hydrology

Editorial

Editorial to the Special Issue "Recent Advances in Hydrological Modeling"

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1. Introduction

Hydrological models play a crucial role as essential tools in the realms of water resources operations, planning, and management practices [1,2]. Hydrological models can be categorized based on their structure (data-driven/statistical, conceptual, physical, hybrid) or spatial representation (lumped, distributed) [3,4]. Core components of the modeling process include model calibration, validation/verification, sensitivity analysis, and uncertainty analysis [5,6]. In operational scenarios, field observations, both in situ and remote sensing, are frequently integrated into hydrological models to enhance model performance by updating states and/or parameters [7,8]. Before informing decision-making, model outputs, particularly those derived from ensemble-based approaches, typically undergo post-processing [9–11]. Progress in computing, such as the utilization of cloud-based systems and parallelization, along with advancements in information technologies like artificial intelligence, create new prospects for enhancing hydrological modeling [12–14]. Moreover, the persisting and anticipated environmental shifts, such as global warming and intensified extreme events, present novel hurdles for hydrological modeling [15]. This necessitates innovative modeling strategies and the integration of modeling across diverse disciplines [16,17].

2. Historical Development and Present Status of Hydrological Modeling

The history of hydrological modeling encompasses a progression from empirical equations to sophisticated numerical models, reflecting advancements in scientific understanding and computational capabilities. Early efforts in hydrological modeling relied on empirical equations such as the Rational Method for estimating peak flows in drainage design [18]. As computing technology advanced, numerical models emerged, allowing for a more comprehensive representation of hydrological processes. Notable milestones include the Soil Conservation Service Curve Number method [19] which provided a semi-empirical approach to predict runoff from rainfall events. Conceptual models emerged as a step towards process-based representations of hydrological phenomena. These models, like the Stanford Watershed Model and the Soil Moisture Accounting model, introduced in the 1960s and 1970s, aimed to incorporate fundamental hydrological processes [20]. They provided a more comprehensive understanding of the interaction between precipitation, infiltration, runoff, and streamflow. Subsequently, physically-based models incorporating fundamental equations governing water movement, such as Darcy's law [21] for groundwater flow, Green-Ampt equation [22] and Horton equation [23] for infiltration, Penman-Monteith equation [24] for evapotranspiration, and Richards equation [25] for unsaturated flow, became prominent. With the advent of remote sensing and Geographic Information Systems (GIS), spatially distributed models gained traction, enabling a finer resolution of hydrological processes over diverse landscapes. Recent advancements in data

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assimilation techniques, machine learning, and artificial intelligence are further enhancing the predictive capabilities of hydrological models.

The present state of hydrological modeling is prominently marked by the advanced development of physically-based distributed models and the rise of data-driven approaches. For instance, Nearing et al. [26] demonstrated the use of Long Short-Term Memory (LSTM) networks for forecasting streamflow, comparing its performance with the Global Flood Awareness System (GloFAS) and highlighting that this AI model can reliably forecast extreme riverine events up to five days in advance, particularly in ungauged basins. Meanwhile, trends in physically-based hydrological modeling have expanded to include larger spatial scales, enhanced representations of hydrological processes, and the integration of climate change projections to assess impacts on hydrological extremes [27,28]. Data assimilation and post-processing approaches have become more actively engaged in high-resolution hydrologic modeling [29–31]. As an example, Siqueira et al. [32] discussed how combining post-processing methods such as Ensemble Model Output Statistics (EMOS) and Ensemble Copula Coupling (ECC) significantly enhances both the reliability and sharpness of streamflow predictions by a medium-range, continental-scale hydrologic-hydrodynamic model ensemble in South America. Moreover, hybrid or unified hydrologic modeling approaches that leverage both physically-based and data-driven methods are gaining attention [33–35]. Shen et al. [35] noted that differentiable modeling, which connects flexible amounts of prior physical knowledge to neural networks, offers better interpretability, generalizability, and extrapolation capabilities than purely data-driven machine learning approaches, achieving comparable accuracy with less training data. Additionally, Wang et al. [36] presented a hybrid deep-learning surrogate model that replicates the physics-based distributed model, HydroPy, significantly enhancing the simulation of hydrological processes in the Amazon Basin.

3. The Current Special Issue

The objective of this Special Issue was to showcase the most recent progress in the field of hydrological modeling development and applications. The papers featured in this collection encompass various subjects related to enhancing hydrological modeling through inventive methodologies and novel datasets. A summary of each paper is provided below.

Rozos et al. (Contribution 1) proposed the use of machine learning models as a tool to assess the performance of conventional hydrological models rather than as a replacement of those conventional models. The hypothesis is that if the machine learning model demonstrates improved performance, it indicates that there is information in the data that the structure or configuration of the hydrological model fails to consider. The applicability of the proposed methodology was illustrated via two case studies with data shuffling (akin to cross-validation) implemented. The case studies indicated that machine learning models can be utilized as an assessment tool to refine hydrological models, either through enhancing calibration or adjusting the physical/conceptual assumptions within the model.

Shen et al. (Contribution 2) developed a new formulation of conditional bias (CB)-penalized Kalman filter (KF), or CBPKF, that reduces computation and algorithmic complexity. They also described adaptively prescribing the weight for the CB penalty in the CBPKF in order to improve unconditional performance. Synthetic experiments indicated that the variance-inflated KF (VIKF)-based approximation of the CBPKF was computationally less expensive than the original CBPKF. The adaptive CBPKF improved the estimation of extremes by 20–30% over the KF while its unconditional performance was comparable to that of the KF. The adaptive implementation of the alternative formulation of the CBPKF offered a significant addition to the dynamic filtering methods particularly for the improved estimation of extremes.

Awad et al. (Contribution 3) assessed changes in the performance of the DRAINMOD model with different time steps, hourly or daily, used in computing daily evapotranspiration (ET_0) via the standardized ASCE Penman-Monteith model. The model was applied to a 12-hectare farmland at the lower reaches of the Yangtze River basin. When the time step changed from daily to hourly, DRAINMOD cumulative predictions of the runoff were increased by 4.8%, and drainage and infiltration were decreased by 3.1 and 1%, respectively. The findings indicated the importance of using a proper time step in computing ET_0 for better utilization of agricultural water alongside high crop yields.

Hatchett et al. (Contribution 4) investigated alterations in snow seasonality across the U.S. Pacific Southwest region during a simulated severe 20-year dry period in the 21st century (2051–2070). The study indicated that substantial declines in median peak annual snow water equivalent and annual streamflow runoff, coupled with changes in snow seasonality across the region were expected. In addition, about 80% of historical seasonal snowpacks are projected to transition to ephemeral conditions, potentially leading to a two-to-four-fold increase in the wildfire burned area. The projected dry spell is anticipated to have negative impacts on water supply reliability, and these impacts are likely to be exacerbated by alterations in snow seasonality and an increase in wildfire activity.

Cardi et al. (Contribution 5) incorporated numerical modeling and machine learning (ML) modeling in forecasting flood events, particularly unprecedented flood events via the data augmentation technique. Specifically, they ran a numerical model to generate a dataset that contains a wide range of plausible future flood events. The dataset was utilized to develop an ML model named the Expanded Framework of Group Method of Data Handling (EFGMDH). The EFGMDH model exhibited high accuracy during both the training and testing processes in the study watershed. The study provided valuable insights for flood management amid a changing climate.

Adams and Quinn (Contribution 6) implemented enhanced versions of the catchment runoff attenuation flux tool (CRAFT), Dynamic CRAFT and multiCRAFT, to predict water quality problems related to phosphorus (P). Dynamic CRAFT was applied to the trans-border Blackwater catchment (UK and Republic of Ireland) to simulate soluble P and particulate P fluxes. Nested modeling at the sub-catchment scale with different mitigation scenarios was implemented by multiCRAFT. The modeling results illustrated that the P load reductions could be best achieved using a combined scenario of mitigation measures targeting diffuse sources contributing to both the surface runoff and fast-subsurface flow pathways.

Gruss et al. (Contribution 7) analyzed the impact of a dam reservoir on streamflow using hydraulic modeling and statistical methods in the Nysa Kłodzka River, Poland. After simulating pre-dam and post-dam streamflow conditions using HEC-RAS, changes in hydrologic regimes were assessed by Mann-Kendall and innovative trend analysis (ITA). The findings suggested that the dam had a significant impact on streamflow patterns by stabilizing flows in response to climate-induced changes.

4. Future Perspectives and Conclusions

With ongoing and rapid changes in societal, environmental, and operational needs, hydrological modeling has been and will continue to be an essential tool to provide viable solutions to problems in hydrology and related disciplines. With the advent of big data and high performance computing resources, we anticipate that data-centric approaches such as machine learning (e.g., Contribution 1 and Contribution 5) and data assimilation (e.g., Contribution 2) will become an integral part of modeling studies in the foreseeable future. Two conventional approaches, data analysis-based experimental or simulation-based derived, can also continue to serve as important hydrological modeling tools to improve understanding of hydrology undergoing transitions and provide valuable insights on hydrological predictions. As hydrological extremes have been increasing in frequency and severity globally, we envision increasing trends in future modeling efforts focused on large-scale hydrology.

This Special Issue showcases recent advancements in hydrological modeling methodologies and operational practices. It underscores the critical need for continued application to validate the effectiveness and generalizability of novel techniques, particularly those involving machine learning and data assimilation.

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List of Contributions

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