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Review

Conceptualizing future groundwater models through a ternary framework of multisource data, human expertise, and machine intelligence

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ABSTRACT

Groundwater models are essential for understanding aquifer systems behavior and effective water resources spatio-temporal distributions, yet they are often hindered by challenges related to model assumptions, parametrization, uncertainty, and computational efficiency. Machine intelligence, especially deep learning, promises a paradigm shift in overcoming these challenges. A critical examination of existing machine-driven methods reveals the inherent limitations, particularly in terms of the interpretability and the ability to generalize findings. To overcome these challenges, we develop a ternary framework that synergizes the valuable insights from multisource data, human expertise, and machine intelligence. This framework capitalizes on the distinct strengths of each element: the value and relevance of multisource data, the innovative capacity of human expertise, and the analytical efficiency of machine intelligence. Our goal is to conceptualize sustainable water management practices and enhance our understanding and predictive capabilities of groundwater systems. Unlike approaches that rely solely on abundant data, our framework emphasizes the quality and strategic use of available data, combined with human intellect and advanced computing, to overcome current limitations and pave the way for more realistic groundwater simulations.

1. Introduction

Groundwater is a critical resource for ecosystems, agriculture, and industry, governed by complex systems that demand precise analysis and management (Aeschbach-Hertig and Gleeson, 2012; Cuthbert et al., 2019; Hilton and Jasechko, 2023; Scanlon et al., 2023; Zhang et al., 2017; Zheng and Guo, 2022). Traditional groundwater models (Prommer et al., 2003; Pruess et al., 1999) often struggle to fully consider the complex nature of groundwater systems. The limitations of these traditional models - dependence on specific statistical assumptions and difficulty in handling large-scale, high-dimensional data (Gómez-Hernández and Wen, 1998; Kitanidis, 1997; Neuman, 1972; Rubin and Journel, 1991; Scheibe et al., 2015) - highlight the need for more advanced methodologies (Tahmasebi et al., 2020).

The advent of machine intelligence, notably deep learning (DL), signifies a new era of groundwater models (Haggerty et al., 2023; Reichstein et al., 2019; Shen, 2018; Sun and Scanlon, 2019; White et al., 2021; Zhan et al., 2023). These advanced algorithms excel in extracting insights from extensive and diverse datasets (Chen et al., 2023; Greenhill et al., 2024; Luedtke et al., 2020; Steyaert et al., 2023; Wen et al., 2021; Zhang et al., 2018). This allows for a more comprehensive and accurate representation of inherently complex and non-linear groundwater systems, leading to more realistic simulations (Chen et al., 2021a; Laloy et al., 2018; Xu and Gómez-Hernández, 2016; Zhan et al., 2022).

Previous approaches in groundwater intelligent models have been primarily driven by machine-focused factors such as DL algorithms and computational power. This machine-focused development path has led to a focus on enhancing machine intelligence performance to improve simulation accuracy (Zhu et al., 2023), often overlooking the inherent limitations of machine intelligence such as lack of interpretability and

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the inability to generalize findings (Eshete, 2021; Liang et al., 2022). For example, a machine intelligent-based classifier model designed to detect pneumonia from X-ray scans performed well in certain hospitals but struggled with scans from new ones, and it managed to make decent predictions without truly learning about the disease itself (Zech et al., 2018). Moreover, the success of machine intelligence in autonomous driving and in healthcare, largely attributed to the availability of big data. However, machine intelligence faces an immense data-scarcity challenge in solving most groundwater problems (Goswami et al., 2022; Xu and Liang, 2021), because the limited accessibility and heterogeneity of the subsurface creates ubiquitous uncertainties (Tsai et al., 2022; Yeh et al., 2015) and data limitations. Data limitations due to scarce measurement availability is common to most DL applications, but inaccessibility impacts subsurface hydrology applications to a much more significant extent than other areas of hydrology. These data availability and access limitations have hindered the application of machine intelligence in practical groundwater simulation problems.

Due to the difficulty in addressing the aforementioned inherent limitations, machine-driven approaches have been proven inadequate when facing the inherent complexity and uncertainty of groundwater systems (Goswami et al., 2022). Instead, there is a need to develop AI centered on the "human expertise", positioning machine intelligence in an appropriate role to assist in addressing issues in groundwater simulation. Additionally, considering the data scarcity in groundwater systems, the role of multisource data is also is crucial for machine intelligence.

Therefore, we advocate a paradigm shift to equally emphasize multisource data, human expertise, and machine intelligence—-transitioning towards a ternary interaction framework (see Fig. 1). In this framework, multisource data, human expertise, and machine intelligence each play a unique and critical role. Multisource data is not only the cornerstone for training machine intelligence but also a crucial basis for the selection and development of machine intelligence algorithms. Human expertise are irreplaceable in transforming multisource data into actionable insights, as well as in interpreting and applying knowledge. Machine intelligence aims to mimic and enhance human abilities, playing a key role in the intelligent analysis and processing of multisource data. Their computational efficiency and advanced analytical capabilities enable them to handle complex datasets on an unprecedented scale and speed. Through the integration of these elements, our conceptual framework proposes a novel approach to enhance transformability in groundwater modeling. This framework aims to inspire

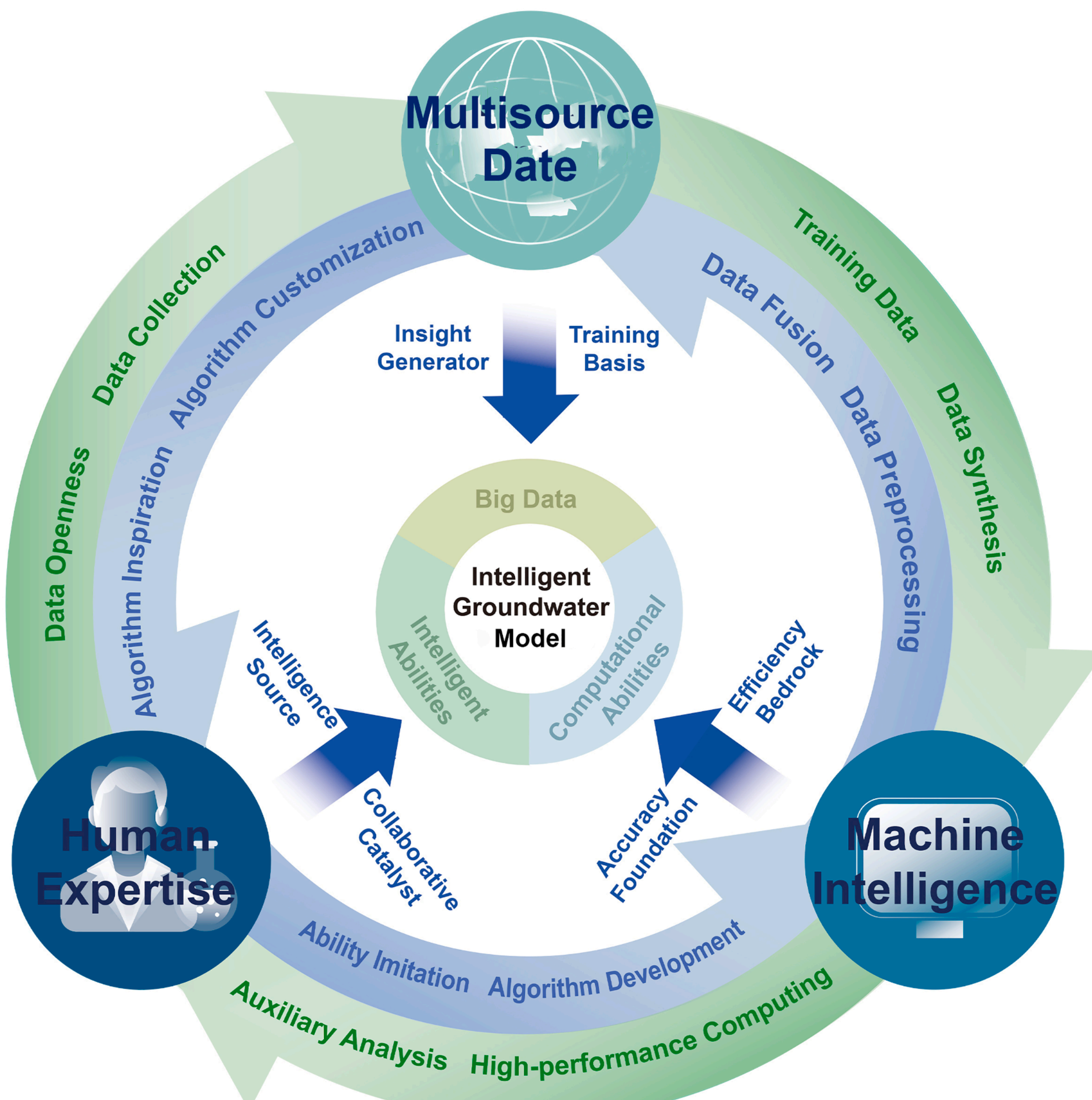

Fig. 1. Schematic diagram of the multisource data - human expertise - machine intelligence ternary framework. Multisource data, Human expertise, and machine intelligence each contribute to the development of groundwater intelligent models through big data, intelligent capabilities, and computational power.

the development of next-generation intelligent models that could more accurately capture the complexities of groundwater systems by synergistically combining multisource data, human expertise, and machine intelligence.

2. Current states for machine intelligence in groundwater models

2.1. Evolutionary stages of machine intelligence in groundwater models

To understand the depth and scope of machine intelligence in groundwater models, we propose a conceptual framework delineating an evolutionary trajectory through four distinct stages (Fig. 2): data intelligence, perceptual intelligence, cognitive intelligence, and autonomous intelligence. This framework not only forecasts a progressive enhancement in the sophistication of groundwater intelligence modeling, facilitated by the adoption of cutting-edge AI technologies, but also organizes and phases the analysis of AI's burgeoning applications in this field. By doing so, it fosters a more comprehensive discussion about the existing and potential constraints of these technologies (Table 1) within the domain-specific context of groundwater simulation.

2.2. Data intelligence

Data intelligence is the initial stage and primarily focused on extracting relevant information from large datasets, using algorithms to identify patterns and trends that may be missed by manual analysis due to their complexity or the time required for human analysis. Key algorithms in data intelligence, including support vector machines, random forests, and early DL models such as backpropagation neural networks, have become integral in deciphering complex relationships within groundwater data (Tsai et al., 2021). Traditional groundwater models are often constrained by human cognitive limitations and typically rely on simplifying assumptions to make effective predictions, struggling to incorporate the rich variety of multisource data available today. Additionally, their development methodologies do not fully leverage advanced computational capabilities, such as the parallel processing power of GPUs (Graphics Processing Units). Consequently, data intelligence not only enhances the accuracy and efficiency of simulations but also deepens our understanding of the dynamic changes within groundwater systems (Sahoo et al., 2017; Wunsch et al., 2022), moving towards models that more accurately reflect these complexities.

In practical applications, data intelligence demonstrates its strength in analyzing correlations between various factors and different states of groundwater systems from extensive datasets. This is particularly advantageous in handling large-scale monitoring data and multifactorial influences (Li et al., 2023b; Vereecken et al., 2022). For example, in forecasting groundwater levels, data intelligence effectively considers factors such as meteorological conditions, human activities, groundwater extraction, and geological conditions (Tao et al., 2022), thus enhancing predictive models for groundwater level changes and informing water resource management strategies.

Despite their promising contributions, data intelligence in groundwater models faces challenges, notably in contexts with insufficient data. This scarcity can lead to issues such as overfitting or underfitting, affecting model reliability (Lever et al., 2016). At this stage, machine capabilities are limited to replicating human logical reasoning and computational skills, without the ability to directly process data from

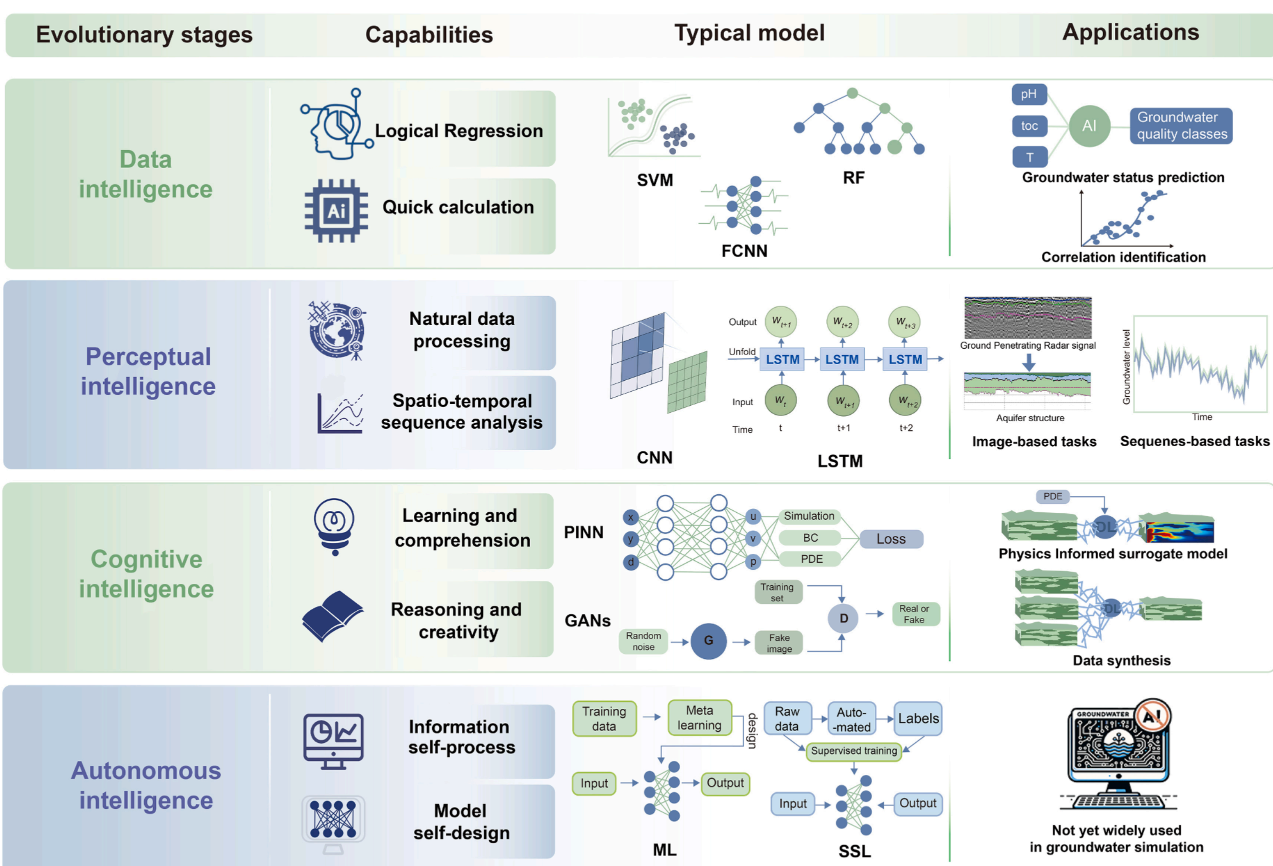

Fig. 2. Evolutionary stages of groundwater intelligent models and corresponding capabilities, typical models, and applications. This evolution marks a shift from basic logic and computation to a more advanced, human-like approach to problem-solving in groundwater simulation. Abbreviations: SVM: Support Vector Machine, RF: Random Forest, FCNN: Fully Connected Neural Network, CNN: Convolutional Neural Network, LSTM: Long Short-Term Memory Networks, PINN: Physics-Informed Neural Network, GANs: Generative Adversarial Networks, ML: Meta-Learning, SSL: Self-Supervised Learning.

Table 1
Key current challenges in groundwater intelligent models.

Challenge Type	Challenges	Explanation
Data-related Challenges	Insufficient training data (Goswami et al., 2022)	Many groundwater models tasks suffer from a lack of adequate data. Limited training data can lead to decreased model performance, as models struggle to learn effectively from a small dataset.
	High data quality demand (Wang et al., 2023)	Incorrect data (including human input errors) can have a significant impact on the effectiveness of DL algorithms. Groundwater observations are often characterized by high levels of noise and the presence of outliers, particularly when using long-term monitoring data, making strict quality assurance/quality control screening essential.
	Underutilization of existing data (Sun et al., 2019)	There is a lack of comprehensive utilization of available indirect data sources that could enhance model training and improve prediction accuracy. Current approaches do not fully exploit the potential of integrating multiple data sources.
	Lack of data sharing (Gewin, 2016)	The restricted use of monitoring data within specific research groups or institutions limits the diversity and volume of data available for intelligent groundwater modeling, thereby impeding the advancement of simulation capabilities.
Algorithm Performance-related Challenges	Poor model generalization (Bergen et al., 2019)	Some models exhibit poor generalization capabilities, performing well on training data but failing on new, unseen data. This overfitting issue hinders the applicability of models to a broader range of scenarios.
	Weak interpretability (Shen et al., 2023)	The results generated by predictive models are often difficult to interpret. This lack of clarity in understanding the physical meaning of model parameters and the logic behind predictions poses a significant challenge.
	Time-consuming parameter tuning (Shen et al., 2023)	Selecting and optimizing model parameters is a labor-intensive process that demands significant expertise and experimentation. This can be more time-consuming than the actual benefits gained from using advanced machine intelligence algorithms.
	Difficult model selection (Lever et al., 2016)	Absence of standardized methodologies for model selection forces users to experiment with various models to attain satisfactory predictions, often without clear guidance.
Computational Capability-related Challenges	High computational resource demand (Bergen et al., 2019)	Complex models such as deep learning require a large amount of computer resources for training, and the size of GPU memory can directly limit the algorithms available.
	Long model training time (Li et al., 2023a)	Long model training time, even for large-scale models, the training time alone is longer than the simulation time using traditional algorithm.

groundwater system. Consequently, humans must process raw data into structured formats, a task that can be labor-intensive. The effectiveness of these models often correlates with the extent of human involvement in data preparation, such as the removal of high-noise observations. This highlights the crucial role of human input in enhancing model intelligence, a contribution that is too often underestimated.

Data intelligence represents the beginning of a collaborative journey between machines and humans, combining computational efficiency and analytical depth. However, this is just the first step towards a deeper interplay between multisource data, human expertise and machine intelligence. The next stage will see machines not only handling data but also developing capabilities akin to human perception, enabling them to discern and interpret complex patterns directly from multisource data.

2.3. Perceptual intelligence

In perceptual intelligence stage, machines develop the capability to perceive and interpret various multisource data from groundwater systems. This evolution marks a shift from processing only structured data to understanding natural data and identifying complex patterns. Unlike traditional numerical groundwater models, which are significantly limited in both the types and volumes of data they can handle, DL models face far fewer restrictions. For example, self-attention mechanisms in DL models allow features of spatial or temporal data as a whole to be taken into account in predictions, regardless of data size (Vaswani et al., 2017). This signifies that machine intelligence at this stage has significantly improved its capabilities in handling the types and quantities of data for both time series forecasting and spatial structure analysis. This advancement is not just an increase in data handling but a critical step towards achieving autonomous intelligence, with machines beginning to match or even surpass human capabilities in data interpretation.

The transition from Data Intelligence to Perceptual Intelligence in groundwater models has been greatly influenced by the development of Convolutional Neural Networks (CNNs) (LeCun and Bengio, 1995) and Recurrent Neural Networks (RNNs) (Lipton et al., 2015). Previously, detailed microscale and macroscale images, such as those from Scanning Electron Microscopes, rock CT scans, and satellite remote sensing, relied heavily on human expertise for analysis (Hart, 1999). Using CNNs, machines can now autonomously recognize and interpret complex patterns in these images, leading to more accurate and efficient simulations (Da Wang et al., 2021; Mousavi and Beroza, 2022; Wu et al., 2023). For example, machines with Perceptual Intelligence can identify aquifer structures from geophysical data (Hermans et al., 2023; Kang et al., 2021) and assess changes in groundwater storage using satellite imagery (Smith and Majumdar, 2020; Sun et al., 2019), which are tasks that were once dependent on human analysis.

Additionally, groundwater models often require understanding of dynamic spatiotemporal patterns (Wallace and Soltanian, 2021; Wallace et al., 2021; Wunsch et al., 2021), a domain in which RNNs and their variants, such as LSTMs and GRUs, excel (Connor et al., 1994; Mandic and Chambers, 2001). They enable the integration of a wide range of factors, including historical and current data, seasonal variations, and anomalous events, into predictive models. This allows for a more comprehensive understanding of temporal relationships, such as the impact of extended droughts or heavy rainfall on groundwater levels (Rajaee et al., 2019).

Despite these advances, Perceptual Intelligence still largely operates within the framework of Data Intelligence. It relies on correlating inputs and outputs, learning from data features to predict various state variables of groundwater systems. Although effective in pattern recognition, this approach does not encompass a deeper cognitive understanding akin to human thought processes. As a result, models based on Perceptual Intelligence often remain opaque or 'black box' in nature, challenging researchers in understanding the underlying mechanisms driving predictions. This lack of transparency can hinder the wider acceptance and trust in these models in both scientific and practical contexts (Novakovsky et al., 2023).

In conclusion, while Perceptual Intelligence has significantly impacted groundwater modeling tasks involving various data types, the current limitations in causal reasoning underscore the need for further integration with cognitive intelligence systems (Table 1). Strengths of AI in pattern recognition, however, are invaluable in leveraging raw geoscience data for practical applications, setting the stage for more advanced, knowledge-driven modeling approaches.

2.4. Cognitive intelligence

In the previous two stages, machines' prediction often relies on statistical likelihoods (Zhu et al., 2023), which may not equate to a true understanding in the human sense. This limitation confines the machines to operating within statistical parameters and can pose challenges in deriving clear explanations from deep learning processes (Alzubaidi et al., 2021). With the transition to Cognitive Intelligence, machines start to emulate human cognitive and logical thinking, dedicated to understanding and interpreting complex patterns and relationships in groundwater systems. This stage goes beyond the basic functions of Data and Perceptual Intelligence, enhancing analytical depth and providing insights beyond simple data analysis (Runge et al., 2023). From this stage forward, traditional groundwater models become inadequate in comparison, as they lack the cognitive capabilities and autonomous thinking that machine intelligence offers.

In the progression of groundwater models, Cognitive Intelligence evolves similarly to human cognitive development. Initially, machines learn basic hydrogeological concepts, including physical equations related to groundwater flow. An application of this is seen in physics-informed deep learning models (Karniadakis et al., 2021) for solute transport forecasting (Haghighat et al., 2021; Raissi et al., 2019; Wang et al., 2021). Progressing beyond these foundational skills, the subsequent advancement sees machines gaining capability to develop more innovative models and predictions. These innovations can reflect the complexities of groundwater systems, which may not be adequately represented by existing models or human cognition (Wang et al., 2023; Xue et al., 2023). For instance, machines can refine and adjust aquifer structure models based on new observational data, thereby generating new structures not previously seen in training samples. That is, the geological statistical characteristics of the generated aquifer structures can extend beyond the range of those in the training samples (Zhan, Dai, Samper, et al., 2022).

This level of Cognitive Intelligence signifies a fusion of machine capabilities with human knowledge, improving both the interpretability and generalizability of models. Machines begin to extrapolate new hydrological insights (Nearing et al., 2021), narrowing the cognitive gap between human and machine intelligence. This represents a significant step towards a future where machine intelligence operates in a manner similar to human cognition.

Yet, advancing Cognitive Intelligence faces challenges. Machines, while skilled in data management and analysis, largely follow learning paths shaped by network architectures and datasets designed by humans. This dependence restricts their development within groundwater modeling. Building cognitive intelligence models is resource-intensive, and human expertise has its limits. Overcoming these barriers necessitates a shift towards autonomous learning and computational logic designed by machines themselves. In the anticipated phase of Autonomous Intelligence, machines will transition from executors to independent thinkers, autonomously designing model and processing data through their learning and analysis.

2.5. Autonomous intelligence

In the evolutionary spectrum of machine intelligence, Autonomous Intelligence represents the apex. It integrates the strengths of Data, Perceptual, and Cognitive Intelligence, distinguishing itself by its capability to handle data and perception, along with rapid adaptation and independent decision-making (Vilalta and Drissi, 2002). This is facilitated by advanced methodologies such as meta-learning, enabling the system to learn from limited examples and swiftly adapt to new tasks (Hospedales et al., 2021), and self-supervised learning, which enables learning predictive models from unlabeled data (Huang et al., 2023; Sun et al., 2023). These methods expand the possibilities of achieving significant results without relying heavily on extensive annotated datasets.

Examples of Autonomous Intelligence applications include autonomous vehicles (Schwarting et al., 2018) and intelligent manufacturing robots (Zhong et al., 2017). In the realm of groundwater models, however, the application of Autonomous Intelligence is still in its early stages. Its potential impact on groundwater models techniques is substantial. With Autonomous Intelligence, machines could independently gather and analyze data from various fields such as hydrology and geology. Depending on the specific issue at hand, they could autonomously select the most suitable model frameworks and algorithms, enabling data fusion and knowledge extraction. The system could autonomously predict outcomes and search for optimal decisions, continuously learning and refining its methods to handle new scenarios. This capability to autonomously predict and make decisions marks a significant advancement over previous stages, characterized by reliance on historical data, limited generalization, and manual interventions. It indicates a new era of efficient and real-time strategic decision-making for groundwater management.

However, we realize that development of autonomous groundwater intelligent modeling system still faces numerous challenges (Table 1). Machine intelligence, regardless of its stage, is still constrained by its algorithms and the data it is trained on (Davenport and Ronanki, 2018). Challenges arise in scenarios beyond the scope of available data or the complexity of the algorithms. Additionally, decisions made by autonomous systems can be biased by their training data. For example, without human intervention, machines find it difficult to eliminate a large amount of data errors, which could lead to simulations that do not accurately reflect real-world scenarios. The nature of these decision-making processes can also create trust issues among users (Araujo et al., 2020).

2.6. Summary of inherent challenges of machine intelligence

Reviewing the four evolution stages of development in groundwater intelligent models, it becomes evident that previous research has emphasized enhancing machines' imitation of human intelligence with continuous augmentation of their intelligence and autonomy in an effort to liberate humans from the tedious task of modeling. However, it is crucial to acknowledge that the application of machine intelligence in groundwater simulation still significantly lags behind the level of fully autonomous AI. In fact, this may remain unachievable for a considerable time in the future. This limitation is primarily due to inherent constraints of machine intelligence, which can be categorized into three aspects: data-related, model performance-related, and computational capacity-related limitations (as detailed in Table 1). Data-related challenges have always been present at each stage of groundwater intelligent models, where the quantity and quality of training data directly impact the effectiveness of DL model training. Challenges related to algorithm performance have received more attention but still face significant hurdles in terms of interpretability and generalizability, and there is still a lack of theoretical guidance in the selection of model parameters and structures. Challenges related to computational capabilities largely depend on the development of computing hardware and the emergence of new computational paradigms, with current research yet to find effective solutions.

Yet, most current studies overlook these limitations, and even employ shortcut learning methods, such as designing simulated scenarios, objectives, or assuming the availability of training samples, to circumvent issues such as poor generalizability and limited data (Geirhos et al., 2020). This approach may yield satisfactory results for the test datasets used but fails to apply in more challenging real-world problems. Such shortcut learning has long obscured these inherent limitations of machine intelligence, which cannot be fully resolved merely by utilizing machines. To overcome these limitations and advance the application of machine intelligence in groundwater modeling, it is essential to leverage the collaborative interaction of multisource data, human expertise, and machine intelligence. This approach should fully utilize the unique characteristics of each element and propose reasonable solutions to these inherent limitations (as discussed in Table 2 and illustrated in Fig. 3).

3. Advancing via ternary framework combining multisource data, human expertise, and machine intelligence

As previously discussed, focusing solely on machine intelligence may not be the most effective approach for the development of intelligent groundwater models. It is essential to re-evaluate the interrelationships among multisource data, human expertise, and machine intelligence, acknowledging the roles of both multisource data and human expertise. This leads to the concept of the " *Multisource data - Human expertise - Machine intelligence Ternary Framework*" as depicted in Fig. 1. This framework emphasizes the efficient collaboration and synergistic enhancement among multisource data, human expertise, and machine intelligence. This approach aims to improve the efficiency and quality of groundwater intelligent models. The forthcoming discussion will explore the distinct characteristics and transformative potential of each component within this ternary framework: multisource data, human expertise, and machine intelligence.

3.1. *Multisource data – training basis and insight generator*

Multisource data is fundamental at every stage of machine intelligence, significantly impacting the effectiveness of groundwater models. To advance in this field, it is crucial to fully harness the extensive data resources of the groundwater system, which requires a comprehensive dual strategy. We must fully utilize the groundwater system data already acquired. Meanwhile, we must intensify our efforts to gather more data directly from groundwater systems. Both strategies demand a collaborative synergy between humans and machines, leveraging their respective strengths to improve our understanding and management of groundwater systems.

Firstly, humans play a crucial role in fostering a culture of data openness (Gewin, 2016), essential for addressing the significant global disparity in data availability. The establishment of open, standardized databases and the promotion of data sharing, as seen in initiatives like the UN-IGRAC's Global Groundwater Information System (GGIS) (https://www.un-igrac.org/global-groundwater--information-system-ggis), are vital for democratizing data access. This not only enables researchers worldwide to utilize a broader and more diverse range of information (Poldrack and Gorgolewski, 2014), enhancing the scientific and practical applications of their work, but also specifically addresses the acute data scarcity in underrepresented regions.

Simultaneously, we must place emphasis on more thorough processing and analysis of existing data. On one hand, the integration of

Table 2
Key opportunities in intelligent groundwater simulation.

Opportunity Type	Opportunities	Explanation
Multisource Data-Human Expertise Interaction	Data synthesis (Theodorou et al., 2023; Yao et al., 2023)	Utilize machine intelligence algorithms to generate new datasets based on natural data characteristics.
	Building public databases (Gewin, 2016)	Create and maintain databases that are accessible to a wide range of users, fostering collaborative research and data sharing
	Hybrid modeling (Sun and Scanlon, 2019)	Combine physical models with machine learning models to enhance both accuracy and efficiency in simulations.
	Physics-informed neural networks (Karniadakis et al., 2021)	Implement neural networks that integrate physical laws into their architecture, improving both accuracy and generalization.
Multisource Data-Machine Intelligence Interaction	Data augmentation (Yang et al., 2022)	Creating new data from existing data to increase dataset size and diversity.
	Data cleaning (Bernhardt et al., 2022)	Utilize machine intelligence algorithms to identify and correct or eliminate errors, inconsistencies and inaccuracies in data sets.
	Data fusion (Zhan, Dai, Soltanian, and de Barros, 2022)	Extracting information from relevant multi-source data through machine intelligence algorithms for more accurate simulations.
Human Expertise-Machine Intelligence Interaction	Semi-supervised learning (Shen, 2018)	Develop machine learning algorithms that can learn from both labeled and unlabeled data, reducing dependency on labeled data.
	Unsupervised learning (Tahmasebi et al., 2020)	Enable machine learning algorithms to analyze unlabeled data and discover inherent patterns and structures.
	Self-supervised learning (Huang et al., 2023; Sun et al., 2023)	Train models on unlabeled data by generating synthetic labels for more efficient learning processes.
	Transfer learning (Goswami et al., 2022):	Apply knowledge gained from one task to enhance simulation accuracy in a related task, reducing reliance on new data.
	Explainable AI (Novakovsky et al., 2023)	Develop AI models and analytical techniques that provide insights into the logic and predictions of machine learning algorithms, enhancing human understanding of these systems.
	Ensemble learning (Sagi and Rokach, 2018)	Combine multiple machine learning models to improve overall accuracy and reduce the likelihood of overfitting.
	Meta-learning (Hospedales et al., 2021; Vilalta and Drissi, 2002)	Enable models to learn how to optimize parameters and design network architectures more effectively.
	Cloud, fog, edge computing (Zhu et al., 2023)	Leverage various computing architectures to distribute processing and storage, maximizing the utilization of existing hardware capabilities.

(*continued on next page*)

Table 2 (*continued*)

Opportunity Type	Opportunities	Explanation
	Quantum, photonic, Biological Computing (Sahimi and Tahmasebi, 2022; Xu et al., 2021)	Explore emerging technologies that use principles of quantum mechanics, photonics, or biological systems for computations, offering potentially significant speed advantages over current computing technologies.

multisource data can help us obtain global properties of the groundwater system, such as upscaled regional parameters, and identify key assumptions and features of groundwater models. On the other hand, when using multisource data, we must also focus on screening and preprocessing of raw data. Machine intelligence technically assists in managing and processing heterogeneous data from multiple sources (Bergen et al., 2019; Li et al., 2023a). Advanced capabilities in data and perceptual intelligence are crucial for tasks such as data cleaning, data standardization, and uncovering valuable insights (Mocanu et al., 2018). For instance, utilizing generative models such as GANs (Generative Adversarial Networks) and VAEs (Variational Autoencoders) can transform non-Gaussian distributed raw data into Gaussian distributions, thereby facilitating subsequent processes like data fusion (Mo et al., 2020).

In addition to training machine intelligence algorithms, multisource data can also inspire the selection and design of intelligent algorithms (Stanley et al., 2019). On the one hand, recognizing and understanding the inherent characteristics of groundwater systems, such as temporal and spatial correlations, is crucial for choosing and tuning artificial intelligence algorithms for groundwater simulation (Zhan et al., 2023). For instance, algorithms like RNNs and LSTMs are more suited for predicting variables with temporal correlations (such as groundwater levels) (Wunsch et al., 2021), while convolutional neural networks can effectively identify variables with spatial correlations in groundwater systems (such as facies distribution) (Shen, 2018).

On the other hand, based on some general DL technologies, making targeted improvements to the DL algorithms used according to the characteristics of groundwater models is also significant for advancing the application of machine intelligence in groundwater models. For example, by adopting Octave Convolution, DL algorithms can focus on areas with high uncertainty in lithological distribution within aquifer structures, while compressing information in other areas (Zhan, Dai, Samper, et al., 2022). This method not only reduces the demand for computational resources but also enhances efficiency while maintaining model accuracy, adapting to the large size of groundwater models.

Moreover, even with the aid of humans and machines, acquiring massive amounts of high-quality data for groundwater systems may still be expensive and challenging. Generating large datasets that reflect natural distribution patterns through machine intelligence, based on observations of natural attributes, might be a potent way to provide

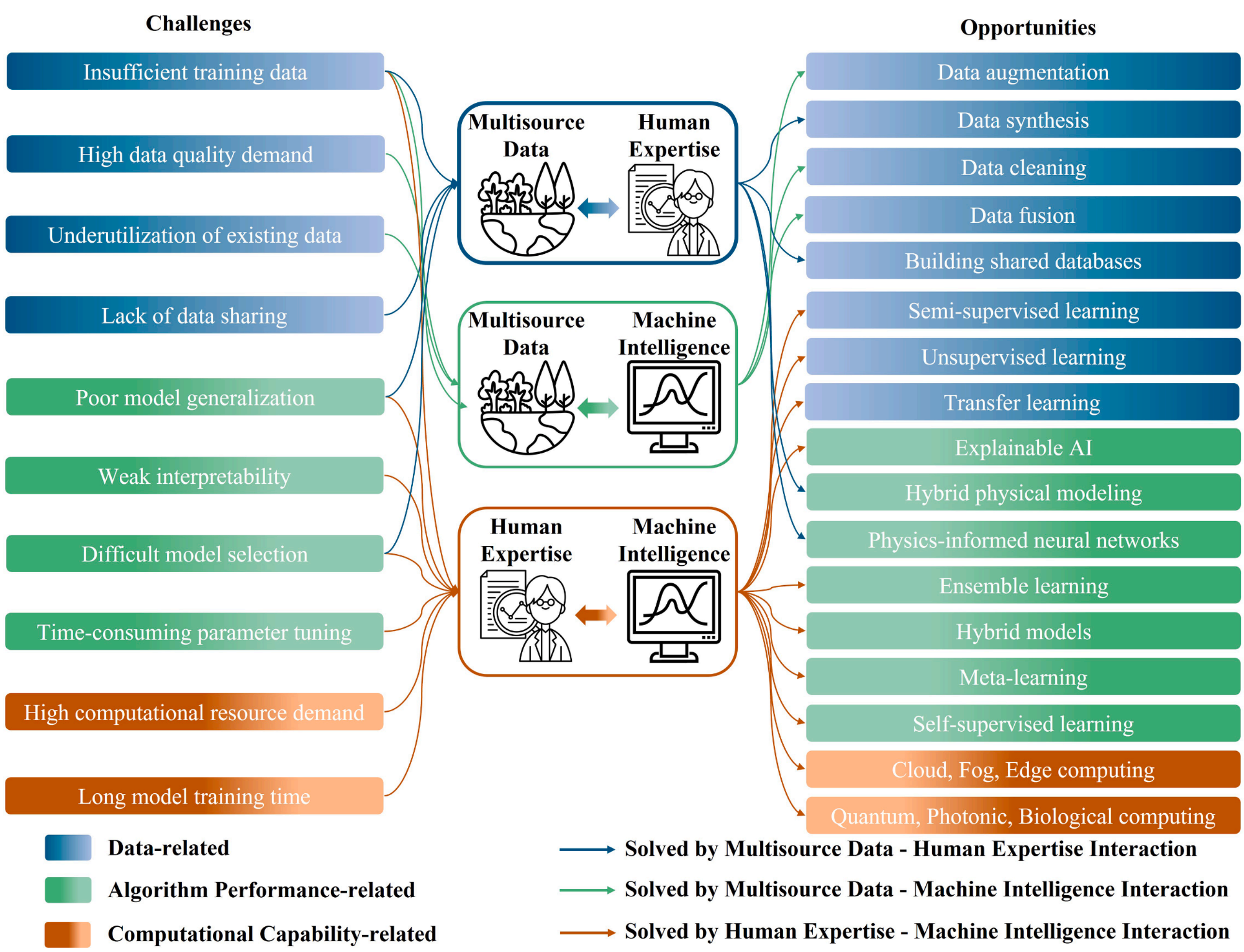

Fig. 3. Challenges and opportunities in intelligent groundwater modeling. All of the current challenges facing intelligent groundwater modeling can be properly addressed through the interactions of multisource data, human expertise, and machine intelligence. A detailed description of the challenges and opportunities can be found in Tables 1 and 2.

extensive and varied datasets (Theodorou et al., 2023; Yao et al., 2023). These generated datasets help train and refine groundwater intelligent models. For example, using sedimentation patterns observed in lithology, reliable aquifer structures can be synthesized and used to train models for recognizing aquifer structures (Zhan et al., 2022).

3.2. Human expertise - intelligence source and collaborative catalyst

Human intelligence forms the foundation for developing machine intelligence (Dehaene et al., 2021; Sternberg et al., 2021). Reflecting on the evolution of machine intelligence in groundwater models, the development has continuously emulated that of human cognitive processes. Therefore, advancing the application of machine intelligence in groundwater models fundamentally involves enabling machines to recognize, perceive, learn, and think, which guides them towards evolving into human-like intelligence.

With the success of AI in other fields, "a gold rush" to apply AI to groundwater simulation has emerged. This trend has led to a "seeking problems for methods" approach within the hydrology community, seeking suitable problems for the application of machine intelligence, rather than addressing inherent issues in traditional methods and considering if AI could offer solutions. To rectify this, humans would need to position machine intelligence appropriately. Additionally, as machine intelligence inches closer to human intelligence, we must consider what roles remain uniquely human, irreplaceable by AI.

Machine intelligence excels in tasks with standardized solutions, surpassing humans in precision and efficiency. For example, when solving partial differential equations (Chen et al., 2021b; Raissi, 2018; Rao et al., 2023) or accelerating a computational process where the inputs and outputs are known, such as surrogate modeling (Tang et al., 2020), machines can effectively replace human involvement, which would transform the human role to machine support. In dealing with complex, non-standard problems, even without clear hydrogeological models, machine intelligence can aid humans in making reliable hydrological predictions. The success of RNNs and LSTMs in groundwater level prediction highlights this capability (Tao et al., 2022).

However, while machine intelligence driven by data often seems to yield accurate results, the underlying logic behind their results may differ significantly from human understanding. Therefore, machine intelligence also needs to fully consider the integrity of their underlying model algorithms, like traditional water flow and solute transport numerical models (Labolle and Fogg, 2002; Labolle et al., 1996). This consideration ensures that machine intelligence maintains sufficient numerical fidelity during the solution process, and that there is a clear understanding of how the solution process operates. This critical task still relies on human involvement.

On the one hand, when addressing complex problems, to ensure that machine intelligence predictions do not deviate from existing physical and chemical principles, humans can impart their deep understanding of groundwater systems to machines. For instance, by incorporating the advection-dispersion equation into the loss functions, we can control the output results, which is an approach known as physics-informed neural networks (see Table 2). On the other hand, understanding the internal workings and theoretical knowledge behind DL models is as important as for traditional numerical models. This understanding also relies on human exploration and research into the interpretability of machine intelligence, such as Explainable AI (see Table 2) (Schneider et al., 2023; Tartakovsky et al., 2020).

Moreover, humans play a pivotal role in creative breakthroughs. The development of large models like ChatGPT (Chat Generative Pre-trained Transformer) showcases AI's potential (Ray, 2023). These models, developed using advanced algorithms, significant computational power, and extensive data, demonstrate capabilities that rival or even surpass humans. However, envisioning a groundwater simulation model of complexity similar to ChatGPT, both in terms of advanced algorithms and the need for extensive, high-fidelity data, remains a challenge given current algorithmic and data collection capabilities without significant technological advancements, which depend on human ingenuity and creativity.

Therefore, regardless of the stage of machine intelligence evolution, humans maintain a critical role. They serve as the link between the vast data reserves of the natural world and the computational capabilities of machines. Humans determine the relevance of data, guide the methods for data processing, and evaluate the significance of outcomes generated by machine algorithms. Their involvement ensures that the application of machine intelligence transcends mere computation, thereby aligning it with broader environmental, societal, and ethical objectives.

3.3. Machine intelligence - accuracy foundation and efficiency bedrock

As previously discussed, the intelligence of machines manifests in an accuracy and efficiency that significantly surpasses human capabilities. This superiority is rooted in advancements in computational hardware and the evolution of algorithmic architectures. Moore's Law states that computational power doubles approximately every two years, but the demands of artificial intelligence have grown at an even more rapid pace. Between 2012 and 2018, the computational requirements for leading AI models have been doubling roughly every 3.4 months (Mehonic and Kenyon, 2022), far outstripping the growth of traditional silicon-based computing. Groundwater simulation, with its extensive spatial and temporal scales and reliance on image data, underscores the need for heightened computational power. The development of large language models such as ChatGPT and other large models reveals a critical insight: when AI models reach a certain threshold of parameters, there is a significant leap in their learning and predictive abilities, comparable to a form of 'enlightenment' (Wei et al., 2022). This indicates the transformative potential of large-scale models for future advancement of intelligent groundwater simulation.

Whether discussing general or specialized DL models, there is a consistent emphasis on the need for innovative computational paradigms. Emerging technologies such as quantum, photonic, and biological computing are poised to revolutionize computational capacities (Sahimi and Tahmasebi, 2022; Xu et al., 2021), particularly in processing speeds that could potentially be hundreds to millions of times faster than those of conventional computers (Harrow et al., 2009). This exponential increase in processing speed could fundamentally resolve the current time-consuming limitations associated with DL model training, structural adjustments, and parameter tuning. Furthermore, it allows groundwater models to fully leverage multisource data, consider a broader range of possibilities, and even complete tasks that could be approached through exhaustive methods. Meanwhile, strategies like cloud computing, fog computing, and edge computing provide practical solutions to maximize the use of current silicon-based units (Zhu et al., 2023), enhancing the computational capabilities of DL models using existing computing hardware. However, advancements in hardware are just part of the equation; algorithmic innovation is equally important. This includes developing new algorithms for quantum and photonic processors and enhancing existing algorithms to surpass current limitations. A significant barrier to applying intelligent groundwater models to practical problems is their immense demand for computational power. Therefore, implementation of these high-performance computing methods is expected to truly advance the practical application of intelligent groundwater models.

Furthermore, enhancing the computational capabilities of existing DL algorithms and combining novel algorithms with abundant multisource data and human expertise are equally crucial in the short term. For example, leveraging hybrid models (Shen et al., 2023; Sun and Scanlon, 2019), ensemble learning (Sagi and Rokach, 2018), and transfer learning (Goswami et al., 2022) can improve the predictive performance and generalizability of DL models on existing frameworks. Semi-supervised learning (Shen, 2018), unsupervised learning (Tahmasebi et al., 2020), and self-supervised learning (Huang et al., 2023;

Sun et al., 2023) can reduce the dependency of DL models on labeled training data, thus minimizing the human effort required in data processing. Additionally, meta-learning represents a potentially significant future direction, enabling machine intelligence to autonomously find optimal model structures and parameters based on training data, thereby liberating humans from the labor-intensive tasks of model tuning and selection (Hospedales et al., 2021; Vilalta and Drissi, 2002). This is even more important as these approaches are expanded into new computing paradigms including quantum computing in the future. Such advancements will enhance our ability to identify patterns, correlations, and causal links in groundwater systems, which will further push the boundaries of our capabilities in this field.

4. Conclusion

In examining the evolution of groundwater simulation, it becomes evident that the integrated approach of multisource data, human expertise, and machine intelligence is not just beneficial but essential. Each component plays a critical role: multisource data as the source of valuable insights and the basis of model training, human expertise as the interpreter and innovator, and computational technology as the tool for efficient computation and advanced analysis. Therefore, to addressing the current challenges in groundwater intelligent models, this paper developed a reforming ternary framework that synergistically integrates these three elements. The proposed "*Multisource Data, Human Expertise, and Machine Intelligence Ternary Framework*" not only offers viable solutions to the limitations of current DL models in groundwater modeling but also charts a clear path for future advancements in this field. By harmonizing these elements, the framework sets a new direction for developing more sophisticated, accurate, and sustainable groundwater management practices.

CRediT authorship contribution statement

Chuanjun Zhan: Writing – review & editing, Writing – original draft, Visualization, Investigation, Conceptualization. **Zhenxue Dai:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Shangxian Yin:** Writing – review & editing, Conceptualization. **Kenneth C. Carroll:** Writing – review & editing. **Mohamad Reza Soltanian:** Writing – review & editing, Conceptualization.

Declaration of competing interest

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Data availability

No data was used for the research described in the article.

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