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Perspective

Artificial intelligence reshapes river basin governance

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River Basins (RBs) are the cradle of human civilization, providing diversified ecosystem services and sustaining fundamental hydrological and biogeochemical cycles on our planet. However, the loss of these ecosystem services from RBs has persisted, e.g., nearly 80% of the world's population faces serious water crisis [1]; and one in three people globally lacks access to safe drinking water. Furthermore, without large-scale structural adaptations, the economic losses and deterioration of river water quality due to extreme hydrological events are projected to escalate significantly at the global level [2].

Human activities, such as land development and hydraulic engineering projects, have profoundly altered RBs, causing severe ecological degradation and environmental pollution [3]. These changes have critically undermined the effectiveness of River Basin Governance (RBG) in achieving the Sustainable Development Goals (SDGs) by the United Nations.

Effective policy-making for sustainable development necessitates balancing trade-offs and considering interactions among SDGs. However, the progresses in achieving these goals remain insufficient. For example, SDG 6 highlights the urgency of achieving sustainable water resource management globally by 2030 and addressing the ongoing water crisis [4]. Research and policy require integrated approaches to the design, implementation, and monitoring of RBs across sectors, actors, and borders [5].

As coupled human-nature systems, RBs embody the interactions among land, biosphere, atmosphere, and noosphere systems. These interactions are characterized by high complexities across temporal and spatial scales, facing unprecedented rates of change and diverse stressors [6,7]. These complexities and uncertainties are, nevertheless, difficult to perceive via traditional RBGs. This, in turn, has led to segregated RBG as ecosystem services trade-offs, deficiencies in pre-governance of RBs adapting climate change and insufficient intergovernmental cooperation.

Traditional RBG involves three main aspects: monitoring, forecasting, and decision-making based on RB observations and models. Together, these three components constitute an integrated paradigm for RBG. Although each aspect has experienced rapid development, the RBG paradigm remains constrained by limited observations, insufficient representation of human systems in RB models, and dysfunctional RB governance.

(i) *Limited RB observation.* Observation of RBs relies either on *in-situ* borehole or gauge measurements or data from remote sensing. However, current *in situ* and remote sensing methods face key limitations in characterizing the spatiotemporal dynamics of many river systems. River scientists and managers are often hindered by data scarcity and system complexity. In addition, data sources for RB monitoring come from diverse spatiotemporal scales, including ground and underground measurements, as well as remote sensing from air or space. Integrating these diverse sources into a standardized product for RB analysis poses significant challenges.

As highly intricate human-natural systems, RBs present unique difficulties for the application of cutting-edge remote sensing techniques, such as penetrating Earth-observing techniques. Simultaneously, the rapid evolution of information technology, exemplified by the Internet of Things (IoT), poses substantial hurdles for achieving higher-quality RB monitoring. To ensure effective and high-quality RB management, the strategic integration of human agents as sensing units within the geographical and social context, a concept known as social sensing, must be seamlessly integrated with the intrinsic natural attributes of RBs.

(ii) *Insufficient representation of human system in RB models.* Since the 1950s, human activities have increasingly shaped the Earth's system, leading to what is now called the Anthropocene, where humans are the main forces driving environmental changes [7]. Human activities play a pivotal role in RB systems. Although RB models have started to incorporate human influences, such as land use changes, water infrastructure, irrigation systems, and urbanization, these influences are often represented in overly simplistic ways [8]. Current RB models struggle to accurately represent the bidirectional feedbacks between human activities and natural processes, leading to limited predictive capabilities.

First, unlike natural processes, the intensity of human activities, a complex and dynamic variable, is challenging to quantify using purely physical models. Human activities encompass a wide range of actions, including water withdrawals, agriculture and industry consumption, urbanization, irrigation, and dam operations. These activities involve diverse decision-making and behaviors that cannot be easily captured by a single physical model, greatly affecting the accuracy of simulation. This challenge is particularly pro-

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nounced in large RBs, where human activities exert a dominant influence. Furthermore, human activities are influenced by policies, regulations, economic development, and other socioeconomic factors, which are often difficult to quantify due to their indirect or nonlinear nature.

Most RB models still treat human activities as external influences rather than integral components of the system. The effects of human activities are usually incorporated through scenarios or external forcing functions, such as land use or climate change, which impact model outputs without altering the model's fundamental structure. This distinction arises from the traditional structure of these models, which are primarily focused on simulating natural processes like precipitation, evaporation and infiltration. Human activities are often considered as modifying factors, represented by relatively independent source-sink terms. For instance, urbanization alters surface runoff patterns but is not treated as an intrinsic part of the hydrological cycle. This results in a weak consideration of the dynamic feedback between natural systems and human activities, despite the fact that this feedback is highly complex and influenced by a broad range of socioeconomic, political, and cultural factors.

Moreover, RB models frequently simplify or use parameterizations to represent human processes and their interactions with natural system. However, accurately estimating these parameters, particularly when direct measurements are unavailable, introduces significant uncertainties. This lack of precise quantification poses a key challenge to fully integrating human systems into RB modeling.

(iii) *Dysfunctional RB governance.* Effective RBG is essential for addressing the global water crisis [9]. Historical management strategies are the key references for decision-makers to modify the operating rules. However, this path dependency constrains addressing adaption for climate change. Climate change is intensifying the hydrologic cycle [10], leading to an increase in floods and droughts, and therefore increasing the complexity of RBG. Robust design of hydrologic infrastructure could be a formidable challenge in a changing climate. Furthermore, in a large RB, implementation of a management policy may result in heterogeneous impacts in different regions. Moreover, the lack of strong connections between decision-makers and RB science analyses reduces the timeliness and effectiveness of RBG [11].

RBG involves multiple stakeholders, necessitating the delicate balancing of multiple interests and demands. Striking an equilibrium between economic development and ecosystem restoration remains a critical challenge. However, in the context of model-based RBG, the efficacy of current multi-scenario simulations in supporting robust RBG remains uncertain.

Limitations arising from recent observations, modeling, and governance pose significant challenges to RBG, hindering the achievement of the SDGs. Thankfully, in this era, advancements in earth science observation methods have unleashed an abundance of data, empowering earth scientists like never before, especially with the aid of rapidly advancing Artificial Intelligence (AI) technology. AI is anticipated to reshape the paradigm of RBGs from observation to modeling and decision-making. This paradigm encompasses three key aspects: holographic observation, hybrid modeling, and intelligent decision-making, as illustrated in Fig. 1. Among these three components, holographic observation serves as the cornerstone, offering substantial 4D spatiotemporally continuous dataset for hybrid models that integrate physical-based and data-driven approaches. Large Language Models (LLM) synergize with Reinforcement Learning (RF), providing a resilient scientific underpinning for intelligent RBG. This, in turn, informs observations and models with essential requirements and constructive suggestions for refinement, thereby facilitating iterative enhancements to both observational methodologies and model frameworks.

(i) *The AI-powered holographic observation network.* The RB involves the entire water-soil-air-plant-human nexus with high complexity, necessitating an IoT-connected holographic observation of RBs. This system integrates in-situ or ground-based observations, wells, space-borne remote sensing, and air-borne measurements. *In-situ* or ground-based stations allow the precise measurement of land properties and atmospheric physics. Space-borne video, optical, or microwave satellites can capture the physical properties of RB on a large scale. Air-borne measurements carried by unmanned airship and unmanned aerial vehicle can be exploited to obtain additional information on ungauged river systems, collecting RB information with high spatial and spectral resolution.

Even specified RBs are monitored at numerous gauges, data remains sparse in both space and time, limiting its use for global hydrology analysis [12]. Deep learning approaches have emerged as promising tools for hydrological prediction, particularly in data-scarce regions, where they can outperform traditional methods. Their ability to analyze large datasets and integrate diverse data types across scales is a significant advantage. Advanced deep learning architectures like Transformers enable the transfer of prior hydrological knowledge between basins, enhancing predictive accuracy and generalizability. This transfer learning capability holds significant promise for improving hydrological modeling in data-sparse regions (e.g., Ref. [13]). Moreover, integrating deep learning with computer vision technologies has significantly enhanced the ability to perform tasks such as identification and analysis of hydrological features from remotely sensed imagery, particularly in the context of river and flood extent patterns. The capacity of AI to integrate diverse data sources across multiple spatial and temporal scales presents a unique opportunity to overcome the limitations of traditional hydrological monitoring. An AI-powered platform, capable of synthesizing data from multiple sources, would enable the creation of a comprehensive, holographic representation of RBs. This integrated approach, by capturing the complex interactions within the water-soil-air-plant-human nexus, holds the potential to advance our understanding of RBs from an Earth system perspective. Multiple time scales, from sub-hour to decades, multiple spatial scales, from millimeters to hundreds of kilometers, and multi parameters, from groundwater to precipitation, to name a few, are characterized. To achieve this, modern AI architectures reconstruct data acquired from the holographic observation network to a continuous 4D dataset, providing insights into many processes such as carbon emission, water cycle, water quality, river biodiversity, anthropogenic invention and natural hazard. Eventually, the holographic gridded RB database can act as an important input for hybrid models.

(ii) *Hybrid models integrating data-driven and physical processes.* The integration of data-driven and physical process-based modeling, known as hybrid models, has garnered considerable attention [14]. These models aim to improve the understanding and accuracy of complex systems by combining observational data with simulations rooted in physical processes. By merging data-driven analysis with process-based simulation, hybrid models aim to overcome the limitations of each approach, offering a more comprehensive and precise depiction and prediction of complex system behaviors. Since data-driven methods are at the core of AI, they offer inherent advantages in capturing and modeling the complex interactions between human and natural systems that are difficult to describe using traditional physical models.

Human activities and their interactions with natural systems involve complex, nonlinear relationships that are challenging to represent accurately with conventional physical models. AI, by learning from historical data patterns and trends, can construct sophisticated, data-driven models that better capture and simulate these intricate interactions. For example, deep learning networks

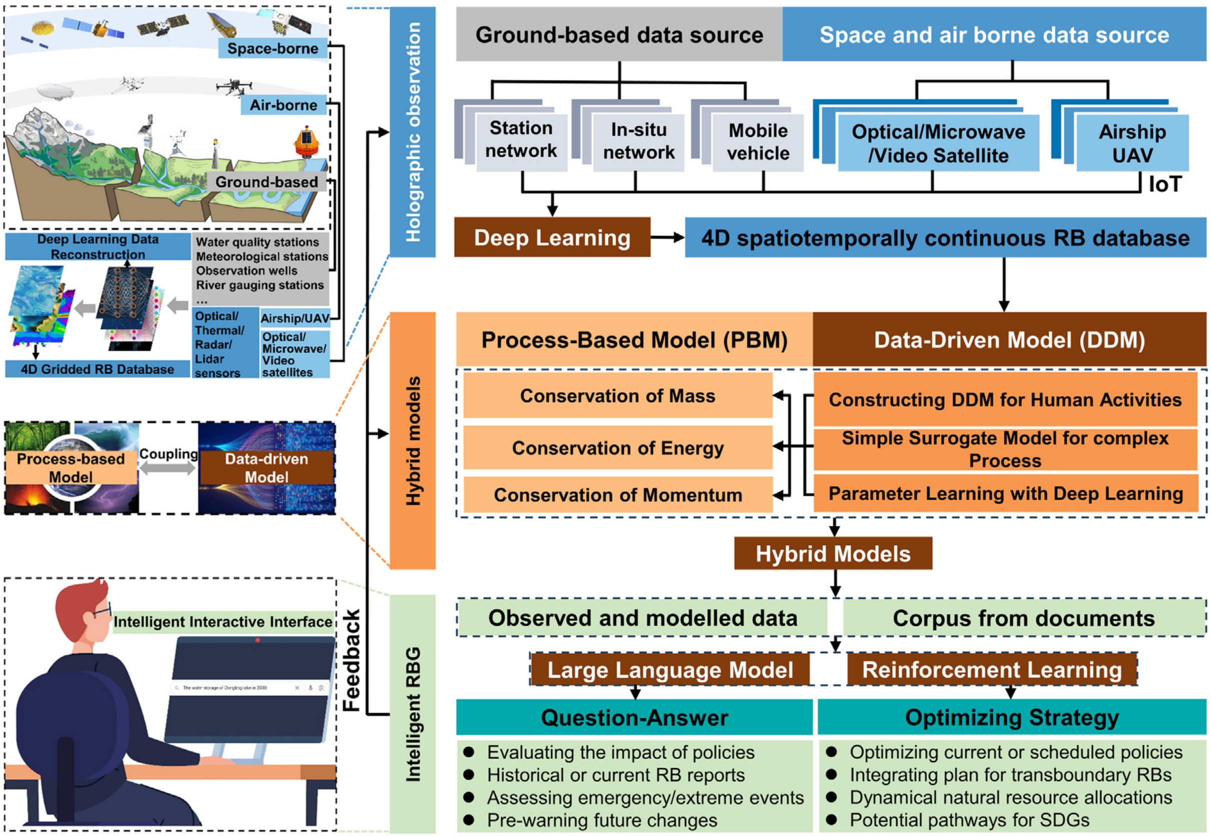

Fig. 1. Flow diagram of the paradigm for the intelligent RBG. The holographic observation network (top) provides a 4D spatiotemporally continuous gridded RB dataset for the hybrid model (middle), which acts as the science fundamental for intelligent RBG (bottom). In return, intelligent RBG enhances the holographic observation and hybrid modelling of RBs.

can be trained to model the complex impacts of urbanization on hydrological cycles.

AI also facilitates the integration of knowledge from various disciplines—such as hydrology, ecology, economics, and sociology—to develop comprehensive RB models. These interdisciplinary models are better equipped to represent the complex interactions between human activities and natural processes. For example, Natural Language Processing (NLP) can analyze large volumes of policy documents, extract critical information, and incorporate it into RB models, thereby improving simulations of how policy changes influence human activities and natural system.

Moreover, AI is powerful in determining model parameters. Hybrid models involve numerous parameters, and their accuracy is crucial for reliable simulation results. Relying on the key assumption of inherent connections between hard-to-determine model parameters and observable elements, core technologies are developed from parameter calibration to parameter learning using big data and deep learning methods. This significantly reduces computational costs and uncertainties associated with manual parameter tuning, enhancing the model's simulation and prediction capabilities [15]. As the holistic monitoring platform accumulates more data, continuous optimization of parameter learning becomes achievable, imparting partial evolutionary capabilities to the model.

In addition, RB models involve highly complex processes with unclear underlying mechanisms. Data-driven models, which build relationships between dependent variables and numerous environmental factors, can effectively characterize these complex processes and thereby reduce uncertainties in RB model simulations. As observational data improves and grows, data-driven modules within hybrid models can be progressively optimized, transforming the RB hybrid model into an evolving RB integrated model, achieving the goal of RB intelligent simulation.

(iii) *Intelligent RBG.* For RB managers and decision-makers, the complexity and uncertainties of RB systems pose significant challenge to comprehensive understanding of RBG. An easy-to-use interface is essential. With the rapid development of LLMs like the Generative Pre-trained Transformer (GPT), outputs from observations and hybrid model can be seamlessly integrated with LLM. These systems convert observation or prediction data into structured natural language enriched with scientific data. Subsequently, this transformed data can be encoded into dense vectors through sentence transformers. Pre-trained or fine-tuned LLMs are adaptable for a range of tasks, including Question-Answer (Q&A) or even generating images and videos using their knowledge of historical records. Additionally, relevant industry data, research reports, social sensing data, and academic papers can be incorporated into the LLM corpus to enhance its richness. Consequently, the Q&A system can complete the tasks such as (1) evaluating the potential impact of a RB policy, such as a planned dam, to human-nature systems, (2) historical or current summary reports on the comprehensive status of RB systems, (3) quantitatively assessments of the impact of emergency or extreme events, and (4) diagnosing and pre-warning the future statuses of river basins responding to climate-related environmental changes. Eventually, this system collectively reduce climate risks, support climate-resilient economy, and facilitate the establishment of sustainable RBs.

Effective RBG requires adaptive planning based on the socio-ecological and socio-economic relationship between human and RB, thereby reducing risks associated with path dependency. Moreover, transnational RB consolidation projects involving balancing water resource exploitation rights, ecological restoration, and territorial space consolidation should be planned and acknowledged from the global to the local. To reduce transaction costs and enhance efficiency, RBG models are necessary to be capable of automatically identifying optimal strategies. The RF model possess remarkable abilities in finding the optimal strategies, providing valuable suggestions for effective natural resource management, not only improving the knowledge of the behaviors of the decision-makers but also assisting them in identifying better management strategies. Through carefully designed prompts, LLMs can utilize their extensive knowledge of observed patterns and data, combined with RF models, to identify the most effective strategy within specific limitations. By integrating LLM, RF, predictions from hybrid model, and observation data, the optimizing system can achieve the following functions: (1) optimizing the current or scheduled RB policies, (2) integrated planning for transboundary RBs or inter-sectoral demands, (3) strategies for regulated or unregulated natural resource allocation, (4) providing potential pathways to achieve one or more SDG goals.

The rapid advancement of AI technology, particularly the potential for Artificial General Intelligence (AGI), offers novel prospects for RBG. Deep learning has demonstrated remarkable achievements in data reconstruction and hydrological modeling, and LLM has exhibited substantial capabilities across diverse domains, enabling a transformative approach to reshaping RBG. While AI technologies offer promising advancements for RGB, several limitations must be acknowledged. They include but not limited to: (1) Challenges in predicting untrained hydrological variables; (2) Ensuring the physical feasibility of process-based models; (3) Dependence on extensive high-quality training data; (4) Reliability concerns due to the lack of human intervention data; (5) Difficulty in transferring a regionally trained model to other fluvial contexts; (6) Complexity in implementing AI for RB managers without deep learning expertise. Despite these challenges, AI can facilitate seamless integration among RB observation, modeling, and governance. Specifically, holographic observations yield continuous 4D data, informing hybrid models for more comprehensive and precise prediction of RB system. Outputs from these models feed into LLMs, which, in conjunction with RL, provide scientifically grounded insights to policymakers. This iterative feedback loop fosters improvements in observation, modeling, and governance frameworks, streamlining complexity and enhancing decision-making for intelligent RBG.

Conflict of interest

The authors declare that they have no conflict of interest.

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Author contributions

Lizhe Wang conceptualized this perspective and led the writing with Jian Zhang, Yunquan Wang, Xiaoqing Song, and Ziyong Sun. Yunquan Wang and Jian Zhang produced the figures.

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