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Smart Hydrology: The Role of Artificial Intelligence in Sustainable Soil and Water Resource Management

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Abstract

Water scarcity and soil degradation present significant barriers to sustainable development, further intensified by the limitations of conventional hydrological models in addressing the complexity and variability of natural systems. Artificial Intelligence (AI) has emerged as a powerful tool for overcoming these challenges by enabling predictive analytics, real-time monitoring, and data-driven decision-making, thereby enhancing the efficiency and adaptability of soil and water resource management. This study explores the application of AI, particularly Machine Learning (ML), Deep Learning (DL) and other computational techniques, in key hydrological processes such as rainfall prediction, evapotranspiration estimation, soil moisture monitoring, groundwater level forecasting, and water quality assessment. Additionally, we examine the integration of AI with remote sensing, IoT-enabled hydrological networks, and simulation models to develop intelligent and responsive water management systems. The paper also discusses major challenges associated with AI-driven hydrology, including robust data infrastructure, improved model interpretability, and ethical considerations. By harnessing AI-driven advancements, hydrological systems can become more resilient, optimise resource utilisation, and contribute significantly to long-term environmental sustainability.

Major Findings: *Artificial Intelligence significantly enhances the performance of Ocean Renewable Energy (ORE) systems by improving energy prediction accuracy, optimizing system operations, and enabling real-time adaptive control. AI techniques such as machine learning, deep learning, and reinforcement learning are effectively utilized for forecasting ocean conditions, managing energy output, and reducing operational costs. These advancements collectively contribute to making ORE systems more reliable, efficient, and scalable for sustainable energy generation.*

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Keywords: *Artificial Intelligence, Deep Learning, Groundwater Monitoring, Hydrological Modelling, Machine Learning, Predictive Analytics, Remote Sensing, Sustainable Water Management*

1.0 Introduction

Hydrology plays a critical role in managing water resources for agricultural, industrial, and domestic applications. However, growing population pressures, climate change, and unsustainable land-use practices are intensifying water scarcity and soil degradation worldwide. Traditional hydrological models, while valuable, often rely on simplified assumptions and struggle to accurately capture the complex interactions within natural systems. Moreover, these conventional approaches face challenges in predicting and managing hydrological processes due to climate variability and increasing anthropogenic influences. This necessitates the adoption of innovative strategies for more effective and sustainable resource management. AI has emerged as a transformative tool in hydrology, offering advanced data-driven solutions that can enhance prediction accuracy, optimise resource utilisation, and support real-time decision-making. AI techniques, including ML, DL, and predictive analytics, enable the modelling of intricate hydrological patterns, thereby improving water availability assessments, flood forecasting, soil moisture monitoring, and groundwater management. Furthermore, integrating AI with remote sensing, IoT-enabled sensor networks, and simulation models facilitates the development of intelligent, adaptive hydrological systems. Climate change-driven hydrological extremes pressure water resources, leading to increased groundwater reliance and extraction. Hydrology, the science concerning the movement, distribution, and quality of water on Earth, underpins the sustainable management of water resources crucial for agriculture, industry, and domestic consumption[1]. However, escalating population densities, the exacerbating effects of climate change, and unsustainable land-use practices are converging to intensify water scarcity and soil degradation on a global scale[2]. Traditional hydrological models, while providing a foundational understanding of water systems, frequently rely on simplifying assumptions that limit their ability to accurately represent the intricate interactions within natural environments[3]. Moreover, these conventional approaches face challenges in predicting and managing hydrological processes due to climate variability and increasing anthropogenic influences[4]. This necessitates the adoption of innovative strategies for more effective and sustainable resource management[5]. AI has emerged as a transformative tool in hydrology, offering advanced data-driven solutions that can enhance prediction accuracy, optimise resource utilisation, and support real-time decision-making. AI techniques, including machine learning, deep learning, and predictive analytics, enable the modelling of intricate hydrological patterns, thereby improving water availability assessments, flood forecasting, soil moisture monitoring, and groundwater management. Furthermore, integrating AI with remote sensing, IoT-enabled sensor networks, and simulation models facilitates the development of intelligent, adaptive hydrological systems.

The convergence of AI and hydrology offers unprecedented opportunities to address the pressing challenges of water resource management in the face of climate change and growing

human demands. Hydrological modelling, while a relatively mature area of study, often lacks reliable forecasts and early warning systems in regions most vulnerable to flood risks, but AI and open datasets are improving the precision, recall, and lead time of short-term forecasts of extreme riverine events[6]. Scientists can analyse extensive Earth and environmental science data, including climatic, atmospheric, pedological, hydrological, ecological, and biodiversity data, using online data sharing platforms, which aids in testing, analysing, and interpreting theories, prediction models, and experimental data, thereby promoting a deeper comprehension of environmental issues[7]. The integration of AI with remote sensing technologies enables the creation of sophisticated systems capable of real-time flood monitoring and prediction, thereby furnishing essential information for early warning systems and disaster preparedness[6]. AI algorithms can automate labour-intensive tasks, such as crop harvesting, pruning, and ploughing in agriculture, with the aid of autonomous tractors and harvesters guided by AI technologies, thus reducing the need for extensive human intervention[8]. Furthermore, the development of high-resolution remote sensing imagery and other geospatial datasets, coupled with AI-driven image processing

techniques, has revolutionised land cover mapping and change detection, providing essential data for hydrological modelling and land-use planning.

The growing frequency and intensity of climate change-driven hydrological extremes are placing unprecedented pressure on water resources, leading to increased groundwater reliance and extraction. AI techniques are especially helpful in creating early warning systems for the release of hazardous materials, self-governing pollution monitoring systems, and decision support systems, which can be applied to soil, air, and water[9]. AI has enabled the creation of flood warning systems that offer alerts ahead of time, even in previously unmonitored basins, showing the rising need for hydrologic data accessibility to enhance global access to reliable flood alerts[10]. The deployment of AI-powered decision support tools can aid water managers in making informed decisions regarding water allocation, reservoir operation, and drought mitigation, thereby enhancing the resilience of water systems to climate variability. Moreover, AI algorithms can optimise irrigation schedules based on real-time soil moisture data, weather forecasts, and crop water requirements, leading to significant water savings and improved agricultural productivity. This is achieved through the application of sensors and other embedded technologies in robots and drones, facilitating optimised irrigation, weeding, and spraying, thereby minimising water waste, and maintaining soil fertility[11]. By analysing energy consumption patterns, identifying inefficiencies, and recommending strategies for energy optimisation, ML algorithms are helping optimise energy systems and reduce greenhouse gas emissions[12].

The integration of AI into hydrological practices extends beyond predictive modelling and decision support, encompassing the development of intelligent sensor networks and autonomous monitoring systems. The capability of AI to swiftly analyse extensive datasets and identify patterns, anomalies, and trends in real-time makes it invaluable for environmental monitoring, including weather forecasting[13]. These systems can autonomously collect and transmit hydrological data from remote locations, providing continuous monitoring of water levels, streamflow, and water quality parameters. This type of AI is extremely useful in wastewater treatment by predicting parameters that are otherwise difficult to determine experimentally[14]. The incorporation of machine learning algorithms in smart irrigation management systems plays a pivotal role in processing vast amounts of data, predicting plant water stress, modelling climate effects, and optimising irrigation[15].

Smartphones, which typically consume between 2–6 W of power, encounter significant thermal management issues during high-performance activities like gaming or extended camera use. This research investigates the use of passive Phase Change Material (PCM) cooling as a superior alternative to conventional methods such as convection and heat pipes, which lose efficiency at elevated power levels[16]. Simulations were carried out on FR4, silicon, and copper-clad boards, each embedding nine components under varying airflow scenarios[17]. Among the materials, copper cladding showed the best performance, reducing component temperatures by 30–47°C at 5 m/s airflow, cutting the airflow requirement by 2 m/s, and improving chip cooling by 1.50–11.12°C. A minichannel PCM cooling setup was also assessed, where N-Eicosane outperformed paraffin wax and Attapulgite (ATP) 78 by lowering temperatures to 51.520°C—a 0.5°C and 1.35°C improvement, respectively[18]. Additional studies encompass minijet impingement cooling[19], nanofluids[20], efficient water faucets[21] and heat transfer improvements using twisted tapes[22–24]. A broader review of electronic cooling technologies highlights recent advances and challenges under extreme conditions. Another study enhances engine efficiency and emissions using biodiesel blends. Innovations like solar collectors using recycled aluminium cans improve drying rates, while numerical analysis assesses thermal properties of cooling substrates, Computational Fluid Dynamics (CFD) and wind tunnel testing improve aerodynamics, and fuzzy logic is used to model heat transfer in twisted tape heat exchangers[25–33]. Studies on corrugated twisted tapes in double-pipe exchangers show notable heat transfer gains, while PCM-based cooling for circuits is explored under extreme environments. Wind rose analysis and sensor data evaluate turbine thermal profiles, and other work investigates deformation behaviour in welded steel plates[34–41]. Comparative studies assess mono-composite and metal leaf spring performance, real-time automation enhances surface roughness measurement, and CFD simulations optimise counter-flow double-pipe heat exchanger performance. Heating, Ventilation, Air Conditioning, and Refrigeration (HVACR) duct design is improved using algorithmic models, nanofluids boost heat exchange efficiency, and vehicle safety systems are

enhanced via energy-absorbing bumpers. Furthermore, eco-friendly adsorbents like *Tinospora cordifolia* biocarbon are tested for zinc ion removal[42–48]. Research on TRIP steel plate thickness examines its role in strengthening Nd: YAG laser-welded joints, while other studies explore the mechanical responses of curved steel plates with varying thickness. Computational studies continue to improve IC chip cooling using PCMs, and fuzzy logic supports the prediction of heat transfer in systems using wavy twisted tape inserts. Finally, the influence of oxygenated additives in gasoline is studied for their impact on emission reduction, offering environmental advantages[49–60].

This paper explores the potential of AI in revolutionising hydrological science by fostering "smart hydrology" systems aimed at sustainable soil and water resource management. We examine key AI applications in hydrological processes, highlight the benefits of AI integration with other emerging technologies, and discuss the challenges and future directions for AI-driven hydrological research and practice. By leveraging AI innovations, hydrological systems can become more resilient, adaptive, and effective in addressing global water and soil resource challenges.

2.0 AI Applications in Hydrology

AI has revolutionised hydrology by enhancing the accuracy, efficiency, and adaptability of water resource management. AI-driven techniques, including ML and DL, are widely applied in various hydrological processes such as rainfall forecasting, streamflow prediction, groundwater level monitoring, and water quality assessment. These models analyse vast

datasets to identify complex patterns, enabling improved decision-making for flood risk management, irrigation optimisation, and climate resilience. Additionally, the integration of AI with remote sensing, IoT-enabled sensor networks, and simulation models facilitates real- time monitoring and predictive analytics, paving the way for intelligent and sustainable hydrological systems. Figure 1 represents the key areas and trends in research growth.

2.1 Machine Learning for Hydrological Forecasting

ML techniques, including neural networks, support vector machines, and decision trees, are widely used

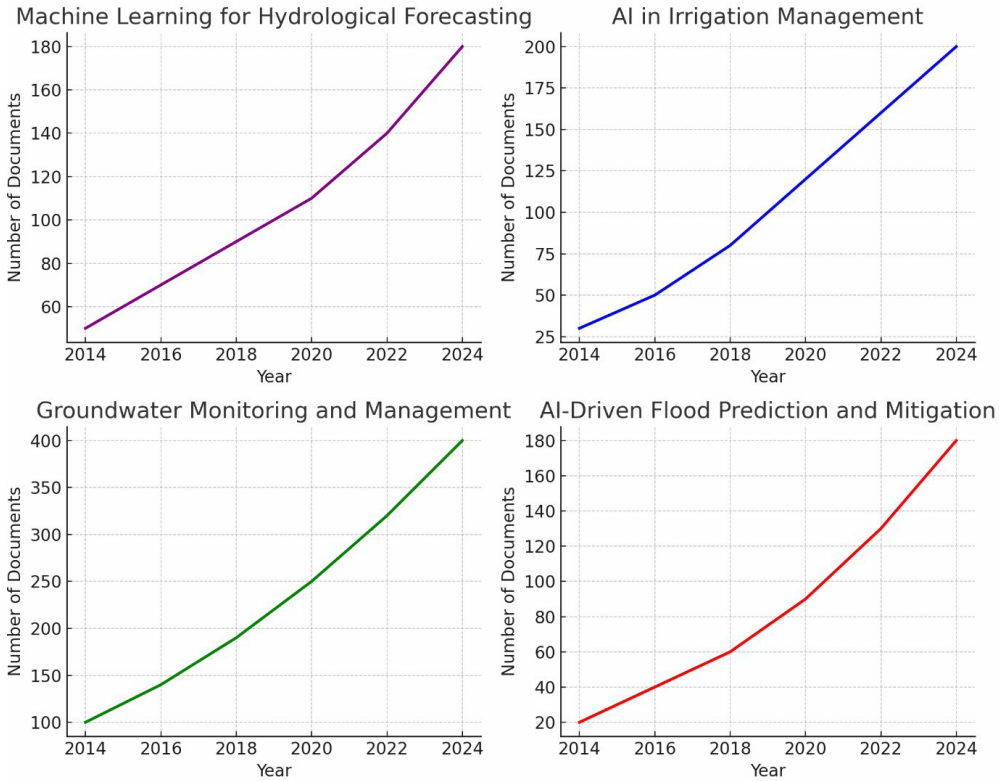


Figure 1. Key areas and trends in research growth

for hydrological predictions. These models analyse historical data to forecast precipitation, streamflow, and drought occurrences, providing actionable insights for water management authorities. The research introduces a novel hybrid machine learning model, WKELM-R, combining MVMD, Boruta-XGBoost, and Gradient Based Optimiser (GBO), to enhance multi-step-ahead streamflow forecasting by addressing non-stationarity, feature selection, and parameter optimisation, demonstrating superior performance in a North Dakota watershed[61].These data-driven approaches offer notable advantages over traditional methods, including enhanced accuracy, computational efficiency, and the ability to capture non-linear relationships within hydrological data[62]. ML models have shown the potential to improve accuracy, reduce calculation time, and lower model development costs in flood forecasting[63,64]. Hybridisation, data decomposition, algorithm ensemble, and model optimisation are effective strategies for improving ML methods, as well[61]. In the field of

drinking water supply, neural-network-based and regression-based models are the predominant choices, which highlights their efficacy in addressing intricate water management challenges[65]. By applying digital solutions and machine learning in irrigation management, it is possible to address issues such as water scarcity and environmental sustainability[66]. Figure 2 represents the ML techniques for hydrological forecasting.

The application of ML and data analytics in digital water metering offers opportunities to promote water conservation by analysing water consumption data and providing feedback to consumers and water utilities[67]. Several models, which employ both statistical and machine learning techniques, have been proposed that predict water demands and successfully identify features impacting water demand trends for rural and metropolitan areas[68]. It has been shown that ML approaches can improve the precision of predicting water quality and quantity, which supports sustainable water management and resource allocation. ML algorithms are used to evaluate and predict source water quality, contributing to early warning and control of pollution in drinking water[69]. Water distribution networks can benefit from machine learning algorithms, which facilitate water loss management by identifying areas with high leakage rates and optimising pressure management. The integration of advanced computing and machine learning algorithms into water distribution networks helps to predict pressure changes and prevent emergencies, enhancing the

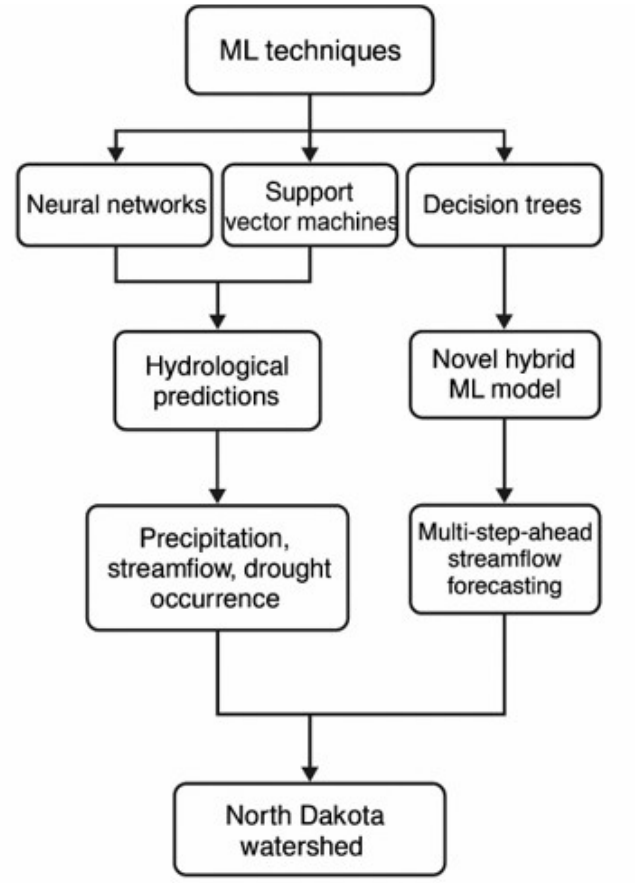


Figure 2. ML techniques for hydrological forecasting.

efficiency and sustainability of resource management[70]. The use of machine learning in flood prediction models has significantly increased over the past two decades, providing cost-effective solutions and better performance. A flood prediction system using machine learning models can deliver flood probabilities based on location and time queries, integrating multi-model deep learning methods like Support Vector Machines, Neural Networks, and Extreme Learning Model to predict flood chances based on environmental, climatic, and geographical factors[71]. By

developing Flood Early Warning Systems using ML techniques that aim to forecast flood warnings with sufficient lead time for decision making, ML techniques have gained popularity among hydrologists. These systems can mimic the complex mathematical expressions of physical flood processes and help to reduce risk, inform policy, minimise loss of life, and reduce property damage. The development of flood prediction models contributes to risk reduction, policy suggestions, minimisation of the loss of human life, and reduction of the property damage associated with floods[72].

2.2 AI in Irrigation Management

Smart irrigation systems leverage AI algorithms to optimise water distribution based on soil moisture levels, weather predictions, and crop requirements. This technology minimises water wastage and enhances agricultural sustainability. AI-driven smart irrigation systems, integrating IoT and data analytics, provide precise water management for sustainable agriculture, facing challenges of cost and expertise, but promising enhanced efficiency and food security. An automatic irrigation control system supported by machine learning and real-time sensor data provides the user with real-time and historical data, adapting water management by predicting the best time of day for water administration[73]. By predicting crop yields, anticipating potential diseases, and providing recommendations for best farming practices by analysing vast amounts of data from various sources, farming becomes more proactive rather than reactive[74]. ML models can be used to predict irrigation water requirements by analysing factors like evapotranspiration, which can help to improve irrigation scheduling and save water. Using machine learning to model and predict the spatial distribution of soil attributes contributes to precision agriculture and optimises irrigation practices. Groundwater supplies are increasingly relied upon and extracted due to climate change-induced hydrological extremes pressing water resources. Methods that improve the accuracy of irrigated areas are critical for supporting decision-making on irrigation expansion[75]. By analysing factors such as meteorological data, soil properties, and crop types, ML techniques can model and predict the spatial distribution of soil attributes, which optimises irrigation practices. Soil moisture loss is a significant factor in irrigation efficiency, and predicting it is challenging due to the numerous influencing factors like soil texture, weather conditions, and plant characteristics[76]. ML algorithms can forecast and optimise irrigation by analysing time series data and other factors impacting soil moisture variations[77]. Integrating remote sensors, such as temperature, humidity, soil moisture, water level, and ph sensors, can provide insights into active farming, increasing accuracy and practicality in dealing with field challenges[78]. ML models are utilised to create decision support tools that aid farmers in making more informed decisions about irrigation timing and water allocation, enhancing water use efficiency and promoting sustainable water management practices[79]. Integrating data from multiple sources, including climate, topography, and soil properties, improves decision-making, soil health monitoring, and our understanding of the interaction between these factors and agricultural land use and crop patterns[80]. Figure 3 represents. AI in irrigation management.

The use of ML in agriculture improves predictions by identifying relationships between input and response variables, while also making it more easily applicable than simulation crop models because it does not require expert knowledge or extensive user skills to calibrate the model[81]. ML algorithms determine patterns and discover knowledge from datasets, which can be used along with smartphone cameras and AI techniques to assess soil elements quickly and inexpensively[82]. By leveraging ML, complex data-driven models can be developed with

minimal feature engineering, eliminating the need for an in-depth understanding of the underlying processes, provided sufficient training data is available[83].

2.3 Groundwater Monitoring and Management

AI-powered models process satellite imagery and sensor data to track groundwater levels and predict depletion trends. This information aids in the sustainable extraction and replenishment of groundwater resources. The study evaluates various Artificial Neural Network (ANN) architectures for robust groundwater level forecasting in the overexploited Messara Valley, aiming to identify an optimal design for accurate predictions up to 18 months ahead. Additionally, ML techniques are employed to model groundwater contamination pathways and optimise remediation strategies, protecting water supplies and minimising environmental impact. By using ML and IoT, smarter and more automatic decision-making mechanisms can be obtained in agriculture. ML is capable of processing large numbers of inputs and handling non-linear tasks[84].

For instance, AI algorithms can identify and classify different soil types using image recognition techniques, providing valuable data for soil mapping and land management[85]. By providing predictive insights, AI enables proactive and adaptive management approaches, ensuring the long-term sustainability of groundwater resources[86]. Using ML algorithms to determine spatial relationships and patterns in large environmental datasets to identify contamination sources. ML algorithms also concentrate on rules from data and apply learned insight

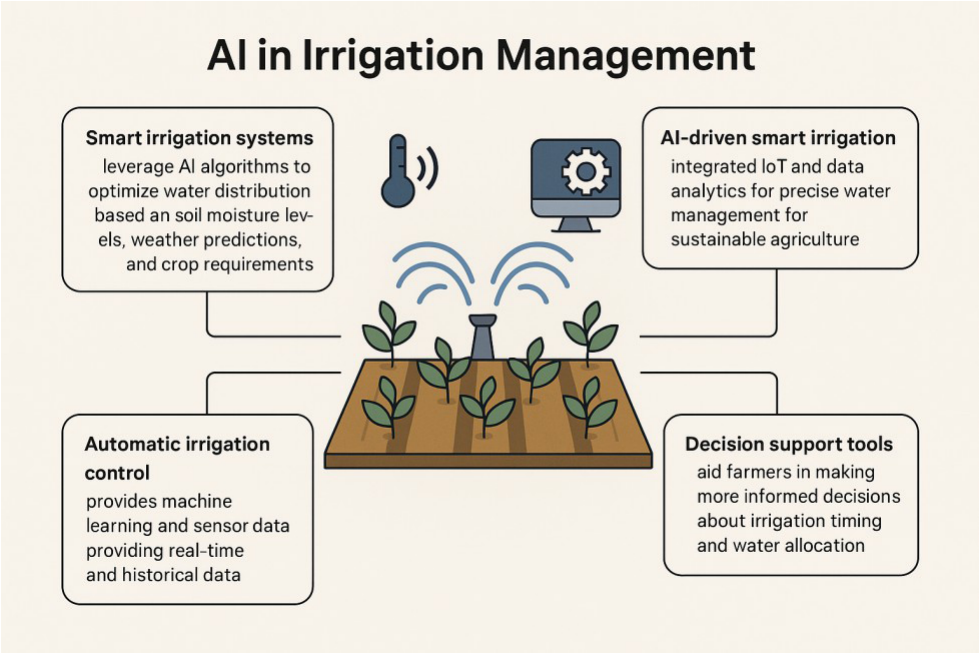


Figure 3. AI in irrigation management.

to assess new data, allowing their gained insights to solve many distinct problems ranging from classification and regression to clustering[87]. Figure 4 represents Groundwater monitoring and management system.

Effective prediction of water quality is essential for controlling water pollution and improving water management to ensure safe drinking water sources in the future. A deep learning-based model is used for predicting groundwater quality and is compared to three other machine learning models, namely, random forest, extreme gradient boosting, and artificial neural network[88]. The ability of ML models to be trained and function with limited data makes them very useful for water quality prediction in developing nations where data are often limited. ML approaches are used to predict full groundwater images based on sequences of monthly groundwater maps. This is especially relevant as groundwater is increasingly used as a source for drinking water.

2.4 AI-Driven Flood Prediction and Mitigation

Advanced AI models integrate climate data, river flow dynamics, and historical flood patterns to predict flood occurrences. Real-time alerts and simulations enable authorities to implement preventive measures and mitigate disaster impacts. Integrating machine learning

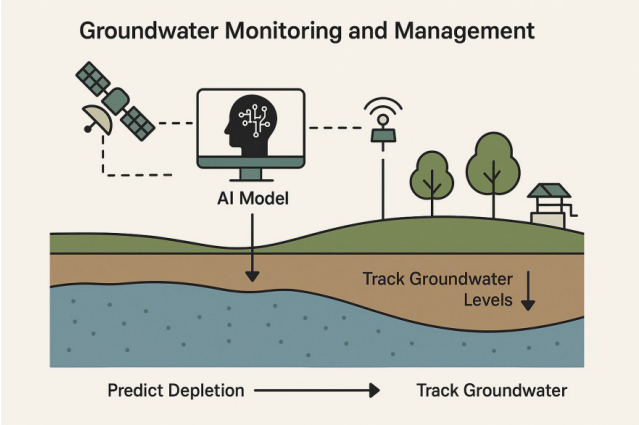


Figure 4. Groundwater monitoring and management.

techniques with geographic information systems and remote sensing data enhances flood susceptibility mapping and risk assessment. These models can assess geological hazard susceptibility by extracting useful information from complex datasets efficiently, reducing reliance on human subjectivity[89]. AI models support the creation of flood inundation maps that show the extent and depth of flooding, aiding in emergency response and urban planning[90]. Furthermore, machine learning techniques, including logistic regression, variance analysis, decision trees, neural networks, K-nearest neighbour algorithms, and support vector machines, are employed to predict

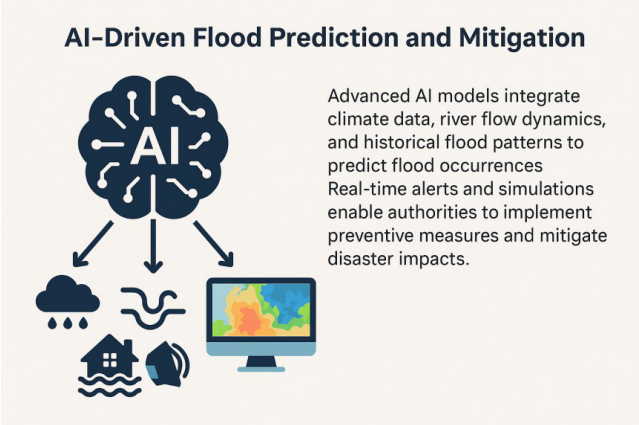


Figure 5. AI-driven flood prediction and mitigation.

debris floods, showcasing the superiority of AI methods over traditional statistical methods. Figure 5 represents AI-driven flood prediction and mitigation system.

By leveraging AI, flood prediction systems provide accurate and timely warnings, enabling communities to prepare and respond effectively, thus minimising economic losses and protecting lives. Some scientists apply conceptual models or artificial intelligence models to predict the typical floods and the debris floods[91]. Deep learning models offer increased accuracy and speed compared to traditional approaches and numerical methods, making them ideal for flood management[92]. Applying convolutional neural network technology for disaster prevention and early warnings is a new trend[93]. The use of deep learning in flood management helps to overcome the limitations of slow numerical models and improve the results of traditional flood mapping methods[92]. One can integrate local parameters, increase the size of acceptable error bounds, and combine different algorithms to achieve better performance of a model for flood prediction[94]. By combining data from diverse sources, AI models improve the accuracy and reliability of flood forecasts, enabling more effective disaster management strategies.

3.0 Challenges in AI-Based Hydrology

Despite its advantages, AI implementation in hydrology faces challenges such as data availability, model accuracy, and computational constraints. The lack of high-quality datasets and standardised methodologies limits the effectiveness of AI applications. Additionally, AI models require significant computational power and expertise, posing barriers to widespread adoption. It's critical to handle uncertainty in model input data, model structure, parameters, and calibration data by quantifying and reducing it. Addressing these challenges through data sharing, collaborative research, and technological advancements is crucial for maximising the potential of AI in hydrology. Overcoming these challenges will facilitate the development of robust and reliable AI solutions for sustainable water resource management[95]. While deep learning models have shown great results when properly trained, the computational cost of training them can be very high.

Climate change is intensifying the pressure on water resources globally, which heightens the importance of effective water management strategies[96]. Addressing the limitations of traditional hydrological models necessitates the adoption of innovative, data-driven solutions. The figure 6 represents the various challenges in AI based hydrology.

Integrating multiple strategies, including modern AI and remote sensing, into hydrological modelling could pave the way for more sustainable and resilient management of water resources in the face of growing environmental challenges[97-99]. Employing AI in hydrology facilitates the development of intelligent systems that enhance prediction accuracy, optimise resource utilisation, and support real-time decision-making, thereby promoting sustainability. The ability of AI to process complex, multi-dimensional data enhances the understanding of hydrological processes and forecasting of future trends[100]. Early warning and emergency response to destructive river floods depend on accurate and timely forecasts[101].

4.0 Overall Summary

This study presents a comprehensive exploration of the transformative role of AI in the domain of hydrology, particularly for sustainable soil and water resource management. With the global challenges of water scarcity, climate variability, and soil degradation intensifying, conventional hydrological models have struggled to offer accurate and timely solutions. AI, especially through ML and deep learning DL techniques, offers a powerful alternative by enabling high-precision predictions, real-time monitoring, and dynamic decision-making capabilities. The paper highlights how AI models have been effectively integrated into various hydrological

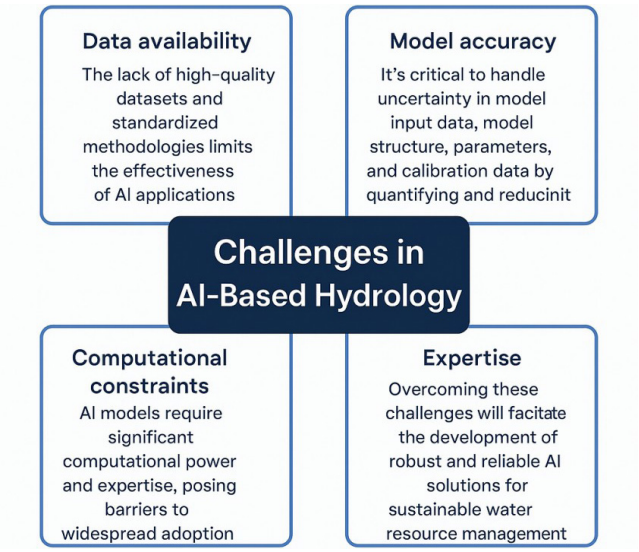


Figure 6. Challenges in AI–based hydrology

applications such as rainfall forecasting, streamflow prediction, groundwater level estimation, irrigation optimisation, and flood risk assessment.

Smart irrigation systems utilising AI and IoT technologies optimise water usage by analysing soil moisture, weather patterns, and crop requirements, thereby reducing waste and promoting sustainable agriculture. Groundwater monitoring, another crucial focus area, benefits from AI-powered remote sensing and ANN-based forecasting, which allow early identification of depletion trends and contamination risks. AI has also greatly enhanced flood prediction capabilities by integrating geospatial data, historical flood records, and real-time river dynamics into ML frameworks, enabling the creation of early warning systems and inundation maps that support emergency responses and urban planning. These developments mark a significant step forward in hydrological resilience and disaster preparedness.

Despite these advancements, the implementation of AI in hydrology faces several challenges. These include the need for large, high-quality datasets, limitations in model transparency and interpretability, high computational demands, and the lack of standardised methodologies. Additionally, the training and deployment of AI models require technical expertise, which can be a barrier for wide-scale adoption in resource-constrained settings. To overcome these issues, the study advocates for increased data sharing, interdisciplinary collaboration, and the adoption of explainable AI approaches to improve model accountability and usability.

Looking ahead, the integration of AI with complementary technologies such as remote sensing, Geographic Information Systems (GIS), blockchain, and IoT will further enhance the

accuracy and scalability of intelligent hydrological systems. Moreover, the development of culturally sensitive, ethically sound, and environmentally sustainable AI frameworks is essential to ensure inclusive and equitable benefits. Overall, this research underscores that AI is not merely a technological enhancement but a paradigm shift toward smart, adaptive, and sustainable water resource governance in the face of escalating global environmental pressures.

5.0 Research Gaps

Despite the significant progress in applying AI to hydrological sciences, several critical research gaps remain that hinder the full realisation of its potential for sustainable soil and water resource management. These gaps span across data infrastructure, model design, integration techniques, interpretability, and practical deployment.

1. **Data Scarcity and Quality Issues:** One of the most pressing challenges is the limited availability of high-quality, long-term, and high-resolution hydrological datasets, particularly in developing regions. Many AI models require large datasets to train effectively, and the lack of standardised data collection protocols leads to inconsistencies across regions. Additionally, missing values, noise, and poor spatiotemporal resolution reduce model accuracy and reliability.
2. **Model Interpretability and Transparency:** While complex AI models such as deep learning networks offer high accuracy, they often operate as "black boxes," making it difficult for hydrologists and decision-makers to understand how predictions are generated. This lack of interpretability undermines trust in AI systems and limits their adoption for critical applications such as flood risk management and groundwater policy design. Research on explainable AI (XAI) in hydrology is still in its infancy and needs further development.
3. **Integration with Physics-Based Models:** Traditional physics-based hydrological models are well-understood but limited in capturing nonlinear

relationships and dynamic feedbacks. On the other hand, AI models are excellent at learning patterns but often disregard physical laws. There is a significant research gap in hybrid modelling frameworks that effectively combine data-driven AI with physically based models to improve robustness, generalisation, and physical realism.

4. **Computational Constraints and Resource Demands:** Deep learning models, especially those with large architectures, are computationally intensive and often require high-end GPUs and cloud infrastructure. This limits scalability and excludes resource-limited institutions or regions from fully utilising AI in hydrology. Research is needed to develop lightweight, energy-efficient, and scalable AI models that can be deployed on low-power devices and embedded systems.
5. **Ethical and Socio-Environmental Considerations:** The ethical implications of AI deployment, including bias in training data, data privacy, and equitable access to AI tools, are often overlooked. There is insufficient attention paid to how AI applications in water management could exacerbate social inequalities or environmental risks. Research must focus on developing ethical guidelines and socially responsible AI strategies tailored to hydrological contexts.
6. **Lack of Interdisciplinary Collaboration:** The success of AI in hydrology depends on the collaboration between computer scientists, environmental engineers, hydrologists, policy makers, and local communities. However, most existing research is disciplinary in nature, lacking integration across fields. There is a need for frameworks that foster co-development and knowledge exchange among stakeholders.
7. **Insufficient Real-Time and Edge-AI Deployment**: While AI models for forecasting and simulation have shown promise in offline environments, real-time deployment using edge computing and embedded systems is under-researched. More studies are needed to test and validate AI algorithms in real-world, time-sensitive hydrological monitoring systems.
8. **Limited Evaluation and Benchmarking:** There is no universally accepted benchmarking system or standardised protocol for evaluating AI models in hydrology, which makes it difficult to compare different methods and establish best practices. Research must focus on developing performance metrics that consider both accuracy and interpretability, especially for critical decision-making applications.

6.0 Future Prospects and Research Directions

Future research should focus on improving AI model interpretability, integrating AI with IoT-enabled smart hydrological networks, and developing more reliable data-sharing frameworks. The combination of AI with remote sensing, GIS, and blockchain technologies presents new opportunities for enhancing hydrological sustainability. Explainable AI methods can improve the transparency of AI models, making their decisions more understandable and trustworthy for operators[102]. AI systems can be further optimised to minimise their own environmental footprints, addressing the sustainability challenges associated with their increasing deployment[103]. Future research should also explore the ethical implications of AI in water management, ensuring equitable access to resources and avoiding unintended consequences[104,105]. Future studies of AI for sustainability should incorporate multilevel views, systems dynamics approaches, design thinking, psychological and sociological considerations, and economic value considerations to show how AI can deliver immediate solutions without introducing long-term threats to environmental sustainability[105]. Culturally appropriate organisational processes and individual practices to reduce the natural resource and energy intensity of human activities can be derived from AI. Addressing these research directions will lead to more effective and responsible AI solutions for sustainable water management. AI technologies have demonstrated potential in classifying waste, facilitating smart water management, and optimising heating, ventilation, and air conditioning systems, contributing to broader sustainability goals[106]. By examining current advancements, challenges, and opportunities at the intersection of AI and sustainability, we aim to inspire collaboration, innovation, and informed decision-making in pursuit of a more sustainable future for generations to come[107]. The use of AI in the field of hydrology promises more precise and sustainable management of water resources, supporting agriculture, industry, and domestic needs while addressing the issues of climate change and environmental degradation.

7.0 Conclusion

AI has emerged as a transformative force in modern hydrology, providing robust, data-driven solutions to some of the most pressing challenges in sustainable soil and

water resource management. This paper comprehensively examined the integration of AI, particularly ML and DL, across various hydrological applications—including flood forecasting, groundwater monitoring, irrigation scheduling, water quality assessment, and early warning systems. By leveraging AI's ability to process and analyse vast and complex datasets in real time, hydrological systems can now achieve greater adaptability, precision, and responsiveness to both natural and anthropogenic changes. Furthermore, the combination of AI with emerging technologies such as remote sensing, IoT-enabled networks, geospatial mapping, and big data analytics has led to the creation of intelligent, autonomous systems capable of continuous

environmental monitoring and real-time decision support. These advancements not only optimise water usage in agriculture and urban planning but also contribute to long-term environmental sustainability and resilience in the face of climate change. Despite these promising developments, several challenges persist, including data scarcity, model transparency, ethical concerns, and computational constraints. Addressing these through interdisciplinary collaboration, improved data-sharing frameworks, and the adoption of explainable AI techniques will be essential to fully harness the benefits of AI in hydrology. Ultimately, the integration of AI into water and soil resource management represents a paradigm shift toward intelligent and sustainable environmental stewardship, with far- reaching implications for global water security and ecological balance.

8.0 Author Contributions

Pallavi Vishnu Kharat: Conceptualisation of the study, primary literature review on AI in hydrology, drafting of the initial manuscript, and coordination among co-authors. **Milind Manikrao Darade**: Supervision, methodology development, review of hydrological modelling techniques, and final revision of the manuscript. **Pramod B. Dhamdhere**: Data collection and integration of AI and remote sensing applications, contributed to the irrigation and groundwater monitoring sections. **Babaso A. Shinde**: Research on machine learning algorithms for predictive water management, diagram creation, and content refinement. **Yogendra Patil**: Validation of AI models, assisted in preparing flood prediction case studies and contributed to data interpretation. **Rupesh Gangadhar Mahajan**: Technical writing, editing, and referencing; contributed significantly to the future research directions and discussion on interdisciplinary integration. **Anant Sidhappa Kurhade**: Review of deep learning applications in hydrology, graphical abstract inputs, and critical manuscript editing. **Shital Yashwant Waware**: Comparative analysis of AI techniques, support in modelling and formatting, and contribution to the summary and conclusion sections.

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