patterns underscore the increasingly international and collaborative nature of PIML research and its role in accelerating innovation across hydrological and water resources sciences.

The combined evidence presented in Figure 5, Table 4, and Table 5 highlights the critical role of international collaboration in advancing PIML research within hydrology and water resources. The observed patterns emphasize the value of fostering inclusive and geographically diverse research partnerships, which facilitate the exchange of expertise, data resources, and methodological innovations across national boundaries. Collectively, these findings

demonstrate that addressing increasingly complex hydrological and environmental challenges through PIML requires sustained global cooperation and coordinated scientific efforts.

3.4. Thematic Analysis and Keyword Mapping

The adoption of PIML across hydrological disciplines is uneven, with research activity concentrated in areas characterized by complex nonlinear processes, limited data availability, and significant operational or management implications. To provide a clearer thematic overview, a keyword extraction and topic clustering analysis was conducted on the publication set. The results are presented in Figure 6, which categorizes the literature into major research themes and subcategories. Analysis of the literature reveals two dominant research themes: Flood and Disaster Management ($n = 113$) and Groundwater Modeling ($n = 96$), each representing the largest share of publications within the corpus.

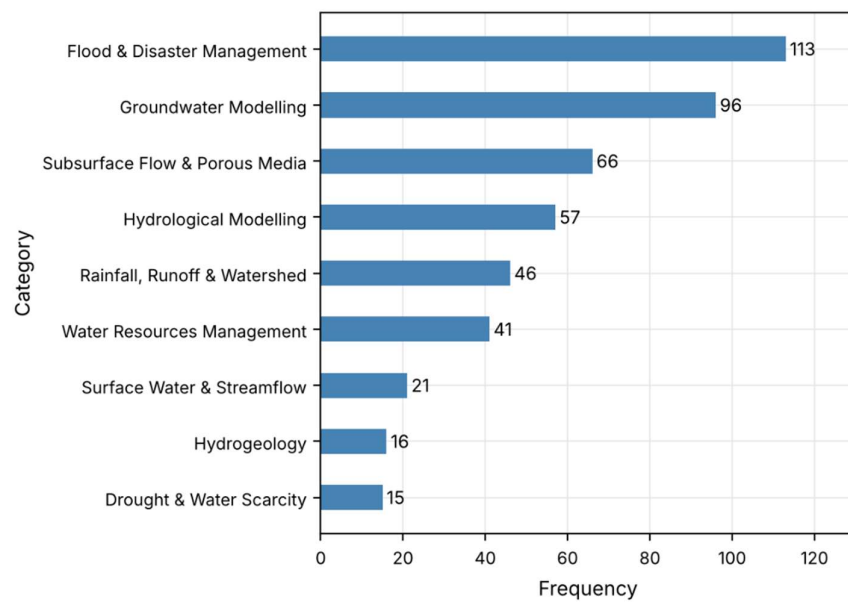


Figure 6. Thematic categorization of the curated literature, highlighting the frequency of PIML applications across diverse hydrological and water resource sub-domains.

The prominence of Flood and Disaster Management reflects the growing demand for computationally efficient and physically reliable predictive systems capable of supporting real-time forecasting and early warning applications (Donnelly et al., 2024; Bhattarai et al., 2024). Conventional data-driven models may produce unrealistic or unstable predictions when confronted with extreme or previously unseen hydrological events. By incorporating physical conservation principles into the learning process, PIML approaches improve model robustness and maintain physically consistent behavior under changing environmental conditions. In contrast, the strong representation of Groundwater Modeling and Management highlights the value of PIML in data-scarce environments. Because subsurface processes are often difficult and expensive to observe directly, integrating established physical laws into machine learning frameworks enables more accurate predictions despite limited observational datasets (Tartakovsky et al., 2020).

Several other major research areas also exhibit substantial levels of activity, including Subsurface Flow and Porous Media ($n = 66$), General Hydrological Modeling ($n = 57$), Rainfall, Runoff, and Watershed Dynamics ($n = 46$), and Water Resources Management ($n = 41$). Emerging applications are increasingly evident in Surface Water and Streamflow Modeling ($n = 21$), Hydrogeology ($n = 16$), and Drought and Water Scarcity Studies ($n = 15$), demonstrating the adaptability of PIML methodologies across a broad range of hydrological scales and processes.

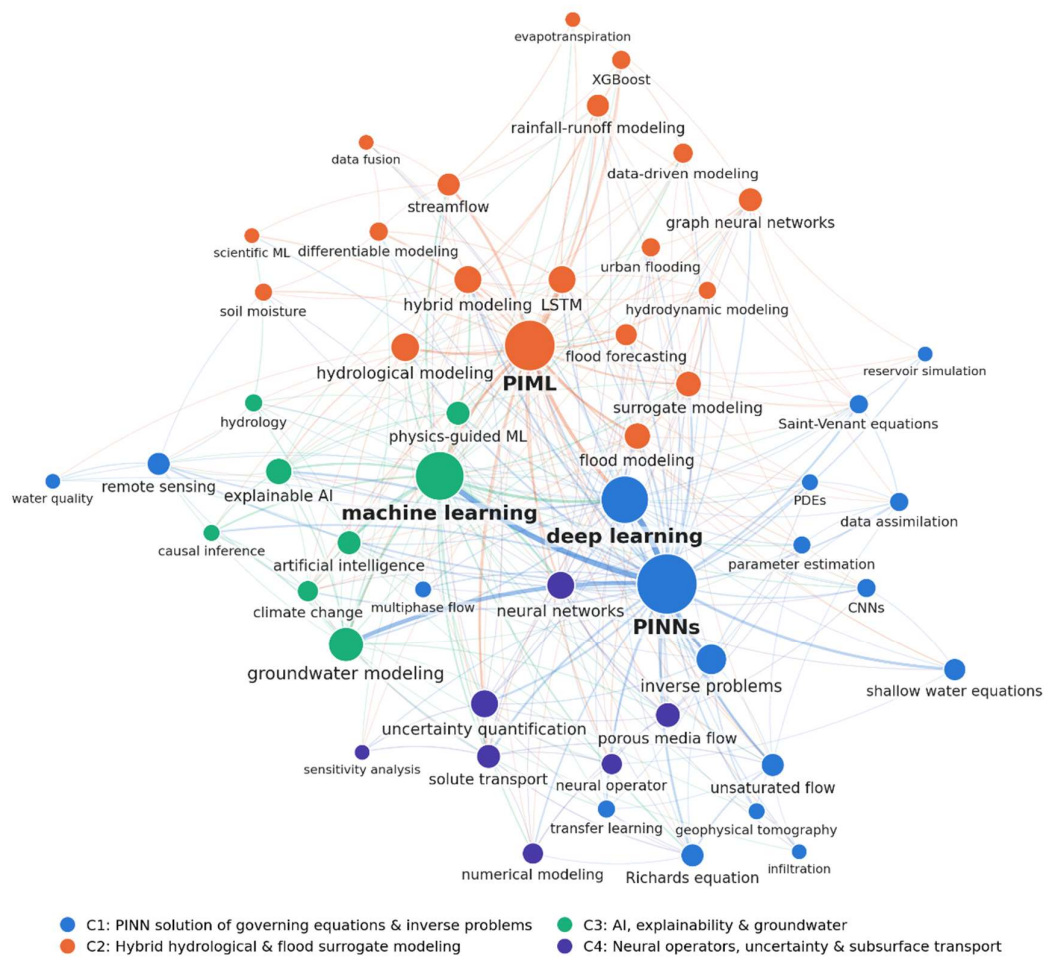


Figure 7. Author keyword network of PIML applications in hydrological research.

Figure 7 complements this thematic analysis with an author keyword co-occurrence network, which shows not only how frequently terms occur, but also which terms are used together in the same publications. Author keywords were available for 403 of the 471 records. Before mapping, spelling variants and synonyms were harmonized using a thesaurus (e.g., PINN, PINNs, and physics-informed neural network(s) were merged into a single term, and British and American spellings were unified), and generic terms such as “prediction” and “modeling” were removed. Keywords appearing in at least four publications were retained, yielding a network of 52 keywords connected by 353 co-occurrence links. Node size is proportional to keyword frequency, link width to the number of publications in which two

keywords co-occur, and node color to the cluster assigned by the Louvain community detection algorithm (Blondel et al., 2008). Physics-Informed Neural Networks (PINNs) form the dominant hub of the network ($n = 185$; total link strength = 248), followed by Physics-Informed Machine Learning ($n = 88$), Machine Learning ($n = 71$), and Deep Learning ($n = 60$). This finding indicates that PINNs have become the principal approach for integrating governing physical equations directly into neural network training and prediction workflows (Raissi et al., 2019; Karniadakis et al., 2021).

Four thematic clusters emerge from the network. Cluster 1 (18 keywords), centered on PINNs, links the method to the forward and inverse solution of governing equations, including the Richards, Saint-Venant, and shallow water equations, unsaturated flow, infiltration, parameter estimation, data assimilation, and geophysical tomography. The strongest links of PINNs are with Deep Learning (27 co-occurrences) and Machine Learning (24), followed by Groundwater Modeling (17) and Inverse Problems (13). Cluster 2 (19 keywords), centered on Physics-Informed Machine Learning, combines catchment-scale hybrid modeling, with LSTM, hybrid and differentiable modeling, streamflow, rainfall–runoff, and soil moisture, and flood applications, with surrogate modeling, graph neural networks, flood forecasting, urban flooding, and hydrodynamic modeling. Cluster 3 (8 keywords) connects Machine Learning and Groundwater Modeling with Explainable AI, physics-guided machine learning, Causal Inference, and Climate Change. Cluster 4 (7 keywords) brings together neural operators, uncertainty quantification, sensitivity analysis, and numerical modeling for porous media flow and solute transport. The relatively low modularity of the partition ($Q = 0.17$) indicates that these clusters are strongly interconnected through the PINN and PIML hubs rather than forming isolated research communities.

The frequent co-occurrence of advanced computational concepts, including Deep Learning, LSTM, Surrogate Modeling, and Transfer Learning, with hydrological applications such as Soil Moisture, Streamflow, Solute Transport, and Climate Change highlights the interdisciplinary nature of contemporary PIML research. Moreover, the increasing prominence of terms such as Uncertainty Quantification and Explainable AI suggests that the field is progressing beyond a primary focus on predictive accuracy (Psaros et al., 2023; Towfiqul Islam et al., 2026). Current research increasingly emphasizes model reliability, physical consistency, interpretability, and uncertainty assessment, all of which are essential for supporting informed decision-making in water resources management and environmental policy.

3.5. Citation Impact

Citation impact analysis was conducted to identify the foundational studies that have shaped the development of PIML in hydrology and water resources. The resulting citation distribution exhibits a highly concentrated structure, indicating that a relatively small group of influential publications has provided the methodological and conceptual foundation for much of the subsequent research in the field, as summarized in Table 6. Among these, the study by Kratzert et al. (2019) stands out as the most highly cited work. By demonstrating the effectiveness of LSTM models for streamflow prediction in ungauged basins, this research showed that adding physical constraints to the deep learning architectures could further improve capturing of complex hydrological relationships and generalize across diverse catchment conditions.

Several highly cited studies have also played a pivotal role in advancing PIML applications in subsurface environments. Notably, Tartakovsky et al. (2020), with 476 citations, and He et al. (2020), with 367 citations, demonstrated the effectiveness of Physics-Informed Deep Neural Networks (PIDNNs) for solving inverse problems and assimilating data in heterogeneous porous media systems. These contributions provided compelling evidence that integrating governing physical laws into ML frameworks can significantly enhance predictive capability in settings where observational data are sparse or difficult to obtain. Their prominence within the citation network highlights the particular value of PIML approaches for groundwater and subsurface modeling applications.

Table 6: Top 10 most cited publications on PIML in hydrology or water resources (Source: Scopus).

Title	Author(s)	# of Citations	Year
Toward Improved Predictions in Ungauged Basins: Exploiting the Power of Machine Learning	Kratzert et al., 2019	713	2019
Physics-Informed Deep Neural Networks for Learning Parameters and Constitutive Relationships in Subsurface Flow Problems	Tartakovsky et al., 2020	476	2020
Differentiable modelling to unify machine learning and physical models for geosciences	Shen et al., 2023	456	2023
Physics-informed neural networks for multiphysics data assimilation with application to subsurface transport	He et al., 2020	367	2020
Physics-informed neural networks as surrogate models of hydrodynamic simulators.	Donnelly et al., 2024	224	2024
Multi-fidelity Bayesian neural networks: Algorithms and applications.	Meng et al., 2021	183	2021
Deep-learning-based surrogate model for reservoir simulation with time-varying well controls.	Jin et al., 2020	160	2020
The suitability of differentiable, physics-informed machine learning hydrologic models for ungauged regions and climate change impact assessment.	Feng et al., 2023	154	2023
Application of physics-informed neural networks to inverse problems in unsaturated groundwater flow.	Depina et al., 2022	153	2022
Hydrologically informed machine learning for rainfall-runoff modelling: Towards distributed modelling.	Herath et al., 2021	150	2021

Another major intellectual contribution is the framework proposed by Shen et al. (2023), which has accumulated 456 citations and introduced differentiable modeling concepts to the hydrological community. This work represents an important methodological progression from traditional hybrid models that incorporate physics through penalty terms toward fully differentiable architectures in which physical process equations are embedded directly within neural network structures. Such approaches offer tighter integration between data-driven

learning and process-based understanding, thereby improving model interpretability and physical consistency.

The highly cited literature also includes influential studies focused on the development of surrogate modeling frameworks. Examples include Donnelly et al. (2024), which explored PIML-based surrogates for hydrodynamic simulations, and Jin et al. (2020), which demonstrated similar approaches for reservoir modeling applications. These studies reflect a growing effort to leverage hybrid AI-physics frameworks to reduce the substantial computational costs associated with traditional numerical simulations while preserving predictive accuracy and physical realism.

Taken together, the citation landscape suggests that the rapid growth of PIML research in the hydrology domain has been driven by two complementary scientific advances. First, PIML approaches enable physically consistent and reliable predictions in data-scarce environments where conventional ML methods often struggle. Second, they provide efficient surrogate modeling capabilities that significantly accelerate computationally intensive simulations, thereby expanding the practical applicability of advanced hydrological models for real-time forecasting, resource management, and decision support.

4. Discussions

4.1. Summary of Findings by Research Question

The bibliometric analysis was structured around five interconnected research questions (RQ1–RQ5), each addressing a distinct dimension of PIML research in hydrology and water resources. Collectively, the findings reveal the rapid evolution of PIML from an emerging computational concept into a widely adopted methodological paradigm with growing scientific, operational, and interdisciplinary significance.

In addressing RQ1, which examined the dominant growth trajectories and published trends of PIML research in hydrology between 2015 and 2026, the findings reveal a clear and accelerating expansion of scholarly activity. Publication output remained limited during the early developmental period (2015–2018), when foundational PINN architectures were still being established. However, from 2019 onward, research productivity increased substantially, culminating in major publication surges in 2024 and 2025. The strong output recorded in just 9 months of 2026 suggests that this growth trajectory is likely to continue.

The publication landscape is dominated by peer-reviewed journal articles (62.6%), supplemented by preprints (17.0%) and conference papers (13.4%). This distribution reflects both the rigorous validation standards of hydrological research and the rapid dissemination culture characteristic of the machine learning community. The predominance of peer-reviewed journal articles and the prominence of leading journals such as the *Journal of Hydrology*, *Water Resources Research*, and *Water Research*, coupled with an average journal Impact Factor of 5.32, demonstrates that PIML has progressed beyond an emerging computational approach and is now firmly established within leading hydrological and environmental science journals.

In response to RQ2, which sought to identify the leading countries, institutions, journals, and collaborative networks driving global PIML research, the results indicate a highly concentrated yet internationally connected research landscape. China and the United States emerged as the dominant contributors, while Activity Index analysis revealed contrasting developmental trajectories characterized by early specialization in the United States and rapid

recent expansion in China. Furthermore, countries such as India and Canada exhibited publication outputs that exceeded expectations relative to their economic scale, suggesting targeted investments in hybrid AI–physics research. The collaboration network highlights the importance of international partnerships, with strong connections linking North America, Europe, and the Asia-Pacific region.

With respect to RQ3, which investigated the principal thematic domains and application areas of PIML in hydrology and water resources, the findings demonstrate that adoption is concentrated within sub-disciplines characterized by complex physical processes, nonlinear system behavior, and limited observational data. Flood and Disaster Management and Groundwater Modeling and Management emerged as the most active research areas, reflecting the ability of PIML to improve predictive reliability in real-time forecasting applications while simultaneously addressing data scarcity in subsurface environments. Additional concentrations of research were identified in subsurface flow, porous media, rainfall-runoff processes, watershed dynamics, and surface water modeling. Keyword analysis reinforces these findings, with PINNs occupying a central position alongside terms such as deep learning, transfer learning, surrogate modeling, streamflow, soil moisture, and climate change. This pattern reflects the hydrological applications' core objective of combining data-driven learning with physically based process understanding.

The findings associated with RQ4 demonstrate that the intellectual foundation of the field is highly concentrated around a relatively small number of influential studies. Kratzert et al. (2019) emerged as the most highly cited publication, establishing the effectiveness of deep learning approaches for streamflow prediction in ungauged catchments and accelerating the adoption of hybrid modeling strategies throughout hydrology. Foundational contributions by Tartakovsky et al. (2020) and He et al. (2020) established the viability of physics-informed deep learning approaches for groundwater modeling, inverse problems, and data assimilation in data-scarce environments. Similarly, Shen et al. (2023) introduced differentiable modeling concepts that further integrated physical process representations within machine learning architectures. Other highly cited studies focused on surrogate modeling applications capable of reducing the computational burden of traditional numerical simulations. Collectively, these influential publications highlight two primary drivers of the field's growth: the ability to generate physically consistent predictions under data scarcity and the capacity to substantially accelerate complex hydrological simulations.

Finally, the results addressing RQ5, which examined emerging research frontiers and the community's strategies for addressing persistent challenges such as uncertainty quantification and model flexibility, indicate that the field is increasingly focused on methodological maturity and operational applicability. The growing prominence of concepts such as uncertainty quantification, XAI, transfer learning, and surrogate modeling suggests a shift beyond predictive performance alone toward model reliability, transparency, and generalizability. Recent studies have emphasized the need for robust uncertainty estimation methods, particularly for high-stakes hydrological applications where decision-making depends on understanding predictive confidence (Psaros et al., 2023; Slater et al., 2025). At the same time, transfer learning and surrogate modeling research seeks to improve model adaptability across diverse hydrological settings while reducing computational costs. The emergence of differentiable modeling frameworks represents a particularly important frontier, enabling

tighter integration between process-based knowledge and machine learning optimization (Shen et al., 2023). Furthermore, the increasing number of review papers reflects a maturing discipline actively engaged in methodological synthesis, standardization, and knowledge consolidation.

Taken together, the five research questions (RQ1-RQ5) reveal a coherent narrative of rapid scientific growth, increasing international collaboration, expanding application domains, influential foundational scholarship, and ongoing methodological refinement. The strong connections among these dimensions suggest that PIML is no longer an emerging niche within computational hydrology but rather an increasingly established paradigm that is reshaping hydrological modeling practices, advancing scientific understanding, and supporting more reliable and efficient solutions to contemporary water resources challenges.

4.2. Applications of PIML in Hydrology and Water Resources

The bibliometric evidence indicates that the adoption of PIML within hydrology and water resources is concentrated in application domains characterized by complex physical processes, limited observational data, and substantial computational demands. Rather than being applied uniformly across all hydrological sub-disciplines, PIML has emerged as a targeted solution for challenges where conventional process-based or purely data-driven approaches exhibit important limitations. Three major areas stand out in the literature: subsurface transport and groundwater systems, flood and disaster management, and the broader pursuit of model interpretability and scientific transparency.

In the domain of subsurface transport and groundwater modeling, physical environments are inherently difficult to characterize because observations are typically sparse, costly to obtain, and unevenly distributed in space and time. Monitoring networks often rely on a limited number of observation wells, making it difficult to capture the complex dynamics of groundwater flow and contaminant transport. These challenges are compounded by the heterogeneity of geological formations and the computational expense associated with traditional numerical simulations (Ma et al., 2026). In response, PINN architecture has emerged as effective tools for solving inverse problems and assimilating diverse data sources under conditions of severe data scarcity (He et al., 2020). By incorporating governing physical principles directly into the learning process, these models can exploit both observational data and prior scientific knowledge to improve predictive performance.

The effectiveness of PIML in groundwater applications stems largely from its ability to embed governing equations such as Darcy's Law and the advection-dispersion equation within the model architecture. This integration allows the simultaneous utilization of heterogeneous datasets, including indirect geophysical observations and point-based groundwater quality measurements. Physical constraints act as regularization mechanisms that guide model learning toward physically realistic solutions, even when observations are limited. Consequently, sparse measurements can be transformed into continuous spatiotemporal representations of subsurface conditions, enabling more reliable forecasting of contaminant transport and groundwater dynamics (He et al., 2020). Recent studies have further demonstrated that PINNs can incorporate sparse field observations as soft constraints during training, reducing the need for large, labeled datasets while maintaining predictive accuracy (Secci et al., 2024). These advances have enhanced the feasibility of using physics-informed surrogate models to support

groundwater management, contamination assessment, and climate-resilient decision-making (Meray et al., 2024).

In contrast to groundwater applications, the adoption of PIML in flood forecasting and disaster management is primarily motivated by the need for computational efficiency. High-fidelity hydrodynamic models based on the shallow water or Saint-Venant equations remain the benchmark for simulating flood dynamics; however, their computational requirements often limit their use in real-time operational settings. To address this challenge, researchers have increasingly developed physics-informed surrogate models capable of approximating the behavior of traditional numerical solvers at a fraction of the computational cost. Qi et al. (2024) showed that PINNs can solve two-dimensional shallow water equations without requiring extensive labeled datasets while maintaining accuracy comparable to conventional finite-volume approaches. Similarly, Donnelly et al. (2024) demonstrated that PINN-based surrogate architectures can significantly reduce the computational burden associated with high-resolution inundation modeling. Once trained, these models can rapidly generate flood extent maps, water depth estimates, and peak flow predictions, making them particularly valuable for early warning systems and emergency response applications.

A key strength of PIML architecture is their ability to represent highly nonlinear hydraulic processes that govern open-channel flow. This is particularly important for modeling streamflow hysteresis, where conventional statistical networks often struggle to reproduce looped rating curves caused by unsteady wave attenuation. Recent studies have improved understanding of these dynamics by analyzing momentum budgets within the process-based Saint-Venant equations to identify the physical and geometric drivers of hysteretic behavior (House et al., 2025a). Using global sensitivity analysis, researchers have further examined how channel slope, roughness, and other parameters influence system responses across different flow regimes (House et al., 2026). Building on these insights, recent deep learning models incorporate physically informed phase-shifting and hysteresis mechanisms directly into network architectures, improving the realism of streamflow simulations (House et al., 2025b). In parallel, modern PIML frameworks increasingly integrate river-network topology through graph attention transformers, embedding physical connectivity into graph structures to support localized and physically consistent flood propagation across large watershed systems (Sarkar et al., 2025).

Beyond their applications in specific hydrological domains, PIML approaches also address a broader challenge facing AI in environmental sciences: model interpretability. Traditional DL models are frequently criticized for their black-box nature, as they may generate accurate predictions without providing insight into the underlying physical mechanisms driving those outcomes. In hydrology and water resources management, where model outputs often support high-stakes decisions, predictive accuracy alone is insufficient. Decision-makers require confidence that model behavior is scientifically credible, physically consistent, and transparent. By incorporating physical laws directly into the learning process, PIML fundamentally alters the relationship between prediction and explanation. Rather than relying exclusively on statistical correlations, these models generate outputs that remain constrained by established scientific principles, thereby enhancing interpretability and trustworthiness.

The growing interest in XAI further reinforces the relevance of PIML within hydrology. Zounemat-Kermani and Kheimi (2026) identified the integration of explainability and physics-

informed modeling as a major methodological frontier in environmental ML. The convergence of these two research directions offers significant opportunities to bridge the gap between data-driven prediction and process-based understanding (Slater et al., 2025). As hydrological systems become increasingly influenced by climate variability, land-use change, and anthropogenic pressures, the ability to generate transparent and physically interpretable predictions will become increasingly important. Consequently, PIML is emerging not only as a tool for improving predictive performance but also as a framework for enhancing the scientific credibility, operational reliability, and decision-making value of machine learning applications in hydrology and water resources.

4.3. Challenges and Limitations

Despite the significant advances enabled by PIML, the bibliometric results indicate that several methodological, operational, and structural challenges continue to constrain its widespread adoption in hydrology and water resources. Among the most persistent technical limitations is the issue of data heterogeneity. Although the incorporation of physical laws reduces dependence on large training datasets by providing additional constraints during model optimization, the performance of PIML models remains strongly influenced by the quality, representativeness, and consistency of the underlying observations. Hydrological datasets are frequently characterized by noise, missing values, uneven spatial coverage, and varying temporal resolutions.

Consequently, many existing PINN implementations continue to exhibit sensitivity to uncertain initial and boundary conditions, particularly when applied to complex real-world environments (Ma et al., 2026; Feng et al., 2024). While promising results have been demonstrated in controlled or idealized settings, challenges remain in transferring these approaches to highly heterogeneous catchments where geological, climatic, and anthropogenic factors introduce substantial uncertainty and complexity.

These technical challenges are further compounded by disparities in global research capacity and data availability. The geographical analysis conducted in this study reveals that the development and application of advanced PIML frameworks are concentrated primarily within countries possessing strong computational infrastructure, extensive monitoring networks, and substantial research funding. As a result, regions such as Africa and South America remain significantly underrepresented within the current literature despite facing some of the world's most pressing hydrological challenges (Ma et al., 2026).

This imbalance presents both scientific and societal concerns. Many regions that are highly vulnerable to floods, droughts, and other climate-related water extremes have limited access to observational data, computational resources, and institutional support required to develop and deploy advanced physics-informed modeling systems (Tabari et al., 2021). Consequently, the benefits of recent advances in hydrological AI may not be distributed equitably across regions that could potentially derive the greatest value from them.

The need to overcome these limitations is driving several important research frontiers. One emerging direction involves the development of multimodal PIML frameworks capable of integrating diverse sources of information, including remote sensing imagery, in situ sensor measurements, geospatial datasets, and numerical model outputs within a unified learning architecture. By combining multiple forms of observational evidence while maintaining

adherence to governing physical principles, such models have the potential to improve predictive accuracy and robustness in data-limited environments.

A second and increasingly prominent research direction focuses on the development of domain-specific foundation models and large language models tailored to hydrological and environmental applications. Emerging systems such as WaterGPT and HydroLLM illustrate how advances in generative AI may be adapted to support hydrological analysis, scientific knowledge synthesis, decision support, and multimodal data interpretation (Ren et al., 2024; Kizilkaya et al., 2025). Although these approaches currently follow distinct methodological pathways, their eventual integration with physics-informed learning frameworks may provide new opportunities for integrating large-scale information processing capabilities with physically consistent prediction.

Recent methodological developments also offer encouraging evidence regarding the transferability and scalability of PIML models. Studies have demonstrated that differentiable physics-informed architectures can generalize beyond the locations on which they were originally trained, including applications in ungauged and data-sparse catchments (Feng et al. 2023). In particular, learned physical parameterizations can be transferred across hydrological settings, reducing the need for extensive retraining and lowering computational costs for deployment in resource-constrained regions. Such advances suggest a pathway toward more accessible and globally applicable hydrological intelligence systems. As the field continues to evolve, the combination of transferable physics-informed models, multimodal learning architectures, and domain-specific foundation models may help address existing inequalities in data availability and computational resources while preserving the physical interpretability that distinguishes PIML from purely data-driven approaches.

Overall, the future success of PIML in hydrology will depend not only on improving predictive performance but also on addressing challenges related to data quality, model generalization, computational accessibility, and global equity. Ensuring that physics-informed artificial intelligence can be effectively applied across diverse environmental and socioeconomic contexts will be essential for realizing its full potential as a tool for sustainable water resources management and climate resilience.

5. Conclusion and Future Directions

The bibliometric analysis conducted in this study highlights the rapid and transformative trajectory of Physics-Informed Machine Learning (PIML) within the hydrological sciences, tracing its evolution from an emerging computational concept into a mature and increasingly influential modeling paradigm. By integrating governing physical principles directly within ML architectures, PIML offers a powerful framework for bridging the longstanding divide between process-based hydrological modeling and data-driven AI. This integration has enabled the development of models that are not only computationally efficient but also physically consistent, thereby improving predictive reliability, mathematical robustness, and operational decision-making across a wide range of hydrological applications.

Several key conclusions emerge from this study. First, the field has experienced remarkable growth over the past decade, with publication output increasing exponentially since 2019 and reaching a peak of 130 publications in 2025. With 176 publications by September 2026, already 35% above the full 2025 total ($n = 130$), research activity is likely to continue expanding in the

coming years. Second, the publication landscape is dominated by peer-reviewed journal articles, reflecting the scientific rigor required for PIML research while simultaneously demonstrating its acceptance within leading hydrology, environmental science, and engineering journals. Third, the field is characterized by a highly collaborative and internationally connected research network, with China and the United States serving as the principal contributors and central hubs of global scientific collaboration. At the same time, countries such as India and Canada have demonstrated notable specialization and productivity relative to their economic scale.

The thematic analysis revealed that PIML adoption is concentrated in hydrological domains where complex physical processes, nonlinear system behavior, and limited observational data present significant modeling challenges. Flood and Disaster Management and Groundwater Modeling and Management emerged as the top two most active application areas, highlighting the ability of physics-informed approaches to improve both computational efficiency and predictive reliability. The growing prominence of methodologies such as PINNs, transfer learning, surrogate modeling, and differentiable modeling further illustrates the field's transition toward more sophisticated and operationally relevant modeling frameworks.

Citation analysis confirmed that the intellectual development of the field is anchored by a relatively small number of highly influential studies that established the theoretical and practical foundations of modern PIML. These foundational contributions collectively demonstrate two major advantages of physics-informed approaches: their ability to generate physically consistent predictions in data-scarce environments and their capacity to substantially reduce the computational burden associated with traditional numerical simulations. Together, these capabilities explain the rapid expansion of PIML across multiple hydrological disciplines and application domains.

This bibliometric analysis also indicates that the field is progressing beyond a primary focus on predictive accuracy toward broader concerns related to model reliability, interpretability, and operational trustworthiness. The increasing prominence of uncertainty quantification, XAI, and model generalization reflects a growing recognition that hydrological ML systems must provide not only accurate predictions but also transparent and scientifically defensible explanations. This shift is particularly important for applications involving water resource planning, disaster risk reduction, and climate adaptation, where decision-making often occurs under substantial uncertainty.

Despite these advances, several important challenges remain. The performance of current PIML models continues to depend heavily on the quality and availability of observational data, and many architectures remain sensitive to noisy datasets and uncertain boundary conditions when applied to heterogeneous real-world environments. In addition, significant disparities persist in the geographical distribution of research activity. The development of advanced PIML systems is concentrated primarily in countries with extensive computational resources, dense monitoring networks, and strong research infrastructure. Consequently, regions such as Africa and South America remain underrepresented in the literature despite facing some of the world's most severe hydrological and climate-related risks. Addressing these imbalances will be essential for ensuring that future advances in hydrological AI contribute to equitable and globally relevant solutions.

Future research should focus on strengthening the integration between process-based hydrological modeling and advanced AI frameworks to better address the growing challenges associated with climate change adaptation and sustainable water resources management. Increasing attention is being directed toward differentiable modeling frameworks in which governing physical equations are embedded directly within neural network architectures. Such approaches enable simultaneous optimization of physical and statistical parameters through gradient-based learning, creating a more seamless interaction between process-based understanding and data-driven prediction.

Another promising research frontier is the development of multimodal PIML architecture capable of integrating heterogeneous data sources within a unified learning framework. Hydrological systems are increasingly monitored through a combination of satellite observations, geospatial datasets, climate reanalysis products, numerical model outputs, and real-time sensor networks. However, effectively combining these different sources of information remains a significant challenge. Future PIML frameworks are expected to leverage advances in multimodal learning to simultaneously process remote sensing imagery, spatially distributed environmental variables, and in situ observations while maintaining adherence to fundamental conservation laws. Such architecture could substantially improve predictive performance in data-limited environments and enhance the capacity of hydrological models to operate across multiple spatial and temporal scales.

Equally important is the need to improve the transferability and accessibility of advanced PIML models. Future research should prioritize the development of architectures capable of generalizing learned physical relationships across diverse hydrological settings, including ungauged and data-scarce catchments. This capability is particularly relevant for developing regions where monitoring infrastructure and computational resources may be limited. By centralizing the computationally intensive stages of model pretraining within well-resourced research institutions and enabling localized fine-tuning for specific watersheds and environmental conditions, future PIML frameworks could significantly reduce barriers to adoption.

In conclusion, the findings of this study indicate that PIML is no longer an emerging niche within hydrological research but an increasingly established paradigm that is reshaping modeling practices, scientific inquiry, and decision-support systems across the water sector. As methodological advances continue to improve model reliability, scalability, and interpretability, PIML is positioned to play a central role in addressing the complex water resources challenges associated with climate change, environmental uncertainty, and sustainable development.

Author Contributions

G.K.F.: conceptualization, methodology, software, data curation, writing—original draft preparation and visualization; O.M.: conceptualization, methodology, validation, formal analysis, writing—review and editing; I.D.: writing—review and editing, validation, supervision, project administration, and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

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

Conflicts of Interest

The authors declare no conflicts of interest.

References

- Adombi, A. V. D. P. (2025). Scientific machine learning in hydrology: a unified perspective. *Earth Science Informatics*, 18(4), 522.
- Asif, M., & Fazel, H. (2024). Digital technology in tourism: a bibliometric analysis of transformative trends and emerging research patterns. *Journal of Hospitality and Tourism Insights*, 7(3), 1615-1635.
- Bahadori-Jahromi, A., Room, S., Paknahad, C., Altekreeti, M., Tariq, Z., & Tahayori, H. (2025). The role of artificial intelligence and machine learning in advancing civil engineering: A comprehensive review. *Applied sciences*, 15(19), 10499.
- Bandai, T., & Ghezzehei, T. A. (2021), Physics-Informed Neural Networks With Monotonicity Constraints for Richardson-Richards Equation: Estimation of Constitutive Relationships and Soil Water Flux Density From Volumetric Water Content Measurements, *Water Resources Research*, 57(2), e2020WR027642.
- Bhattarai, Y., Bista, S., Talchabhadel, R., Duwal, S., & Sharma, S. (2024). Rapid prediction of urban flooding at street-scale using physics-informed machine learning-based surrogate modeling. *Total Environment Advances*, 12, 200116.
- Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10), P10008.
- Blöschl, G., Bierkens, M. F., Chambel, A., Cudennec, C., Destouni, G., Fiori, A., ... & Renner, M. (2019). Twenty-three unsolved problems in hydrology (UPH)—a community perspective. *Hydrological sciences journal*, 64(10), 1141-1158.
- Brunton, S. L., & Kutz, J. N. (2019). Methods for data-driven multiscale model discovery for materials. *Journal of Physics: Materials*, 2(4), 044002.
- Chen, J., Chen, Y., Xu, X., Zhou, W., & Huang, G. (2022). A physics-guided machine learning for multifunctional wave control in active metabeams. *Extreme Mechanics Letters*, 55, 101827.
- Chen, K., & Guan, J. (2011). A bibliometric investigation of research performance in emerging nanobiopharmaceuticals. *Journal of Informetrics*, 5(2), 233-247.
- Chen, N., Duan, M., Lin, A. H., Wang, Q., Wu, J., & He, B. (2025). Position: The current AI conference model is unsustainable! Diagnosing the crisis of centralized AI conference. *arXiv preprint arXiv:2508.04586*.
- Chen, R. T., Rubanova, Y., Bettencourt, J., & Duvenaud, D. K. (2018). Neural ordinary differential equations. *Advances in neural information processing systems*, 31.
- Chen, S., Kalanat, N., Xie, Y., Li, S., Zwart, J. A., Sadler, J. M., ... & Jia, X. (2023). Physics-guided machine learning from simulated data with different physical parameters. *Knowledge and Information Systems*, 65(8), 3223-3250.

- Chew, A. W. Z., He, R., & Zhang, L. (2025). Physics Informed Machine Learning (PIML) for design, management and resilience-development of urban infrastructures: A review. *Archives of Computational Methods in Engineering*, 32(1), 399-439.
- Chukwu, S. E., & Jibril, I. (2025). The Role of Explainable AI in Flood Modelling and Risk Assessment in the Era of Climate Change: A Systematic Review. *Bayero Journal of Engineering and Technology (BJET)*, 20(2), 65–78.
- Cuomo, S., Di Cola, V. S., Giampaolo, F., Rozza, G., Raissi, M., & Piccialli, F. (2022). Scientific machine learning through physics-informed neural networks: Where we are and what's next. *Journal of Scientific Computing*, 92(3), 88.
- Davoodi, S., Wood, D. A., Al-Shargabi, M., Vanovski, V., Rukavishnikov, V., & Burnaev, E. (2025). Emerging applications of physics-informed and physics-guided machine learning in geoenery science: A review. *Communications in Nonlinear Science and Numerical Simulation*, 109551.
- Demir, I., Conover, H., Krajewski, W.F., Seo, B.C., Goska, R., He, Y., McEniry, M.F., Graves, S.J. and Petersen, W., (2015). Data-enabled field experiment planning, management, and research using cyberinfrastructure. *Journal of Hydrometeorology*, 16(3), pp.1155-1170.
- Demiray, B. Z., Sit, M., Mermer, O., & Demir, I. (2024). Enhancing hydrological modeling with transformers: a case study for 24-h streamflow prediction. *Water Science & Technology*, 89(9), 2326-2341.
- Depina, I., Jain, S., Mar Valsson, S., & Gotovac, H. (2022). Application of physics-informed neural networks to inverse problems in unsaturated groundwater flow. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, 16(1), 21-36.
- Devia, G. K., Ganasri, B. P., & Dwarakish, G. S. (2015). A review on hydrological models. *Aquatic procedia*, 4, 1001-1007.
- Donnelly, J., Daneshkhah, A., & Abolfathi, S. (2024). Physics-informed neural networks as surrogate models of hydrodynamic simulators. *Science of the Total Environment*, 912, 168814.
- 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.
- Fatichi, S., Vivoni, E. R., Ogden, F. L., Ivanov, V. Y., Mirus, B., Gochis, D., ... & Tarboton, D. (2016). An overview of current applications, challenges, and future trends in distributed process-based models in hydrology. *Journal of Hydrology*, 537, 45-60.
- Feng, D., Beck, H., De Bruijn, J., Sahu, R. K., Satoh, Y., Wada, Y., ... & Shen, C. (2024). Deep dive into hydrologic simulations at global scale: harnessing the power of deep learning and physics-informed differentiable models (δ HBV-globe1.0-hydroDL). *Geoscientific Model Development*, 17(18), 7181-7198.
- Feng, D., Beck, H., Lawson, K., & Shen, C. (2023). The suitability of differentiable, physics-informed machine learning hydrologic models for ungauged regions and climate change impact assessment. *Hydrology and Earth System Sciences*, 27(12), 2357-2373.
- Floryan, D., & Graham, M. D. (2022). Data-driven discovery of intrinsic dynamics. *Nature Machine Intelligence*, 4(12), 1113-1120.

- Frame, J. D. (1977). Mainstream research in Latin America and the Caribbean. *Interciencia*, 2(3), 143-148.
- Ganguly, A. R., Kodra, E. A., Agrawal, A., Banerjee, A., Boriah, S., Chatterjee, S., ... & Wuebbles, D. (2014). Toward enhanced understanding and projections of climate extremes using physics-guided data mining techniques. *Nonlinear Processes in Geophysics*, 21(4), 777-795.
- Habib, M., Habib, A., & Alibrahim, B. (2025). Applications of physics-informed neural networks in geosciences: From basic seismology to comprehensive environmental studies. *Open Geosciences*, 17(1), 20250853.
- He, Q., & Tartakovsky, A. M. (2021), Physics-Informed Neural Network Method for Forward and Backward Advection-Dispersion Equations, *Water Resources Research*, 57(7), e2020WR029479.
- He, Q., Barajas-Solano, D., Tartakovsky, G., & Tartakovsky, A. M. (2020), Physics-informed neural networks for multiphysics data assimilation with application to subsurface transport, *Advances in Water Resources*, 141, 103610.
- Herath, H. M. V. V., Chadalawada, J., & Babovic, V. (2021). Hydrologically informed machine learning for rainfall–runoff modelling: towards distributed modelling. *Hydrology and Earth System Sciences*, 25(8), 4373-4401.
- House, E., Meselhe, E., Muste, M., & Demir, I. (2025a). Streamflow hysteresis analysis through a deep-dive budget of the St Venant equation momentum terms. *Water resources research*, 61(8), e2024WR038103.
- House, E., Kim, K., Muste, M., Meselhe, E., & Demir, I. (2025b). Back to basics: On the proper determination of free-surface slope (FSS) in gradually varied open channel flows. *Flow measurement and instrumentation*, 106, 102979.
- House, E., Meselhe, E., Muste, M., Kim, K., & Demir, I. (2026). A Sensitivity Analysis Approach to Identifying Drivers of Streamflow Hysteresis. *JAWRA Journal of the American Water Resources Association*, 62(3), e70126.
- Hu, X., & Rousseau, R. (2009). A comparative study of the difference in research performance in biomedical fields among selected Western and Asian countries. *Scientometrics*, 81(2), 475-491.
- Huang, S., Kong, X., Yang, X., Jin, X., Li, S., Yang, L., ... & Jin, H. (2025). A physics-informed machine learning (PIML) framework for projecting 21st- century permafrost extent in Northeast China. *EGUsphere*, 2025, 1-32.
- Huang, Y. H., Xu, Z., Qian, C., & Liu, L. (2023). Solving free-surface problems for non-shallow water using boundary and initial conditions-free physics-informed neural network (bif-PINN). *Journal of Computational Physics*, 479, 112003.
- International Monetary Fund. (2026). World Economic Outlook Database, April 2026. <https://data.imf.org/en/datasets/IMF.RES:WEO>
- Jagtap, A. A., Mane, P. B., & Shedge, D. K. (2026). Mapping the Scientific Evolution of Flood Risk Modelling with GIS: A Bibliometric and Thematic Analysis (1987–2024). *International Journal of Geoinformatics*, 22(2), 97-110.
- Ji, Y., Zha, Y., Yeh, T. C. J., Shi, L., & Wang, Y. (2024). Groundwater inverse modeling: Physics-informed neural network with disentangled constraints and errors. *Journal of Hydrology*, 640, 131703.

- Jin, Z. L., Liu, Y., & Durlinsky, L. J. (2020). Deep-learning-based surrogate model for reservoir simulation with time-varying well controls. *Journal of Petroleum Science and Engineering*, 192, 107273.
- Kadeethum, T., Jørgensen, T. M., & Nick, H. M. (2020). Physics-informed neural networks for solving nonlinear diffusivity and Biot's equations. *PloS one*, 15(5), e0232683.
- Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, 3(6), 422-440.
- Kizilkaya, D., Sajja, R., Sermet, Y., & Demir, I. (2025). Toward HydroLLM: a benchmark dataset for hydrology-specific knowledge assessment for large language models. *Environmental Data Science*, 4, e31.
- Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2018). Rainfall–runoff modelling using long short-term memory (LSTM) networks. *Hydrology and Earth System Sciences*, 22(11), 6005-6022.
- Kratzert, F., Klotz, D., Herrnegger, M., Sampson, A. K., Hochreiter, S., & Nearing, G. S. (2019). Toward improved predictions in ungauged basins: Exploiting the power of machine learning. *Water Resources Research*, 55(12), 11344-11354.
- Li, Z., Duque, F. Q., Grout, T., Bates, B., & Demir, I. (2023). Comparative analysis of performance and mechanisms of flood inundation map generation using Height Above Nearest Drainage. *Environmental Modelling & Software*, 159, 105565.
- Ma, Q., Gong, Q., Ge, W., Jing, M., Guo, F., Butscher, C., & Taher Dang Koo, R. (2026). Physics-informed neural networks for groundwater: evidence, limits, and a roadmap. *Environmental Earth Sciences*, 85(5), 123.
- Maganur, S., & Kejriwal, M. (2026). Structural shifts in institutional participation and collaboration within the AI arXiv preprint research ecosystem. *arXiv preprint arXiv:2602.03969*.
- Maier, H. R., Taghikhah, F. R., Nabavi, E., Razavi, S., Gupta, H., Wu, W., ... & Huang, J. (2024). How much X is in XAI: Responsible use of “Explainable” artificial intelligence in hydrology and water resources. *Journal of Hydrology X*, 25, 100185.
- Martín-Martín, A., Orduna-Malea, E., Thelwall, M., & López-Cózar, E. D. (2018). Google Scholar, Web of Science, and Scopus: A systematic comparison of citations in 252 subject categories. *Journal of informetrics*, 12(4), 1160-1177.
- Meng, C., Griesemer, S., Cao, D., Seo, S., & Liu, Y. (2025). When physics meets machine learning: A survey of physics-informed machine learning. *Machine Learning for Computational Science and Engineering*, 1(1), 20.
- Meray, A., Wang, L., Kurihana, T., Mastilovic, I., Praveen, S., Xu, Z., ... & Wainwright, H. (2024). Physics-informed surrogate modeling for supporting climate resilience at groundwater contamination sites. *Computers & Geosciences*, 183, 105508.
- Mermer, O., & Demir, I. (2025). Multivariate regression analysis for identifying key drivers of harmful algal bloom in Lake Erie. *Applied sciences*, 15(9), 4824.
- Mermer, O., & Demir, I. (2026). The Evolution of Digital Twins in Hydrology and Environmental Science: From Physical Models to AI-Assisted Autonomous Systems. *EarthArxiv*, 12563. <https://doi.org/10.31223/X5DJ2D>

- Mermer, O., Zhang, E., & Demir, I. (2025). A comparative study of ensemble machine learning and explainable AI for predicting harmful algal blooms. *Big data and cognitive computing*, 9(5), 138.
- Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *BMJ*, 339.
- Mongeon, P., & Paul-Hus, A. (2016). The journal coverage of Web of Science and Scopus: a comparative analysis. *Scientometrics*, 106(1), 213-228.
- Nageye, A. Y., Jimale, A. D., Abdullahi, M. O., & Ahmed, Y. A. (2024). Emerging trends in data science and big data analytics: A bibliometric analysis. *parameters*, 8, 9.
- Nourani, V., Baghanam, A. H., Adamowski, J., & Kisi, O. (2014). Applications of hybrid wavelet–artificial intelligence models in hydrology: a review. *Journal of Hydrology*, 514, 358-377.
- Nydrioti, I., Sebos, I., Kitsara, G., & Assimacopoulos, D. (2024). Effective management of urban water resources under various climate scenarios in semiarid mediterranean areas. *Scientific Reports*, 14(1), 28666.
- Okkan, U., Ersoy, Z. B., Kumanlioglu, A. A., & Fistikoglu, O. (2021). Embedding machine learning techniques into a conceptual model to improve monthly runoff simulation: A nested hybrid rainfall-runoff modeling. *Journal of Hydrology*, 598, 126433.
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372.
- Palmitessa, R., Grum, M., Engsig-Karup, A. P., & Löwe, R. (2022). Accelerating hydrodynamic simulations of urban drainage systems with physics-guided machine learning. *Water research*, 223, 118972.
- Psaros, A. F., Meng, X., Zou, Z., Guo, L., & Karniadakis, G. E. (2023). Uncertainty quantification in scientific machine learning: Methods, metrics, and comparisons. *Journal of Computational Physics*, 477, 111902.
- Qi, X., de Almeida, G. A., & Maldonado, S. (2024). Physics-informed neural networks for solving flow problems modeled by the 2D Shallow Water Equations without labeled data. *Journal of Hydrology*, 636, 131263.
- Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2017). Physics informed deep learning (part i): Data-driven solutions of nonlinear partial differential equations. *arXiv preprint arXiv:1711.10561*.
- Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational physics*, 378, 686-707.
- Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat, F. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), 195-204.
- Ren, Y., Zhang, T., Dong, X., Li, W., Wang, Z., He, J., ... & Jiao, L. (2024). WaterGPT: Training a large language model to become a hydrology expert. *Water*, 16(21), 3075.
- Rosińska, W., Jurasz, J., Przestrzelska, K., Wartalska, K., & Kaźmierczak, B. (2024). Climate change's ripple effect on water supply systems and the water-energy nexus—A review. *Water Resources and Industry*, 32, 100266.

- Rossi, R., Gelfusa, M., Murari, A., & JET contributors. (2023). On the potential of physics-informed neural networks to solve inverse problems in tokamaks. *Nuclear Fusion*, 63(12), 126059.
- Sajja, R., Xiong, S., Mermer, O., Sermet, Y., & Demir, I. (2025). A Bibliometric Overview of Conversational AI in Hydrology and Environmental Sciences. *Information Geography*, 100030.
- Sarkar, A., Hakimi, A., Chen, X., Huang, H., Lu, C., Demir, I., & Jannesari, A. (2025, November). HydroGAT: Distributed Heterogeneous Graph Attention Transformer for Spatiotemporal Flood Prediction. In *Proceedings of the 33rd ACM International Conference on Advances in Geographic Information Systems* (pp. 1019-1030).
- Schubert, A., & Braun, T. (1986). Relative indicators and relational charts for comparative assessment of publication output and citation impact. *Scientometrics*, 9(5), 281-291.
- Secci, D., Godoy, V. A., & Gómez-Hernández, J. J. (2024). Physics-informed neural networks for solving transient unconfined groundwater flow. *Computers & Geosciences*, 182, 105494.
- Shen, C. (2018). A transdisciplinary review of deep learning research and its relevance for water resources scientists. *Water Resources Research*, 54(11), 8558-8593.
- Shen, C., Appling, A. P., Gentine, P., Bandai, T., Gupta, H., Tartakovsky, A., ... & Lawson, K. (2023). Differentiable modelling to unify machine learning and physical models for geosciences. *Nature Reviews Earth & Environment*, 4(8), 552-567.
- Sit, M., Seo, B. C., Demiray, B., & Demir, I. (2024). EfficientRainNet: Leveraging EfficientNetV2 for memory-efficient rainfall nowcasting. *Environmental Modelling & Software*, 176, 106001.
- Slater, L., Blougouras, G., Deng, L., Deng, Q., Ford, E., Hoek van Dijke, A., ... & Zhang, B. (2025). Challenges and opportunities of ML and explainable AI in large-sample hydrology. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 383(2302).
- Solomatine, D. P., & Ostfeld, A. (2008). Data-driven modelling: some past experiences and new approaches. *Journal of hydroinformatics*, 10(1), 3-22.
- Song, Y., Bindas, T., Shen, C., Ji, H., Knoben, W. J., Lonzarich, L., ... & Lawson, K. (2025). High-resolution national-scale water modeling is enhanced by multiscale differentiable physics-informed machine learning. *Water Resources Research*, 61(4), e2024WR038928.
- Stare, J., & Kejžar, N. (2014). On standardization of the Activity Index. *Journal of Informetrics*, 8(3), 503-507.
- Tabari, H., Hosseinzadehtalaei, P., Thiery, W., & Willems, P. (2021). Amplified drought and flood risk under future socioeconomic and climatic change. *Earth's Future*, 9(10), e2021EF002295.
- Taghizadeh, M., Zandsalimi, Z., Nabian, M. A., Shafiee-Jood, M., & Alemazkoo, N. (2025). Interpretable physics-informed graph neural networks for flood forecasting. *Computer-Aided Civil and Infrastructure Engineering*, 40(18), 2629-2649.
- Tartakovsky, A. M., Marrero, C. O., Perdikaris, P., Tartakovsky, G. D., & Barajas-Solano, D. (2020). Physics-informed deep neural networks for learning parameters and constitutive relationships in subsurface flow problems. *Water Resources Research*, 56(5), e2019WR026731.

- Thiyagalingam, J., Shankar, M., Fox, G., & Hey, T. (2022). Scientific machine learning benchmarks. *Nature Reviews Physics*, 4(6), 413-420.
- Towfiqul Islam, A. R. M., Mamun, M. A. A., Uddin, M. N., Faysal Sowrav, S. F., Alam, M. N. E., Khan, S. R., ... & Choudhury, T. R. (2026). Explainable and physics-informed machine learning for seasonal water quality prediction in the monsoon-driven Padma River Basin, Bangladesh. *Environmental Geochemistry and Health*, 48(3), 140.
- Vinuesa, R., & Brunton, S. L. (2022). Enhancing computational fluid dynamics with machine learning. *Nature Computational Science*, 2(6), 358-366.
- Wibowo, A., Amri, I., Surahmat, A., & Rusdah, R. (2025). Leveraging artificial intelligence in disaster management: A comprehensive bibliometric review. *Jambá-Journal of Disaster Risk Studies*, 17(1), 1776.
- Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. (2022). Integrating scientific knowledge with machine learning for engineering and environmental systems. *ACM Computing Surveys*, 55(4), 1-37.
- Xiang, Z., Demir, I., Mantilla, R., & Krajewski, W. F. (2021). A regional semi-distributed streamflow model using deep learning. *EarthArxiv*, 2152. <https://doi.org/10.31223/X5GW3V>
- Xiang, Z., & Demir, I. (2021). High-resolution rainfall-runoff modeling using graph neural network. *arXiv preprint arXiv:2110.10833*.
- Xu, Q., Shi, Y., Bamber, J. L., Tuo, Y., Ludwig, R., & Zhu, X. X. (2025). Physics-aware machine learning revolutionizes scientific paradigm for process-based modeling in hydrology. *Earth-Science Reviews*, 105276.
- Yang, D., Yang, Y., & Xia, J. (2021). Hydrological cycle and water resources in a changing world: A review. *Geography and sustainability*, 2(2), 115-122.
- Yaseen, Z. M., El-Shafie, A., Jaafar, O., Afan, H. A., & Sayl, K. N. (2015). Artificial intelligence based models for stream-flow forecasting: 2000–2015. *Journal of Hydrology*, 530, 829-844.
- Ye, S., Li, J., Chai, Y., Liu, L., Sivapalan, M., Ran, Q., & Tang, H. (2026). Explainable artificial intelligence (XAI) for scaling: An application for deducing hydrologic connectivity at watershed scale. *Hydrological Processes*, 40(5), e70559.
- Yeşilköy, S., Baydaroğlu, Ö., Singh, N., Sermet, Y., & Demir, I. (2024). A contemporary systematic review of cyberinfrastructure systems and applications for flood and drought data analytics and communication. *Environmental Research Communications*, 6(10), 102003.
- Yuan, B., Choo, C. S., Yeo, L. Y., Wang, Y., Yang, Z., Guan, Q., ... & Chen, X. (2025). Physics-informed machine learning in geotechnical engineering: a direction paper. *Geomechanics and Geoengineering*, 20(5), 1128-1159.
- Zhou, X., Prigent, C., & Yamazaki, D. (2021). Toward improved comparisons between land-surface-water-area estimates from a global river model and satellite observations. *Water Resources Research*, 57(5), e2020WR029256.
- Zounemat-Kermani, M., & Kheimi, M. (2026). Explainable Artificial Intelligence in Hydrology: A Review. *Water Resources Management*, 40(106).