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Editorial

Artificial Intelligence Techniques in Hydrology and Water Resources Management

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Abstract: The sustainable management of water cycles is crucial in the context of climate change and global warming. It involves managing global, regional, and local water cycles—as well as urban, agricultural, and industrial water cycles—to conserve water resources and their relationships with energy, food, microclimates, biodiversity, ecosystem functioning, and anthropogenic activities. Hydrological modeling is indispensable for achieving this goal, as it is essential for water resources management and mitigation of natural disasters. In recent decades, the application of artificial intelligence (AI) techniques in hydrology and water resources management has made notable advances. In the face of hydro-geo-meteorological uncertainty, AI approaches have proven to be powerful tools for accurately modeling complex, non-linear hydrological processes and effectively utilizing various digital and imaging data sources, such as ground gauges, remote sensing tools, and in situ Internet of Things (IoTs). The thirteen research papers published in this Special Issue make significant contributions to long- and short-term hydrological modeling and water resources management under changing environments using AI techniques coupled with various analytics tools. These contributions, which cover hydrological forecasting, microclimate control, and climate adaptation, can promote hydrology research and direct policy making toward sustainable and integrated water resources management.

Keywords: machine learning; deep learning; hydroinformatics; hydrological modeling; early warning; uncertainty; sustainability

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1. Introduction

Artificial intelligence (AI) encompasses a broad range of computer-related disciplines that focus on creating intelligent models to conduct work previously carried out by humans [1,2]. AI enables computers to model or even surpass human cognitive abilities, thereby rapidly rationalizing and taking steps to achieve specific objectives, such as several-steps-ahead predictions and pattern recognition. AI is also recognized for its ability to manage massive amounts of data and sophisticated models with ease [3]. Since the mid-20th century, the use of AI techniques has grown in a wide variety of engineering and scientific disciplines [4,5]. With numerous interdisciplinary scientific approaches, recent advancements in AI have triggered a paradigm shift in almost every field, including engineering, hydrology, technology, and medical imaging [6–9].

Over the past two decades, AI approaches have rapidly emerged as a solution to overcome the challenges presented by the high complexity, dynamics, non-linearity and non-stationarity observed in hydrological processes [10,11]. The increase in severe natural disasters resulting from climate change and global warming has posed a significant threat to sustainable hydrology and water resources management. As a result, there has been a notable surge in exploring AI models to characterize and predict hydrological variability under growing hydro-geo-meteorological uncertainty [12–14]. AI techniques offer a promising alternative or supplement to conventional physical-based or statistical approaches to hydrological modeling [15–19]. By utilizing data from various sources, including micro-sensing, imaging, in situ, and remote sensing devices, AI techniques are currently enabling the creation of reliable and robust hydrological models at finer spatio-temporal resolutions of interest, which is crucial for addressing highly nonlinear hydro-meteorological processes [20–24]. Therefore, there is a need to explore innovative AI models to better allocate, regulate, and conserve water resources, which will significantly contribute to sustainable their management.

In 2021 and 2022, Water (MDPI) published thirteen research papers in a Special Issue entitled "Artificial Intelligence Techniques in Hydrology and Water Resources Management".

The objectives of the current Special Issue are as follows:

- ✧ To advance the use of AI techniques in hydrological modeling and water resources management.
- ✧ To develop innovative solutions for hydrological forecasting and problem-solving in watershed hydrology under changing environments.
- ✧ To improve water and environmental systems.
- ✧ To promote urban water–energy–food nexus synergies.
- ✧ To quantify uncertainty of hydrological modeling.

This editorial provides an overview of the Special Issue, offering insights and suggestions for future research.

2. Highlights of the Articles in the Special Issue

The thirteen articles presented in the Special Issue have made substantial contributions across five main research areas:

- ✧ The application of machine learning and deep learning techniques in hydro-meteorological forecasting, classification and time series generation under changing environmental conditions;
- ✧ The use of AI techniques for smart microclimate control;
- ✧ The current and future roles of Geospatial Artificial Intelligence (GeoAI) in hydrological and fluvial systems;
- ✧ Adaptation strategies for extreme hydrological events to mitigate hazards;
- ✧ The utilization of AI for processing hydro-geo-meteorological data.

These articles are grouped and highlighted as follows.

2.1. Smart Microclimate Control System Using AI

The prediction of a short-term microclimate is a challenging task due to the rapid changes and strong interconnections among meteorological variables. To address this issue, Chen et al. introduced a water-centric smart microclimate control system (SMCS) that incorporates system dynamics and machine learning techniques, which can regulate the micro-environment within a greenhouse canopy to induce environmental cooling while improving resource-use efficiency [25]. The proposed SMCS demonstrates the practicality of machine-learning-enabled greenhouse automation that enhances crop productivity and resource-use efficiency, thereby contributing to the mitigation of carbon emissions and a sustainable water–energy–food nexus.

2.2. Weather Typing for Smart Urban Agriculture Using AI

In outdoor agricultural production, weather is a crucial factor that affects crop growth. Climate information can be utilized to help farmers plan their planting and production schedules, especially for urban agriculture. Huang and Chang used a self-organizing map (SOM) to investigate the spatiotemporal weather features of Taipei City by analyzing the observed data of six key weather factors from five weather stations in Northern Taiwan between 2014 and 2018 [26]. The results provide practical references for anticipating upcoming weather types and features within designated time frames, arranging potential cultivation tasks or making necessary adjustments, and efficiently utilizing water and energy resources to achieve sustainable production in smart urban agriculture.

2.3. AI-Driven Forecasting

2.3.1. Precipitation Forecasting

Abnormal changes in precipitation and temperature caused by climate change have increased the risks of climate disasters and rainfall damage. Despite quantitative rainfall estimates from weather forecasts, it remains difficult to estimate the damage caused by rainfall. To address this issue, Chu et al. employed various methods, such as support vector machine (SVM), random forest, and eXtreme Gradient Boosting (XGBoost), finding that XGBoost has the best performance [27]. Using XGBoost, the threshold rainfall of ungauged watersheds was calculated and verified using past rainfall events and damage cases, enabling the accurate prediction of flooding-induced rainfall and preparation for vulnerable areas. Alternatively, Pakdaman et al. proposed a learning approach based on an artificial neural network (ANN) and random forest algorithms to provide multi-model ensemble forecasting of monthly precipitation in Southwest Asia [28]. The approach employed four forecasting models from the North American multi-model ensemble (NMME) project, including GEM-NEMO, NASA-GEOSS2S, CanCM4i, and COLA-RSMAS-CCSM4, and used the ERA5 reanalysis dataset to train the models. The results show that the ANN and random forest post-processing both performed better than individual NMME models, with random forest outperforming ANN for all lead times and months of the year.

2.3.2. Temperature Forecasting

Temperature is a crucial weather variable required for various studies. Changes in temperature and precipitation can have a significant impact on river basins. Hernández-Bedolla et al. developed a stochastic model for daily precipitation occurrence and its effect on maximum and minimum temperatures [29]. The study employed a Markov model to identify the daily occurrence of rainfall and a multisite multivariate autoregressive model (MASCV) to represent the short-term memory of daily temperature. The research was conducted on the Jucar River Basin in Spain, where the proposed model could accurately represent both the occurrence of rainfall and the maximum and minimum temperature using a two-state and a lag-one multivariate stochastic model.

2.3.3. Streamflow Forecasting

Ghobadi and Kang proposed a probabilistic forecasting model for multi-step-ahead daily streamflow forecasting, which uses Bayesian sampling in a long short-term memory (BLSTM) neural network to address the subproblem of univariate time series models and quantify epistemic and aleatory uncertainty [30]. The proposed method was validated by three case studies in the USA, and three forecasting horizons demonstrate that BLSTM outperformed the other models in terms of forecasting reliability, accuracy, and overall performance. Moreover, BLSTM can handle data with higher variation and peaks, particularly for long-term multi-step-ahead streamflow forecasting, compared to other models. Alternatively, Forghanparast and Mohammadi compared the performance of three deep learning algorithms, including convolutional neural networks (CNN), long short-term memory (LSTM), and self-attention LSTM models, against a baseline extreme learning machine (ELM) model for monthly streamflow prediction in the headwaters of the Colorado River in Texas [31]. The LSTM model was identified as a more appropriate, effective, and parsimonious streamflow prediction tool for the headwaters of the Colorado River in Texas, with better evaluation metrics than the ELM and CNN algorithms and a more competitive performance then the SA-LSTM model.

2.3.4. Dam Inflow Prediction

Kim et al. illustrated the process and methodology for selecting the most suitable deep learning model using 16 design scenarios to predict dam inflow using hydrologic data from the past two decades [32]. The study focused on Andong Dam and Imha Dam, located upstream of the Nakdong River in South Korea. The optimal recurrent-neural-network-based models demonstrated a better prediction of observed inflow than the storage function model (SFM), which is currently used by both dams. Most deep learning models provided more accurate predictions than the SFM under various typhoon conditions. Therefore, it is crucial to make an informed decision by comparing the inflow predictions of both the SFM and deep learning models for efficient dam operation and management.

2.3.5. Real-Time Inundation Depths Estimation

Wu et al. developed a stochastic model (SM_EID_IOT) for estimating the inundation depths and associated 95% confidence intervals at the specific locations of the roadside water-level gauges (IoTs) sensors under observed water levels/rainfalls and the precipitation forecasts [33]. The goal was to improve the accuracy and reliability of inundation depth estimations at the IoT sensors. The model was tested in the Nankon catchment in northern Taiwan, and the results show that the SM_EID_IOT model was capable of estimating inundation depths at various lead times with a high reliability and accuracy, as validated by the datasets. The corrected inundation depth estimates also exhibited a good agreement with the validated data over time, with an acceptable bias.

2.3.6. Rainfall Time Series Generation

Nguyen and Chen employed a Monte Carlo simulation, a bivariate copula, and a modified Huff curve method to create a stochastic rainfall generator to produce continuous rainfall time series at a high temporal resolution of 10 min [34]. The created rainfall generator was then applied to duplicate rainfall time series for the Yilan River Basin in Taiwan, with statistical indices staying close to those of the observed rainfall time series. The results suggest the need and appropriateness of the newly generated rainfall type for rainfall type classification. In summary, the developed stochastic rainfall generator is capable of adequately reproducing continuous rainfall time series at a 10 min resolution.

2.4. Review of Geospatial Artificial Intelligence (GeoAI)

Gonzales-Inca et al. conducted a review of the current applications of GeoAI and machine learning in various hydrological and hydraulic modeling fields [35]. GeoAI is an effective tool for handling vast amounts of spatial and non-spatial data. GeoAI demonstrates advantages in non-linear modeling, computational efficiency, integration of multiple data sources, high prediction accuracy, and revealing new hydrological patterns and processes. However, a significant drawback of most GeoAI models is the lack of physical interpretability, explainability, and model generalization due to inadequate model settings. Recent GeoAI research has focused on integrating physical-based models with GeoAI methods and developing autonomous prediction and forecasting systems.

2.5. Data Processing Using AI

Measuring water levels in rivers is crucial for producing early warnings and detecting risks. However, data collected by devices installed in remote locations may contain errors due to malfunctions, which can result in missed or false alarms. Khampuengson and Wang investigated deep reinforcement learning (DRL) due to its ability to automatically detect anomalies. They found that this approach lacked consistency despite achieving a higher accuracy than some machine learning models [36]. Thus, an ensemble approach combining multiple DRL models was proposed and achieved higher consistency and accuracy than other models such as multilayer perceptrons (MLP) and LSTM. On the other hand, Papailiou et al. proposed a methodology using ensembles of ANNs to estimate the missing data of daily precipitation in Chania, Greece [37]. The methodology aimed to generate precipitation time series based on observed data from neighboring stations. The results indicate that ANNs achieved more accurate results but were more time-consuming compared to multiple linear regression (MLR) models.

3. Conclusions

In recent decades, the field of hydrology and water resources management has witnessed significant advances in the use of AI techniques. This Special Issue includes 12 research articles and 1 review article that propose innovative AI-based solutions for addressing the critical challenges associated with hydrology and water resources, with promising outcomes.

As AI techniques continue to rapidly evolve across the globe, future research should focus on developing AI techniques and methodologies and integrating advanced hydrological monitoring devices with varying spatial and temporal scales to conduct comprehensive analyses of complex nonlinear hydrological processes in light of scientific and socio-economic considerations. Furthermore, AI-powered solutions can also incorporate low-carbon pathways to support hydrological and engineering sectors in achieving the net zero goal by 2050.

The foundations of Earth and environmental studies lie in the modeling of dynamic geophysical phenomena. While the geoscientific community has conventionally depended on physically based models, the emergence of big Earth data and the widespread success of AI tools suggest a more in-depth adoption of AI. A new grand vision for geoscience involves the fusion of physically based mechanisms and AI techniques to generate hybrid models, but the question of how to implement these approaches remains open.

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