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EDITORIAL: INTEGRATION OF HYDROLOGICAL MODELS AND MACHINE LEARNING TECHNIQUES FOR WATER RESOURCES MANAGEMENT

Ren Jie Chin[1] and Sai Hin Lai[2*]
[1]Department of Civil Engineering, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, 43000 Kajang, Malaysia
[2]Department of Civil Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia

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*Corresponding author's email: shlai@unimas.my
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Abstract — Hydrology and water resources management ensure the sustainable use, conservation, and allocation of water in natural and engineered systems. Climate change, urbanization, and rising water demand necessitate advanced modeling approaches to enhance water security and resilience to extreme hydrological events. This editorial scope explores the integration of conventional hydrological models with machine learning to improve predictive accuracy, decision-making, and resource optimization. Physics-based models such as SWAT, VIC, and HEC-HMS simulate watershed processes, while hydraulic models like HEC-RAS and MIKE SHE assess flood risks. Groundwater models (e.g., MODFLOW) analyze aquifer dynamics, and optimization models support efficient reservoir and watershed management. Despite their reliability, these models require extensive calibration, high-resolution data, and struggle with capturing nonlinear hydrological complexities. Advancements in computational power and data availability enable machine learning to complement traditional models. Algorithms such as ANNs, SVMs, and RF enhance hydrological forecasting, while deep learning methods (LSTMs, CNNs) improve spatio-temporal predictions. Hybrid models integrating physical-based simulations with machine learning-driven corrections reduce uncertainties, enhance computational efficiency, and enable adaptive water management. Machine learning applications extend to flood forecasting, drought risk assessment, and climate change impact analysis, strengthening disaster mitigation efforts. Integrating AI with hydrological models offers promising advancements in real-time monitoring, infrastructure resilience, and water governance. However, challenges related to data availability, model interpretability, and computational complexity remain. Future research should focus on explainable AI, refined hybrid modeling, and machine learning-based decision-support systems. As AI, remote sensing, and big data evolve, their convergence with hydrological sciences will drive more intelligent and sustainable water management solutions.

***Keywords*:** hydrological modelling, integration, machine learning, water resources management

1.0 INTRODUCTION

Hydrology and water resources management are vital disciplines focused on the sustainable use, conservation, and distribution of water in both natural and engineered systems. With global challenges such as climate change, rapid population growth, and urban expansion intensifying pressure on water supplies, innovative research and advanced methodologies are crucial for ensuring efficient water management and bolstering resilience against hydrological extremes [1, 2].

This editorial scope spans a wide range of topics in hydrology and water resources management, addressing both theoretical and applied research. Areas of special interest include surface and groundwater hydrology, hydroclimatic variability, flood and drought forecasting, water quality assessment, and integrated water resources management (IWRM).

Approaches to water resources management can generally be divided into conventional modelling and machine learning-based techniques. Traditional methods rely on physical-based, process-driven models to simulate hydrological processes and manage water distribution. These models include: (i) hydrological models such as the

Soil and Water Assessment Tool (SWAT) [3, 4], Variable Infiltration Capacity (VIC) model [5, 6], and the Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) [7, 8]; (ii) hydraulic models for simulating floods and river flows, including Hydrologic Engineering Center's River Analysis System (HEC-RAS) [9, 10] and MIKE-Systeme Hydrologique Europeen (MIKE SHE) [11, 12]; (iii) groundwater flow and transport models like the Modular Three-Dimensional Finite-Difference Ground-Water Flow Model (MODFLOW) [13, 14]; and (iv) optimization and decision-support tools for managing reservoirs and watersheds [15, 16].

Advancements in computational power and the availability of large datasets have paved the way for machine learning (ML) as a powerful tool in water resources management. ML techniques offer data-driven insights and enhanced predictive capabilities, such as: (i) the application of Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests for hydrological forecasting [17, 18]; (ii) the use of deep learning models, including Long Short-Term Memory (LSTMs) networks and Convolutional Neural Networks (CNNs), for spatio-temporal water resource predictions [19, 20]; (iii) the development of hybrid models that integrate conventional hydrological modeling with ML to achieve higher accuracy [21, 22]; and (iv) innovative applications in flood prediction, drought assessment, and evaluating the impacts of climate change [23, 24].

By merging traditional modeling techniques with emerging machine learning methods, modern water resources management achieves greater precision, efficiency, and adaptability in response to environmental changes. Conventional hydrological models such as SWAT, HEC-HMS, and MODFLOW often face challenges when dealing with complex, nonlinear processes and demand extensive calibration. In contrast, machine learning—especially deep learning and hybrid approaches—enhances these simulations by learning from extensive datasets, correcting residual errors, and providing real-time forecasts with improved accuracy. This integration streamlines computational processes, automates feature extraction from satellite and sensor data, and refines water allocation through intelligent decision-support systems. Additionally, as ML-driven models continuously incorporate new climatic and hydrological data, they enhance flood and drought predictions, improve assessments of climate change impacts, and support resilient planning for water infrastructure. The synergy between conventional and AI-driven approaches ultimately creates a robust, data-informed, and adaptive framework for sustainable water resources management.

2.0 CONVENTIONAL MODELLING IN WATER RESOURCES MANAGEMENT

Traditional water resources management relies on models as essential tools for understanding and predicting water system behavior, supporting decision-making in water allocation, flood mitigation, and climate adaptation strategies.

Hydrological models are designed to simulate the movement and storage of water within a watershed, considering factors such as precipitation, infiltration, and runoff generation. The commonly used models include SWAT which is widely applied for evaluating land use changes and climate impacts; VIC model that is known for large-scale hydrological assessments; and HEC-HMS which provides detailed precipitation-runoff simulations for flood forecasting. Hydrological models offer a structured approach to understanding the water balance, including streamflow, evapotranspiration, and groundwater recharge. The models allow researchers and policymakers to assess the impacts of land-use changes, climate variability, and water management strategies. Many hydrological models incorporate satellite data to improve the accuracy of precipitation and soil moisture estimates [3, 5, 11]. Nevertheless, hydrological models require high-quality input data (e.g., rainfall, soil properties, land cover), which may be difficult to obtain in data-scarce regions. The accuracy of simulations depends on extensive calibration and validation, which can be time-consuming and computationally demanding. Also, many models assume homogeneity in watershed characteristics, leading to oversimplifications that may affect reliability [6, 7].

Hydraulic models focus on simulating water movement in rivers, floodplains, and engineered structures such as dams and levees. The examples of hydraulic models include HEC-RAS that is widely used for flood risk assessment and river hydraulic studies, and MIKE SHE which integrates surface and subsurface hydrology for catchment-scale simulations. The models provide detailed floodplain mapping and water surface elevation estimates, which are critical for disaster management. In addition, the hydraulic models assist in designing and evaluating flood control structures, drainage systems, and stormwater management plans. Furthermore, many hydraulic models now support 2D and 3D simulations, improving spatial resolution for complex hydrodynamic studies [9–12]. However, high-resolution hydraulic simulations require significant computational resources, especially when modelling large river basins. The accuracy of hydraulic models depends on well-defined boundary conditions, which may be uncertain or unavailable. Also, detailed topographic and bathymetric data are essential for accurate hydraulic simulations, but such a dataset is often limited or costly [10, 11].

Groundwater models are essential for understanding subsurface water movement, aquifer storage dynamics, and pollutant transport. The MODFLOW is the most widely used tool for simulating groundwater flow, supporting studies related to groundwater depletion, contamination, and sustainability. The models provide insights into recharge rates, aquifer storage changes, and groundwater-surface water interactions. In addition, groundwater models are valuable for monitoring pollution plumes and designing remediation strategies for contaminated sites. The output of the models may help policymakers to evaluate the impacts of groundwater extraction, climate change, and land-use changes on water availability. Despite the advantages, groundwater models require detailed information on aquifer properties, which may not be readily available. Model accuracy depends on rigorous calibration using historical groundwater level and flow data, which can be time-consuming. Furthermore, many models use simplified assumptions about subsurface heterogeneity, which may not fully capture local groundwater dynamics [13, 14].

Optimization models and decision-support systems are designed to enhance water allocation strategies, reservoir management, and policy formulation. These tools incorporate multi-objective decision-making frameworks, real-time data integration, and economic considerations to guide sustainable water resource planning. The tools optimize water distribution among competing users, improving resource efficiency. Decision-support systems integrate climate projections, helping policymakers develop adaptive water management strategies. Furthermore, modern decision-support tools utilize real-time sensor data and remote sensing observations for enhanced monitoring and forecasting. Nevertheless, large-scale optimization models require substantial processing power, limiting their application in real-time decision-making. The effectiveness of decision-support tools depends on stakeholder participation, which can be challenging to achieve. Also, many optimization models rely on simplified representations of socio-economic and environmental factors, potentially leading to biased outcomes [15, 16].

3.0 MACHINE LEARNING IN WATER RESOURCES MANAGEMENT

Unlike the conventional models, which rely on explicit equations and assumptions about hydrological and hydraulic processes, ML techniques are data-driven and can identify complex, nonlinear relationships between input variables and water-related outcomes. These capabilities make ML particularly useful for improving hydrological forecasting, flood prediction, drought assessment, and climate change impact analysis.

Supervised ML algorithms, such as ANNs, SVMs, and RF, have been widely employed in hydrology for streamflow prediction, precipitation forecasting, and water quality assessment. The models learn patterns from historical datasets and generalize them to make future predictions. Supervised ML models can efficiently capture nonlinear relationships between hydrological variables, leading to improved forecasting performance. Once trained, ML models can generate real-time predictions much faster than conventional model simulations. The models can integrate diverse data sources, including remote sensing, satellite observations, and sensor networks, enhancing prediction reliability. Nevertheless, the accuracy of ML models heavily depends on the quality and quantity of available training data. Data scarcity or bias can lead to unreliable predictions. Unlike process-based models, ML techniques do not explicitly account for hydrological principles, making it a challenge to interpret results from a scientific perspective. Furthermore, if not properly trained and validated, ML models may overfit to historical patterns and fail to generalize to new conditions [17, 18].

Deep learning models, such as LSTMs and CNNs, are particularly effective for capturing complex spatiotemporal patterns in hydrological data. LSTMs excel in processing time-series data (e.g., river discharge trends, precipitation variations), while CNNs are useful for spatial pattern analysis (e.g., flood extent mapping using satellite imagery). Deep learning models outperform traditional ML techniques in detecting intricate spatial and temporal dependencies in hydrological systems. Unlike conventional models that require manual selection of input variables, deep learning automatically extracts relevant features from raw data. In addition, the models can handle massive datasets from satellite sensors, remote sensing platforms, and IoT-based hydrological monitoring networks. However, there are some drawbacks for the deep learning models which training these models requires substantial computational resources, including powerful GPUs and large memory capacity. Also, deep learning models require extensive hyperparameter tuning and optimization, which can be time-consuming and resourceintensive. While deep learning models perform well in data-rich environments, they may struggle in regions with limited historical observations [19, 20].

A promising research direction involves hybrid modelling, where ML techniques are combined with traditional physical-based hydrological models to enhance accuracy, reduce uncertainty, and improve computational efficiency. These models leverage the process-based understanding of traditional hydrological simulations while incorporating ML-based corrections and uncertainty quantification. Hybrid models outperform standalone ML or traditional models by leveraging the strengths of both approaches. By integrating ML with physical-based constraints, hybrid models maintain the interpretability of traditional hydrological frameworks. The integrated ML techniques can help correct systematic biases in traditional ML models, improving overall prediction reliability. However, hybrid approaches require expertise in both hydrological modelling and ML, making the implementation more challenging. The integration process must be carefully calibrated to ensure that ML-based adjustments do not introduce inconsistencies into the physical model. While hybrid models improve accuracy, they may still require significant computational resources depending on the size and complexity of the dataset [21, 22].

Machine learning has proven highly effective in flood prediction, drought assessment, and climate change impact analysis by integrating historical climate data, real-time hydrological monitoring, and remote sensing observations. ML models can provide early warnings for floods and droughts, improving disaster preparedness and mitigation strategies. By analyzing historical climate trends, ML models help policymakers design adaptive water management strategies. Also, ML algorithms enhance the accuracy of flood extent mapping, groundwater depletion assessments, and land use change detection. However, ML-based climate models are subjected to uncertainties due to incomplete climate datasets, changing atmospheric conditions, and model extrapolation errors. The implementation of AI-driven disaster management strategies requires stakeholder collaboration, data transparency, and regulatory frameworks to ensure equitable water distribution. In addition, ML models trained on historical data may fail to account for future hydrological extremes influenced by climate change [22, 23].

4.0 CONCLUDING REMARKS

While conventional water resources management models provide robust, physics-based approaches for understanding hydrological and hydraulic processes, they also have inherent limitations in computational efficiency, uncertainty handling, and data requirements. The integration of machine learning in water resources management offers significant improvements in prediction accuracy, computational efficiency, and adaptability to environmental changes. However, challenges such as data dependency, model interpretability, and computational complexity must be addressed to maximize ML's potential. Future research should focus on developing hybrid ML-hydrological models by combining ML with physical-based models to enhance prediction robustness and uncertainty quantification. Also, in order to improve the interpretability of ML model, explainable AI (XAI) techniques can be used to make ML predictions more transparent and scientifically justifiable. On the other hand, expanding ML applications in water policy and governance can be achieved by integrating ML-driven decision support tools into real-time water allocation, disaster response, and infrastructure resilience planning. As advancements in artificial intelligence, remote sensing, and big data analytics continue to evolve, ML will play an increasingly vital role in shaping resilient, data-driven, and adaptive water management strategies for the future.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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