frontiers | Frontiers in Water

TYPE Editorial
PUBLISHED 27 June 2025
DOI 10.3389/frwa.2025.1637341

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OPEN ACCESS

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RECEIVED 29 May 2025
ACCEPTED 09 June 2025
PUBLISHED 27 June 2025

CITATION
He M and Rozos E (2025) Editorial: Harnessing artificial intelligence to address climate-induced challenges in water resources management.
Front. Water 7:1637341.
doi: 10.3389/frwa.2025.1637341

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Editorial: Harnessing artificial intelligence to address climate-induced challenges in water resources management

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KEYWORDS

artificial intelligence, machine learning, deep learning, water resources, climate, drought, flood

Editorial on the Research Topic
Harnessing artificial intelligence to address climate-induced challenges in water resources management

The intensifying effects of climate change are increasingly disrupting the hydrological cycle (Barnett et al., 2005; Wu et al., 2013), contributing to more extreme droughts (Satoh et al., 2022), erratic precipitation and flow (O'Gorman and Schneider, 2009; Diffenbaugh et al., 2017; Gudmundsson et al., 2021; Swain et al., 2025), and frequent flooding (e.g., Hirabayashi et al., 2013). These shifting patterns pose significant challenges for water resources planning and management, especially as traditional models often fall short in capturing the complex, non-linear dynamics of climate-driven hydrologic systems (Milly et al., 2008). Accurate and timely forecasting of hydrological extremes has become more critical than ever—not only to reduce loss of life and property but also to guide long-term planning in water supply and ecosystem protection. However, the high variability and uncertainty associated with climate impacts demand approaches that can learn from data, adapt to changing conditions, and operate at finer spatial and temporal resolutions.

Artificial intelligence (AI) offers a promising path forward—enabling the integration of vast and heterogeneous data sources, improving the precision of predictions, and supporting proactive decision-making (Kratzert et al., 2019; Camps-Valls et al., 2025). In particular, machine learning (ML) (Jordan and Mitchell, 2015) and deep learning (DL) (LeCun et al., 2015) models have shown great potential in extracting meaningful patterns from complex datasets such as remote sensing imagery, senor networks, reanalysis data, and hydrometeorological time series (Avand et al., 2021; Han et al., 2017; Nearing et al., 2024; Zhu et al., 2017). These AI techniques not only enhance predictive capabilities but also offer the flexibility to develop location-specific solutions, capture interactions between physical drivers, and improve lead times for early warning systems.

Early contributions have laid the groundwork for AI applications in the field of hydrology and water resources. For instance, Kratzert et al. (2018) provided one of the first comprehensive applications of Long Short-Term Memory (LSTM), a type of

DL model, in hydrology, demonstrating superior predictive skill over traditional models. Shen (2018) offered a broader perspective by reviewing DL applications across water sciences, highlighting how these models can not only enhance prediction but also serve as tools for scientific discovery by revealing underlying physical patterns. Complementing these efforts, Fang et al. (2017) employed DL to extend the Soil Moisture Active Passive satellite data, achieving seamless spatiotemporal coverage across the continental United States. Their approach significantly improved the resolution and continuity of soil moisture datasets, which are critical for hydrologic modeling and drought monitoring. Building on these advancements, Sawadekar et al. (2025) introduced a differentiable hydrologic modeling framework that fuses multiple precipitation datasets using interpretable neural networks. This fusion approach enhanced streamflow simulations, particularly for high-flow events, and provided spatially adaptive weighting of data sources, offering a more nuanced and accurate representation of precipitation inputs across diverse regions. Together, these foundational works underscore both the promise and the complexity of applying AI in hydrology and water resources, setting the stage for the more targeted and diverse studies included in this Research Topic.

This Research Topic brings together cutting-edge studies that apply AI methods to three central challenges in climate-impacted water systems: predicting precipitation and flood, downscaling coarse scale remote sensing water-related data, and developing interpretable deep learning models. The selected contributions span a range of modeling strategies—from LSTM-based neural networks and convolutional frameworks to ensemble machine learning techniques—each demonstrating how AI can be tailored to address specific needs while advancing scientific insight and practical application. A summary of each contribution is provided below.

The contribution by Hamou-Ali et al. demonstrates the application of Random Forests (RF) for generating high-resolution Total Water Storage (TWS) maps. This approach integrates multiple remote sensing datasets, including precipitation (GPM, 10 km resolution), normalized difference vegetation index (NDVI, 1 km), land surface temperature (LST, 1 km), actual evapotranspiration (AET, 500 m), a digital elevation model (DEM, 30 m), and the normalized difference snow index (NDSI, 500 m). The initial RF output is a TWS map at 1 km resolution. To enhance its reliability, the model output is rectified using data from GRACE satellites, which provide TWS information at a coarser resolution of 100 km. Specifically, the RF output is first aggregated to match the GRACE resolution, and the residuals (differences from GRACE data) are then disaggregated back to 1 km. This correction step yields a more accurate TWS estimation, enhancing our understanding of groundwater resources—particularly crucial in arid regions where groundwater plays a vital role in drought resilience.

Hafyani et al. explore the use of six ML models—Decision Tree, Random Forest, K-Nearest Neighbors (KNN), AdaBoost, XGBoost, and Long Short-Term Memory (LSTM)—for monthly precipitation forecasting. After comparing the performance of individual models, the study proposes a two-layer stacked learning approach. The first layer is trained on the original data, while the second layer, a meta-learner, is trained on the output of the first. This ensemble method achieved outstanding results, reducing the Root Mean Squared Error by more than 50% compared to the best-performing single model. Such improvement is particularly valuable in arid regions affected by the El Niño Southern Oscillation (ENSO), where climate complexity challenges forecasting efforts, and effective water management depends on accurate precipitation predictions.

Oddo et al. present an early warning system for extreme flood events using a hybrid deep learning architecture known as ConvLSTM, which combines a Convolutional Neural Network (CNN) with an LSTM model. The CNN processes four spatiotemporal datasets: NEXRAD Mosaic 8-bit Base Reflectivity, Noah LSM Soil Moisture, IMERG Final Precipitation L3 Rate, and KLWX Level-III NEXRAD 1-h Accumulated Precipitation. The CNN output is then passed to the LSTM, which captures temporal dependencies. In their case study, ConvLSTM outperforms a baseline LSTM model by effectively uncovering non-linear relationships between input variables and flood outcomes—without the need for explicit representation of a specific catchment. This makes it particularly suited to flashy watersheds with frequent and intense flood histories.

Zhang et al. introduces an interpretable DL architecture tailored for flood prediction in 531 watersheds across the continental United States. While LSTM models are widely adopted in hydrology for their strength in modeling sequential and non-linear patterns, they often lack transparency. To overcome this limitation, the authors embed a streamlined gating component between the inputs and the LSTM layers. This intermediary unit selectively filters and highlights influential meteorological variables and time lags, facilitating insight into the model's decision-making process. The filtered information is organized into four impact groups—short- and long-duration effects of both precipitation and temperature—enabling a clearer understanding of which drivers most affect flood outcomes. Compared to conventional LSTM models, the proposed method offers comparable predictive skill while introducing interpretability mechanisms. These enhancements contribute to the growing field of explainable AI in hydrology and help bridge the gap between black-box performance and actionable scientific understanding.

Taken together, these contributions highlight three cross-cutting themes in the application of AI in hydrology: the adaptation of advanced machine learning architectures, the fusion of diverse data sources, and the exploration of model interpretability. While each study targets a distinct challenge, they collectively demonstrate the transformative potential of AI in improving hydrologic forecasting, particularly under a changing climate.

In a nutshell, this Research Topic highlights the growing strengths of ML approaches in hydrology, particularly for predictive tasks such as early warning systems and water resource management. The contributions showcase innovative methods that not only outperform standard ML models but also address some of their known limitations, such as interpretability. We extend our sincere thanks to all the authors and reviewers for their valuable contributions. We are confident that this Research Topic of work will significantly advance knowledge in this important and evolving field.

Author contributions

MH: Writing – original draft, Writing – review & editing. ER: Writing – review & editing, Writing – original draft.

Acknowledgments

We express our gratitude to all the authors and reviewers whose contributions made this Research Topic possible. We also appreciate the support and coordination provided by Frontiers throughout the editorial process.

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