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Review

Revolutionizing Groundwater Management with Hybrid AI Models: A Practical Review

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Abstract: Developing precise soft computing methods for groundwater management, which includes quality and quantity, is crucial for improving water resources planning and management. In the past 20 years, significant progress has been made in groundwater management using hybrid machine learning (ML) models as artificial intelligence (AI). Although various review articles have reported advances in this field, existing literature must cover groundwater management using hybrid ML. This review article aims to understand the current state-of-the-art hybrid ML models used for groundwater management and the achievements made in this domain. It includes the most cited hybrid ML models employed for groundwater management from 2009 to 2022. It summarises the reviewed papers, highlighting their strengths and weaknesses, the performance criteria employed, and the most highly cited models identified. It is worth noting that the accuracy was significantly enhanced, resulting in a substantial improvement and demonstrating a robust outcome. Additionally, this article outlines recommendations for future research directions to enhance the accuracy of groundwater management, including prediction models and enhance related knowledge.

Keywords: state-of-the-art; hybrid machine learning; groundwater management; performance models

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1. Introduction

As one of the world's most valuable and vital water sources, groundwater is integral to many facets of human life, including food production, economic growth, and safe drinking water [1]. However, uncontrolled urbanisation and the growing burden of human activities on hydrogeomorphology systems threaten the environment by altering the existing recharge mechanism and groundwater quality [2–4]. The enormous growth and uneven distribution of population, poor irrigation practices, industrialisation, rapid urbanisation, widespread deforestation, inappropriate land use practices, and climatic changes have affected groundwater resources' quantity and quality [5–9].

To manage and conserve groundwater resources effectively, it is crucial to comprehend the influence of hydrological and meteorological variables on groundwater [10]. However, accurate descriptions are challenging due to the nonlinear changes in these variables, which make it difficult to manage groundwater effectively [11,12]. Therefore, utilising new methods such as artificial intelligence (AI) is inevitable.

Researchers have used AI to simulate and predict groundwater resource management behaviour. AI models can find and describe structural patterns in data to help predict and decide [13–15]. AI methods can assess groundwater potential, predict contaminants, and inform groundwater management decisions by processing large amounts of multidimensional data [16–18].

However, managing groundwater is a difficult and intricate task that demands an extensive comprehension of multiple essential hydrological parameters, including geology, hydrogeology, land use, and climate change. As the references [19–21] state, these parameters are challenging to model accurately. Additionally, limited data is often available [22,23], particularly in developing countries [24], making training and validating AI models challenging.

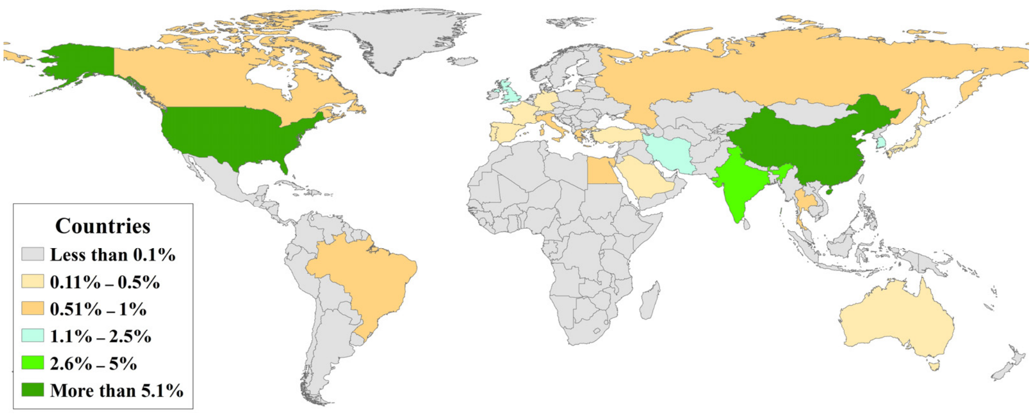
One approach that has gained increasing attention in recent years is the use of hybrid AI models, which combine different AI techniques with traditional models or expert knowledge to improve performance and address some of the limitations of AI in groundwater management [25–27]. For example, a hybrid AI model might combine a neural network for predicting groundwater levels with a physically-based model for simulating flow and transport processes [28,29]. This approach can help to address issues such as data scarcity, model interpretability, and uncertainty by incorporating domain knowledge and ensuring that the AI model is grounded in the physical processes that govern groundwater behaviour [30,31].

Hybrid AI consists of multidimensional systems combining various mathematical and statistical components and arithmetic and heuristic algorithms. Hybrid AI has been extensively employed in different fields of science, engineering design, energy, robotics, and economics. It has also been intensively used for solving various civil and environmental engineering problems, including groundwater management (GWM). Among the other promising AI techniques for groundwater assessment are hybrid methods that combine different approaches, such as Artificial Neural Networks (ANN), Machine Learning (ML), Metaheuristic Optimization Algorithms (MOA), Fuzzy Inference Systems (FIS), and combinations of ANNs and MOAs [32–35]. Hybrid AI techniques have improved the accuracy and reliability of groundwater assessments, outperforming traditional methods in predicting groundwater quality and quantity. These techniques are particularly effective in dealing with nonlinear and intricate problems that traditional numerical models struggle with. By applying hybrid AI models, hydrogeology scientists can better understand the complexities of groundwater systems and develop effective strategies to conserve and manage this vital resource [36–38]. In recent years, more attention has been paid to the successful use of Hybrid AI in different hydrogeological fields, including Assessing groundwater potential [39,40], Estimating groundwater recharge [41,42], Managing and predicting groundwater levels [43,44], Simulating groundwater flow [45], Assessing groundwater quality [27,46–48], Estimating aquifer parameters [49], Identifying sources of pollution in groundwater [48,50], Managing and planning groundwater resources [51], Designing groundwater remediation strategies [52], Managing water allocation [53,54], Assessing vulnerability to groundwater depletion or contamination [55,56], Predicting future groundwater conditions [57,58], including seawater intrusion in coastal areas [59,60].

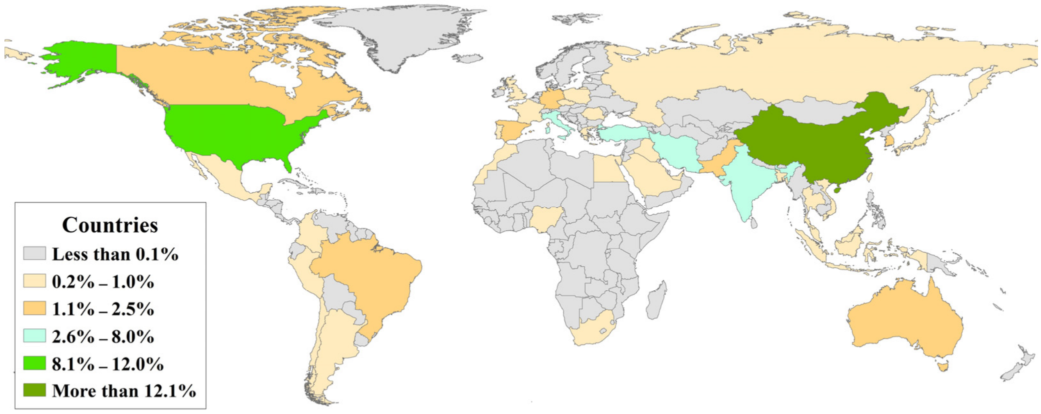
As per Figure 1, there has been a significant increase in studies using Hybrid AI in this field in the last few years; however, more studies should be done, based on different geographical locations, to test the efficiency of the proposed models. Figure 2a,b present the goal map, depicting the two significant pieces of information: the most studied geographical locations and another yet to be studied. Furthermore, Figure 1 highlights the four major countries with extensive GWM modelling-related studies using Hybrid AI. In contrast, the grey colour zone reveals the areas where the application of Hybrid AI has yet to gain popularity. Around 50% of sites have yet to use GWM, as many do not need GW-related studies, due to sufficient surface water or fewer habitats, such as in polar areas, African countries, etc. Moreover, some underdeveloped regions in Asia and South America may still need to explore Hybrid AI techniques.

Groundwater management is critical for ensuring water security and sustainability, yet there need to be more review articles on this topic and the use of hybrid models. Reviews are crucial in identifying knowledge gaps and research needs, especially given the complexity of groundwater systems. There is a pressing need to explore the use of hybrid models that combine different techniques, such as artificial intelligence and statistical methods, to improve accuracy and reliability. Therefore, a review article focusing on recent advances in applying hybrid AI techniques in groundwater management must fill the knowledge gap and provide insights for future research.

Figure 1. Arithmetical conceptualisation of growth observed in groundwater quality and quantity research using a Hybrid AI-based model during 2009–2022. Note that while these databases are comprehensive, they may not include every article published on a topic, as not all journals and conference proceedings are indexed in the Scopus database.



(**a**)



(**b**)

Figure 2. Map shows the global distribution of articles on groundwater quality (**a**) and quantity (**b**) management that use Hybrid AI models. The (**a**) map indicates articles that focus on quality approaches. The percentage values are based on the number of articles published per country and all Hybrid AI articles related.

This review article addresses recent advances in hybrid AI techniques for groundwater management. To provide readers with a comprehensive understanding of these techniques, we also discuss AI's history and main tasks in Section 2. In Section 3, we delve into the research methods improved by hybrid AI, followed by a review of the most cited applications. Finally, in Section 4, we explore the challenges and opportunities associated with specialised databases, proposing several feasible approaches to enhance the collaboration between groundwater researchers and data scientists. Overall, this review article provides a valuable resource for researchers and practitioners interested in using hybrid AI techniques for groundwater assessment and management.

2. Machine Learning History and Groundwater

Machine learning has a rich history dating back to 1959 when Arthur Samuel coined the term to describe a checker program [61]. A machine learning model is data-driven, learning from data and improving accuracy without explicit programming. Over time, machine learning has evolved into various learning technologies, including connectionism, symbolism, and statistical learning [62]. In the context of groundwater, machine learning has several important tasks. One of its primary uses is to help predict the behaviour of groundwater systems, which can be done by analysing various data inputs, such as recharge, water levels, and groundwater quality, and using machine learning algorithms to predict future trends. Another important task of machine learning in groundwater is to help identify and analyse groundwater contaminants. Machine learning algorithms can be trained to detect anomalies in water quality data, which can help identify potential contaminants and their sources [63].

Machine learning can also be used to optimise groundwater management strategies. By analysing water abstraction and supply data, machine learning algorithms can help identify areas of inefficiency and recommend more effective management practices [64]. Overall, machine learning has become an essential tool in groundwater management, helping to improve our understanding of groundwater systems and optimise our use of this critical resource.

2.1. Symbolism

One of machine learning's key learning technologies is symbolism. Logic involves manipulating symbols, rules, and operations [62]. Symbolism has been used to create groundwater expert systems, which are rule-based systems that mimic human decision-making [63]. Expert systems were used extensively in groundwater hydrology in the 1980s and 1990s to solve complex groundwater management problems like aquifer characterisation, well-field design, and contamination remediation [65]. These systems model a domain expert's expertise as rules to solve a problem using knowledge representation techniques. The system uses data to make predictions, classifications, and recommendations. Expert Symbolism systems have advanced groundwater management using machine learning [63]. It has automated complex decision-making tasks and transferred knowledge from experts to non-experts [66]. However, Symbolism's inability to handle uncertain or incomplete data has led to developing other learning technologies, such as statistical learning, which are better at handling such data [67]. In groundwater management, a hybrid model that combines symbolic and other AI techniques can help address the challenges associated with incomplete and uncertain data and nonlinear relationships between hydrological and meteorological variables, offering a promising avenue for advancing the field of machine learning and groundwater management.

2.2. Statistical Learning

Statistical learning, a form of machine learning that utilises statistical models for classification and prediction, has long been utilised in groundwater studies [38,68]. Initially, linear regression and analysis of variance (ANOVA) were the common statistical methods used to model relationships between groundwater variables. More complex patterns and relationships in groundwater datasets were identified as researchers developed more sophisticated statistical techniques, including principal component analysis (PCA), cluster analysis, and discriminant analysis [69,70].

The most important uses of statistical learning in groundwater studies are groundwater quality and quantity; by analysing historical groundwater data and environmental factors like temperature, precipitation, and land use. Another significant application of statistical learning is identifying sources of groundwater contamination, allowing researchers to determine if pollutants arise from natural sources or anthropogenic activities such as industrial or agricultural [71,72]. However, one of the most important limitations of statistical learning is its reliance on assumptions about the data, such as normality or linearity, which can result in inaccurate or unreliable models if these assumptions are not met [73,74]. Additionally, statistical models may overfit or underfit data, leading to poor performance on new data. They may need to be better suited to handle large, complex datasets due to computational and resource requirements [75,76]. One solution to these limitations is combining statistical learning with other machine learning techniques, such as symbolism, called hybrid AI.

For example, Symbolic models can provide a way to represent and reason about uncertain or incomplete data, which is a challenge for statistical models [77]. They can also encode domain knowledge, such as physical laws or expert rules, to improve the accuracy and interpretability of the resulting hybrid model [78]. Additionally, symbolic models can generate hypotheses that can be tested using statistical models, further improving the overall performance of the hybrid model [77].

2.3. Connectionism

Neural networks and deep learning are two significant machine learning technology connectionism components.

2.3.1. Neural Network

Neural networks, inspired by the structure and functioning of the human brain, are composed of interconnected nodes that receive inputs, process information, and produce outputs [79]. Warren McCulloch and Walter Pitts [80] developed the first artificial neuron in the 1940s, and since then, neural networks have been significantly developed and applied in various fields, including groundwater management. In groundwater management, one of the primary uses of neural networks is predicting water quality parameters by training the network on historical data [81,82] to recognise the relationship between various water quality variables and accurately predict future values, which is critical for maintaining water quality in aquifers and wells.

However, neural networks' black-box nature is a significant limitation, as it can be challenging to understand how the network makes its decisions [83]. This lack of interpretability can be a significant issue in applications where understanding the reasoning behind the model's outputs is essential. Additionally, neural networks may be prone to overfitting, leading to a poor generalisation of new, unseen data [84,85].

To address these limitations, neural networks can be combined with other models, such as symbolic models and statistical learning. Symbolic models provide a transparent and interpretable representation of the domain knowledge and rules underlying the data, enabling the development of hybrid models that can leverage both the power of neural networks for complex pattern recognition and the interpretability of symbolic models [86,87]. Similarly, statistical learning techniques like regularisation and cross-validation can prevent overfitting by constraining the model's complexity and ensuring it performs well on new data [88]. Statistical learning can also preprocess the data, extracting meaningful features to be used as inputs to the neural network, improving its performance and interoperability [89].

2.3.2. Deep Learning

Utilising interconnected nodes to perform complex tasks, deep learning is a neural network subfield that has gained popularity due to its ability to learn and improve from large datasets [90]. Groundwater management applications have successfully employed deep learning models for tasks such as groundwater quality prediction [91], aquifer characterisation [92], and groundwater flow modelling [93]. The use of deep learning in groundwater quality management has shown promising results in improving the accuracy of water quality monitoring and prediction. To comprehensively understand the water quality status, these models can analyse large amounts of data from various sources, including remote sensing data, well measurements, and water quality sensors [93,94]. The information can then be used to make informed decisions regarding water quality management strategies, such as source protection, pollution prevention, and remediation.

However, deep learning has limitations, such as overfitting and requiring large amounts of labelled data. Popular AI techniques, such as reinforcement learning and symbolic models, e.g., can be combined with deep learning to overcome these limitations.

Reinforcement learning is an AI technique enabling an agent to learn and make decisions through trial and error. When feedback is given as rewards or punishments, the agent can learn to maximise its reward over time. Combining reinforcement learning with deep learning can create more efficient and effective models to learn and adapt to changing environments and tasks. Furthermore, reinforcement learning can provide feedback and insight into how a deep learning model makes decisions, leading to more explainable AI.

Symbolic models are another popular AI technique that can be combined with deep learning to improve interpretability [95]. Symbolic models provide a transparent and interpretable representation of the domain knowledge and rules underlying the data. Combining deep learning with symbolic models makes it possible to develop hybrid models that can use the power of deep learning for complex pattern recognition and the interpretability of symbolic models [96].

Statistical learning techniques such as regularisation and cross-validation can also be combined with deep learning to prevent overfitting [97]. These techniques constrain the model's complexity and ensure it performs well on new data [98]. Additionally, statistical learning can be used to preprocess the data and extract meaningful features that can be used as inputs to the deep learning model, improving its performance and generalisation capability [99].

Finally, Bayesian networks, decision trees, and support vector machines are other AI techniques that can be combined with deep learning to improve performance. Bayesian networks can model complex relationships between variables, while decision trees can handle nonlinear and non-parametric relationships [100,101]. Support vector machines can handle high-dimensional data and improve classification performance [102].

2.4. ML Basic Tasks and Groundwater

Machine learning has several basic tasks that can be applied to quantity and quality groundwater management (Figure 3): 1. Classification: This task involves categorising data into specific classes or groups [103]. In quantitative and qualitative groundwater management, classification can identify areas with water contamination or categorise water quality levels. 2. Regression: Regression involves predicting a constant value based on input data [104]. In quantity and quality groundwater management, a regression can predict water quality parameters such as pH, temperature, and dissolved oxygen levels. 3. Clustering: Clustering groups similar data points [103]. Clustering can identify areas with similar water quality characteristics or group water samples based on their chemical compositions in quality groundwater management [105]. 4. Anomaly detection: This task involves identifying data points that deviate significantly from the norm. In quality groundwater management, anomaly detection can identify areas with unusual water quality characteristics or detect changes in water quality over time [105]. 5. Feature selection involves identifying the most important variables or features contributing to a particular outcome. In quality and quality groundwater management, feature selection can be used to identify the most important water quality parameters that affect human health or the environment [105]. 6. Optimisation refers to identifying optimal values for a parameter group that minimises a specific cost or loss function. Optimising these parameters allows decision-makers to focus their efforts and allocate resources towards the most significant variables impacting water quality and quantity management [106].

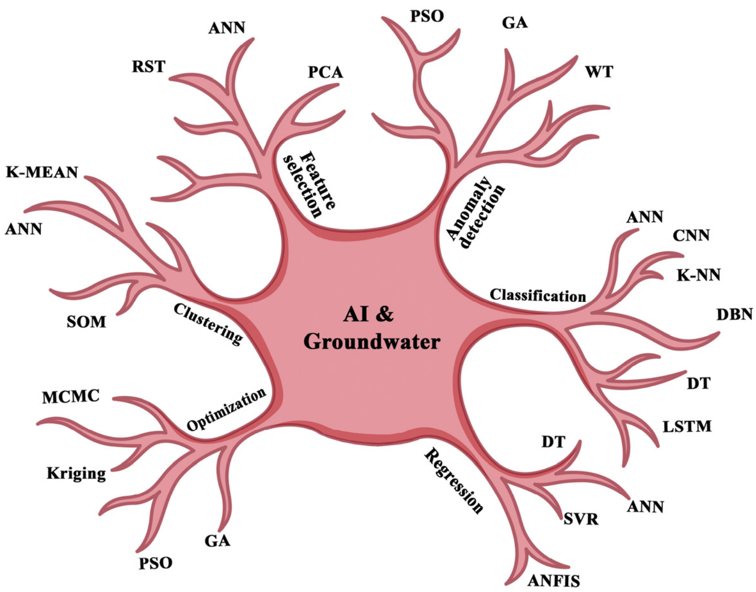


Figure 3. Artificial intelligence tasks and groundwater management. The code description is as follows: ANN: Artificial Neural Networks, SVM: Support Vector Machines, GA: Genetic Algorithm, QT: Wavelet Transform, SVR: Support Vector Regression, DT: Decision Tree, RF: Random Forest, DBN: Deep Belief Networks, PSO: Particle Swarm Optimisation, RST: Rough Set Theory, SOM: Self-Organizing Map, PCA: Principal Component Analysis, CNN: Convolutional Neural Network, LSTM: Long Short-Term Memory, MCMC: Markov Chain Monte Carlo. Note that not all algorithms exist, and some can be used for multiple tasks.

These machine-learning tasks can help improve the management and understanding of water quality and groundwater resources, leading to better decision-making and more effective resource management [105]. Machine learning algorithms also allow for integrating multiple data sources, including remote sensing data, sensor networks, and hydrological models, improving understanding of groundwater systems [107], identifying the most relevant variables contributing to changes in groundwater quality [46], and providing insights into the drivers of groundwater quality changes, and allowing for more targeted and efficient monitoring and management strategies [108].

While machine learning (ML) has proven to be a valuable tool in groundwater management, some limitations to its basic tasks can hinder its effectiveness. For example, ML algorithms may need help identifying the underlying causal relationships between water quality parameters and their impact on human health or the environment, limiting their ability to make accurate predictions or optimise management strategies [106]. Additionally, ML algorithms may be prone to overfitting, where the model fits the training data too closely and needs to generalise to new data.

3. Hybrid AI in Groundwater

Hybrid artificial intelligence (AI) models combine different AI techniques to enhance the accuracy and robustness of predictions for groundwater quality and quantity management [109]. Traditional modelling approaches have limitations in capturing complex nonlinear relationships between input and output variables, and hybrid AI models have emerged as promising solutions to overcome these limitations [110]. Hybrid AI models can improve the accuracy and reliability of groundwater forecasting by integrating multiple AI techniques, such as neural networks, fuzzy logic, and support vector machines, leading to more informed decision-making for groundwater quality and quantity management and ultimately contributing to sustainable use and protection of this vital resource. The use of hybrid artificial intelligence techniques in groundwater quality and quantity management has shown promise in improving prediction accuracy and optimising management strategies.

Several methods and applications are used in hybrid AI, including rule-based systems, machine learning, neural networks, evolutionary algorithms, fuzzy logic, expert systems, reinforcement learning, genetic algorithms, natural language processing, and computer vision. Each method has unique benefits and limitations, and researchers can choose the most appropriate method for their specific application. To help researchers analyse trends and patterns in scientific literature, we have developed a Python code that extracts data from the Scopus database and retrieves the 14 most frequently cited hybrid AI models in groundwater management, sorted by citation count (Table 1). The code uses the Scopus API to search for data based on a specific query and field and extracts the relevant information from the response JSON. In the following discussion, we will focus on the top 10 cited hybrid AI models (Section 3.1) and explore their potential benefits and limitations in the context of groundwater sciences. In addition, we provide a brief overview of the lesser-known hybrid AI models in Section 3.2. While these models have shown promise in improving groundwater management and decision-making, it is important to note that each model has advantages and disadvantages. Researchers should carefully consider the specific requirements of their application and choose the most appropriate hybrid AI model accordingly.

Table 1. The most cited Hybrid AI model in groundwater management driven from the Scopus database. It is important to note that the development and use of hybrid AI models in groundwater sciences are ongoing, and new models are constantly being developed and tested. These databases are comprehensive, but not all articles and conference proceedings are indexed.

Hybrid AI Model	Most Common Applications in Groundwater Sciences (2009 to 2022)	Citations Count
Artificial Neural Networks (ANN) and Support Vector Machines (SVM)	Groundwater monitoring network optimisation	1127
Genetic Algorithm (GA) and Artificial Neural Networks (ANN)	Groundwater level prediction, groundwater pumping optimisation	795
Wavelet Transform (WT), Artificial Neural Networks (ANN), and Support Vector Regression (SVR)	Groundwater level forecasting and trend/pattern identification	658
Adaptive neuro-fuzzy inference system and genetic programming	Groundwater level prediction in complex hydrogeological conditions	462
Support Vector Machines (SVM) and Random Forest (RF)	Impact of land use changes on groundwater resources prediction	353
Artificial Neural Networks (ANN) and Kriging	Groundwater quality parameter mapping and identification of contamination risk areas	310
Genetic Algorithm (GA) and Decision Tree (DT)	Groundwater quality data classification, groundwater remediation	254
Deep Belief Networks (DBN) and Support Vector Regression (SVR)	Groundwater level prediction, assessment of climate change impacts on groundwater resources	241
Particle Swarm Optimisation (PSO) and Support Vector Regression (SVR)	Groundwater recharge rate prediction	201

Table 1. *Cont.*

Hybrid AI Model	Most Common Applications in Groundwater Sciences (2009 to 2022)	Citations Count
Rough Set Theory (RST) and Support Vector Machines (SVM)	Decision-making for groundwater quality	156
Self-Organizing Map (SOM) and Decision Tree (DT)	Groundwater data classification and identification of contamination risk areas	112
Neural Network (NN) and Principal Component Analysis (PCA)	Groundwater quality assessment and identification of contamination sources	109
Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM)	Groundwater level prediction in the urban area	78
Artificial Neural Networks (ANN) and Markov Chain Monte Carlo (MCMC)	Groundwater data classification and identification of contamination risk areas	68

3.1. More Common Hybrid AI Models

3.1.1. Artificial Neural Networks (ANN) and Support Vector Machines (SVM)

The high citation number approves that ANN, and SVM are popular hybrid machine learning techniques widely used in groundwater sciences. One of the main advantages of ANNs and SVMs is their ability to model complex relationships between variables, which is often difficult to achieve using traditional analytical and numerical modelling approaches [111,112]. They can also handle large amounts of data and are relatively fast and efficient [113]. Another advantage of these techniques is their flexibility, as they can be used for a wide range of applications, from predicting groundwater levels and flow rates to identifying potential sources of contamination. However, ANNs and SVMs have their limitations. One of the main challenges of using these techniques is the need for large amounts of high-quality data to train the models, which can be costly and time-consuming to collect [114]. In addition, these models are often considered black boxes, meaning it is difficult to understand how they arrive at their predictions [115]. This lack of transparency can make it challenging to interpret the results and may limit their usefulness in decision-making processes. Another disadvantage of ANNs and SVMs is the potential for overfitting, which occurs when the model is too closely fitted to the training data and performs poorly on new data [68]. It can be addressed using appropriate techniques such as regularisation and cross-validation [116]. In conclusion, while ANNs and SVMs offer significant advantages for modelling groundwater systems, their limitations should be addressed to ensure accurate and reliable predictions.

AI models' overall accuracy and performance for various applications in hydrogeology issues have shown promising results after integrating ANN and SVM as hybrid AI. For instance, researchers used a hybrid AI model comprising ANN and SVM to aim to build a unique ensemble model based on a high-resolution groundwater potentiality model [117]. Using ROC curves confirms that the hybrid model outperformed (around 10%) than ANN and SVM models individually. Also, an ANN-SVM hybrid AI model was used for groundwater level prediction in urban areas [118]. They reported that the hybrid model improved the prediction accuracy by up to 62% compared to one based model. However, the degree to which the hybrid AI model improves accuracy and speed may be context- and problem-specific.

3.1.2. Genetic Algorithm (GA) and Artificial Neural Networks (ANN)

GA and ANN are two popular artificial intelligence methods used in groundwater quality management [105,119]. ANN is a type of AI that mimics the structure and function of the human brain to process information. It consists of interconnected processing units that receive input data and output a prediction or decision [120]. ANN is particularly suitable for groundwater quality management because it can handle large amounts of complex data, including uncertain and imprecise data [116,121]. It can also adapt to changing conditions and learn from experience, making it a useful tool for predicting groundwater quality.

As mentioned earlier, GA optimises the parameters of models used in groundwater quality management. The advantages of genetic algorithms include their ability to search an ample parameter space efficiently and handle nonlinear relationships between variables. Using these methods as a hybrid AI, ANN, and GA can complement each other by providing a powerful tool for modelling and predicting groundwater quality [121,122]. However, the disadvantage of this approach is that it requires a considerable amount of data and computing power, which can be a challenge in some applications [121,123]. Additionally, the results of this approach may be difficult to interpret, making it challenging for decision-makers to understand the basis for their decisions. Nonetheless, the advantages of using ANN and GA as hybrid AI in groundwater quality management outweigh their disadvantages, making them an essential tool for improving the management of groundwater resources.

For an instance of the integration of GA and ANN as a hybrid, AI is seen in the study by Pandey et al. [124], where they employed the GA-ANN hybrid approach for predicting seasonal groundwater table depth. The study reported a significant improvement of around 43% in R^2 compared to the individual models. Another study assessed the development of hybrid ANN models and their critical assessment for simulating groundwater levels at 17 sites in an alluvial aquifer system [125]. According to the findings of this study, the hybrid model was identified as the most efficient method for predicting spatiotemporal fluctuations of groundwater at almost all of the sites, with the Nash-Sutcliffe efficiency ranging from 0.828 to 0.998.

3.1.3. Wavelet Transform (WT) and Artificial Neural Networks (ANN)

Generally, Wavelet Transform (WT) and Artificial Neural Networks (ANN) have emerged as powerful groundwater forecasting and modelling tools. The WT-ANN model has been applied in various groundwater studies, including predicting groundwater levels [126,127], identifying trends and patterns in groundwater data [128], and modelling groundwater recharge [129]. One advantage of this hybrid model is its ability to handle nonlinear relationships between the input and output variables, which is common in groundwater systems. Moreover, wavelet analysis can help identify important frequency components in the data, improving the accuracy of the predictions [127]. Despite its advantages, the development of a WT-ANN model can be a challenging task. The model requires a large amount of data for training, and selecting appropriate wavelet basis functions can significantly impact its performance.

Additionally, interpreting the results can be challenging due to the black-box nature of the ANN component [115]. Therefore, it is essential to carefully design and optimise the model to achieve the best results. Overall, the WT-ANN hybrid AI model has shown promising results in groundwater applications and has the potential to improve our understanding of complex groundwater systems. However, it is crucial to investigate this model's strengths and limitations and identify ways to optimise its performance in different hydrogeological settings. The use of hybrid AI models, such as the WT-ANN, can significantly advance the field of groundwater sciences and contribute to sustainable management and protection of this vital resource.

Many researchers used WT and ANN as HA integrated into groundwater for prediction and modelling purposes. For example, to predict the groundwater levels of a dry inland river on multiple scales, Wen et al. [127] tested the efficacy of a wavelet analysis-artificial neural network (WA-ANN) conjunction model. They hypothesised that the WA-ANN model would be especially useful for predicting the intricate dynamics of groundwater level variations. A related study [130] assessed the performance of the hybrid WA-ANN approach in predicting the quality of shallow groundwater using the improved Nemerow pollution index. The evaluation was based on metrics such as MAE and R^2. The findings indicated that the WA-ANN hybrid method outperformed the individual methods, as demonstrated by the higher accuracy achieved with the hybrid approach.

3.1.4. Adaptive Neuro-Fuzzy Inference System and Genetic Programming

The adaptive neuro-fuzzy inference system (ANFIS) and genetic programming (GP) are widely used hybrid AI techniques in groundwater quality management. The ANFIS method combines the strengths of fuzzy logic and neural networks, making it a powerful tool for modelling complex systems [38,131]. The GP method, on the other hand, is a search algorithm that uses natural selection and genetic operations to evolve a population of computer programs that can solve a particular problem [132].

One advantage of using the ANFIS-GP hybrid AI method in groundwater quality management is that it integrates different data types, including spatial and temporal data, which are essential for accurately predicting and managing groundwater quality [133]. Additionally, this method can handle missing data, which is common in groundwater quality management and can take noisy data [119,133]. Another advantage is that the ANFIS-GP hybrid AI method can accurately model complex systems, allowing for more efficient and adequate decision-making in groundwater quality management.

However, there are also some disadvantages to using the ANFIS-GP hybrid AI method. One such drawback is that the technique requires significant data to build an accurate model, which can sometimes be challenging [133,134]. Additionally, the ANFIS-GP method can be computationally intensive, leading to longer processing times and increased costs. Finally, the ANFIS-GP method can be difficult to interpret and understand, which can be a significant challenge for stakeholders and decision-makers who need to use the modelling process results [134].

3.1.5. Support Vector Machines (SVM) and Random Forest (RF)

SVM and RF are famous and influential machine-learning algorithms in various fields, including groundwater analysis. While they have their respective strengths and weaknesses, combining these two algorithms as a hybrid model can result in improved performance and more robust predictions [135]. The hybrid model that combines SVM and RF takes advantage of the strengths of both algorithms, resulting in a more accurate and stable model [136]. SVM can handle high-dimensional data and nonlinear relationships, while RF can identify important variables and handle missing values and noisy data [137,138]. Combining these algorithms allows the hybrid model to manage complex groundwater systems with many variables better and provide more reliable predictions. The hybrid model also addresses some disadvantages of SVM and RF, such as overfitting, sensitivity to hyperparameters, and difficulty in interpretation [116,139]. The hybrid model can provide better generalisation and performance on new data by using RF to select important variables and SVM to build a more accurate model with reduced dimensions.

Additionally, the hybrid model can measure uncertainty and confidence in the model's predictions. Thus, combining SVM and RF as a hybrid model can result in improved performance and more robust predictions for groundwater analysis. While the specific implementation of the hybrid model depends on the dataset and research question, researchers should consider the advantages of each algorithm and the potential benefits of combining them to develop a more accurate and reliable model.

3.1.6. Artificial Neural Networks (ANN) and Kriging

ANN and Kriging are two common methods used in groundwater analysis. ANN is a machine learning algorithm inspired by the structure and function of biological neural networks, which can predict groundwater levels, flow rates, or other hydrogeological parameters based on input data, such as precipitation, temperature, and soil properties. Kriging is a geostatistical method used for the spatial interpolation of data. It involves using statistical models to estimate the values of unsampled points based on the importance of nearby sampled points. In groundwater analysis, Kriging can be used to interpolate groundwater levels or flow rates from a limited number of monitoring wells to create a spatially continuous prediction [140,141].

A hybrid model that combines ANN and Kriging can take advantage of the strengths of both algorithms, capturing the complex spatial relationships between groundwater parameters and improving the accuracy of the predictions by incorporating spatial correlation information, which results in a robust and stable solution to groundwater prediction problems [142,143]. Researchers can use this hybrid model to predict groundwater levels, flow rates, or other hydrogeological parameters based on input data and incorporate spatial correlation information to create a more accurate and reliable prediction [141,144,145].

For instance, a study by Hosseini et al. [146] integrated ANN and Kriging to model and increase the efficiency of the groundwater-level monitoring networks. The results showed that the hybrid approach had a higher accuracy of up to 78% in predicting the spatial distribution of hydraulic heads than either ANN or Kriging alone. Another study by Moasheriet al. [147] used the ANN-Kriging hybrid model to predict groundwater quality parameters in a Kashan area. The study reported that the hybrid model provides more accurate results (up to 11%) than the geostatistical method in Kriging. However, it's important to note that these results are specific to the study areas and dataset used and may need to be generalisable to other areas. However, the improvement in accuracy or time, the results can vary depending on the specific study area, the size and complexity of the dataset, and the specific algorithms used for ANN and Kriging.

However, Machine learning algorithms, such as deep neural networks, genetic algorithms, and decision tree algorithms, can also be integrated with other physical models, such as fracture flow models, multiphase flow models, analytical models, finite element models, finite difference models, and geostatistical models like kriging interpolation, as discussed above, to create hybrid models [148].

One example of a hybrid model is combining a finite element model with an ANN and ANFIS to simulate spatiotemporal groundwater levels [149]. This hybrid model was shown wavelet-based de-noised data enhanced the performance of the modelling by up to 14%. Another study proposed a hybrid model that combines a multiphase flow model with a machine-learning algorithm to simulate groundwater contamination [150]. The hybrid model was more accurate and efficient than the traditional multiphase flow model by 13%.

Additionally, a study proposed a hybrid model that combines a finite element model with an SVM algorithm for groundwater anomaly detection [151]. The hybrid model was shown to improve the accuracy of the simulation and reduce the computational cost.

3.1.7. Genetic Algorithm (GA) and Decision Tree (DT)

GA and DT are popular machine-learning algorithms in various fields, including groundwater analysis. GA is a search heuristic that is inspired by the process of natural selection and genetics. It is used to find the optimal solution to a problem by exploring an ample search space [135]. GA can be used to optimise parameters for groundwater models, such as determining the best values for hydraulic conductivity or recharge rates. GA generates a population of potential solutions, selects the fittest solutions, and uses genetic operators such as mutation and crossover to create new solutions. The process continues until an optimal solution is found.

DT, conversely, is a decision-making algorithm that builds a tree-like model of decisions and their possible consequences [152]. DT is a supervised learning algorithm used for classification and regression tasks. In groundwater analysis, DT can predict groundwater quality, identify contaminated sites, or classify different groundwater types based on hydrogeochemical characteristics. DT works by recursively partitioning the data into subsets based on the values of other features and then creating decision nodes to predict the target variable based on the partitioned data. However, GA's slow computation speed and complex gene encoding/decoding processes pose challenges for groundwater researchers, particularly in dealing with complex problems. A hybrid model that combines GA and DT can take advantage of the strengths of both algorithms. GA can optimise the parameters of the DT model to improve its performance and accuracy. For example, GA can be used to determine the best features to include in the DT model or to optimise the hyperparameters of the DT algorithm.

Additionally, GA can be used to reduce the size of the dataset and eliminate irrelevant features, which can improve the efficiency and accuracy of the DT model [153,154]. Compared to single AI methods, the GA-DT hybrid approach can reduce the computational time required to optimise the model parameters. However, the time improvement can also depend on the size and complexity of the dataset. Therefore, GA and DT are two powerful machine-learning algorithms that can be used for groundwater analysis. A hybrid model that combines these algorithms can take advantage of their respective strengths and improve the performance and accuracy of the model. Researchers can use this hybrid model to predict groundwater quality, identify contaminated sites, or classify different groundwater types depending on their research question and dataset.

3.1.8. Deep Belief Networks (DBN) and Support Vector Regression (SVR)

DBN is a type of artificial neural network that is used for unsupervised learning. It comprises multiple layers of hidden units that learn to represent the input data hierarchically. DBN can extract complex features from large datasets, which can be used for other machine-learning tasks such as classification or regression. In groundwater analysis, DBN can be used to analyse large datasets of hydrogeological parameters and extract meaningful information to understand the groundwater system better [155]. SVR, on the other hand, is a regression algorithm that is used to predict continuous variables. It finds a hyperplane in a high-dimensional space that maximally separates the input data points. SVR can predict groundwater levels, flow rates, or other continuous variables important for groundwater management [156,157]. SVR is beneficial when dealing with nonlinear and complex relationships between variables.

A hybrid model combined with DBN and SVR can take advantage of the strengths of both algorithms. DBN can extract complex features from large datasets and reduce the dimensionality of the input data, which can then be used as input to the SVR algorithm, resulting in better performance and accuracy of the predictions and helping overcome some of the limitations of each algorithm [157].

Where DBN can suffer from overfitting if the number of hidden units is too large, or SVR can be sensitive to the selection of hyperparameters, the hybrid model can provide a more robust and stable solution to groundwater prediction problems, including groundwater levels, flow rates, or other important continuous variables for groundwater management [142,155,158]. In a study [157], researchers proposed the innovative DBN-SVR method, which accurately predicts water quality parameters and outperforms models such as SVR and DBN. This method significantly improves (up to 85%) performance indicators such as MAE, MAPE, RMSE, and R^2 compared to DBN and achieves a high fitting effect and surpasses BP. However, the combined model takes longer; it provides the best prediction accuracy. Thus, the determination coefficient indicates that hybrid AI is superior to BP, SVR, and DBN in predicting water quality, with better accuracy and robustness.

3.1.9. Particle Swarm Optimisation (PSO) and Support Vector Regression (SVR)

PSO and SVR are popular methods for groundwater quality management. PSO is a global optimisation algorithm that can hold discrete and continuous variables [159,160], while SVR is a regression capability. When used together as a hybrid AI system, PSO and SVR can overcome the limitations of each method and improve the accuracy of groundwater quality predictions [161]. The advantages of using POS-SVR in groundwater quantity management include its ability to handle nonlinear relationships and model complex systems and its ability to provide accurate predictions even when the available data is limited or incomplete. Additionally, POS-SVR can optimise the pumping schedule for groundwater extraction, resulting in significant cost savings and helping preserve the groundwater resource. However, POS-SVR also has some disadvantages, such as the need for high computational resources to optimise the model and the potential for overfitting the data. Despite these limitations, POS-SVR is a promising tool for groundwater quantity management. It could improve our understanding of groundwater systems and inform decision-making for sustainable management of groundwater resources.

3.1.10. Rough Set Theory (RST) and Support Vector Machines (SVM)

Groundwater quality management is a complex and challenging task that requires the integration of various data sources and decision-making tools. One promising approach is hybrid artificial intelligence methods, such as RST and SVMs. RST is a mathematical approach that can handle uncertain and incomplete data by defining lower and upper approximations of sets [162]. SVMs, on the other hand, are a type of supervised learning algorithm that can classify data by finding the optimal hyperplane that separates different classes [162,163]. Combining these two approaches can lead to a powerful and robust decision-making tool for groundwater quality management. The advantages of combining rough set theory and SVMs as a hybrid AI method in groundwater quality management include their ability to handle complex and high-dimensional datasets, their flexibility in dealing with uncertain and incomplete data, and their capability to provide accurate and reliable predictions [145,164,165]. However, there are also some disadvantages, such as the potential for overfitting, the requirement for a large amount of training data, and difficulty interpreting the results.

3.2. Less Commonly Hybrid AI Models

In groundwater sciences, hybrid AI models that combine different machine learning techniques have become increasingly popular for various purposes, such as predicting groundwater levels, mapping groundwater, and assessing quality. A table has been compiled, which lists 15 such models, including Hybrid Decision Tree (HDT) and Genetic Algorithm (GA), Self-Organizing Map (SOM) and Decision Tree (DT), Neural Network (NN) and Principal Component Analysis (PCA), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), and Artificial Neural Networks (ANN) and Markov Chain Monte Carlo (MCMC). These models offer several advantages over single methods. For example, HDT-GA can improve the accuracy and interpretability of decision trees by selecting the best attributes for splitting [166]. SOM-DT can be used to cluster data into classes, and then the decision tree can be applied to each cluster separately [167]. NN-PCA can reduce the dimensionality of data and increase the efficiency of neural network training [168]. CNN-LSTM can capture spatial and temporal data features, making them suitable for image and speech recognition tasks [169]. ANN-MCMC can be used to estimate the posterior distribution of parameters in neural networks, allowing uncertainty to be incorporated into predictions [170].

Despite their potential benefits, these hybrid models have yet to be fully explored, and their limitations and applicability must be thoroughly investigated. The less popular hybrid methods, such as HDT-GA, SOM-DT, NN-PCA, CNN-LSTM, and ANN-MCMC, have received less attention in the literature. Developing and implementing these hybrid models can be challenging, requiring significant expertise in different areas of machine learning. Additionally, the effectiveness of these methods can depend highly on the specific problem being addressed and the quality of the data available. Furthermore, there is often a need for more understanding of how these methods work and how to interpret their results, making it challenging to apply them in practice. Nonetheless, using hybrid AI models in groundwater sciences is a rapidly evolving field, with researchers continuously developing new models and algorithms to manage groundwater resources more effectively. There is, therefore, immense potential for developing new hybrid AI models to advance our understanding and management of groundwater resources.

4. Discussion and Prospective

Hybrid models have shown great promise in groundwater quality and quantity management over the past few years. These models combine different artificial intelligence techniques to achieve better accuracy and efficiency than traditional models. However, despite the promising results achieved with hybrid artificial intelligence (AI) models, some limitations and research gaps still need to be addressed to exploit their potential fully.

Interpretability is a key challenge in developing hybrid AI models for groundwater sciences. Although these models can deliver accurate predictions, understanding the reasoning behind their outputs can be challenging [171,172]. This lack of interpretability can hinder their adoption in certain domains where transparency and explainability are critical. Therefore, further research is necessary to enhance the interpretability of hybrid AI models for groundwater sciences and develop models that provide accurate predictions and insights into the decision-making process.

Another limitation of hybrid AI models is their high computational cost. These models often require large amounts of data and complex computations, which can be time-consuming and expensive, especially when dealing with real-time applications [66,173]. Additionally, the training process of these models can be difficult and requires expertise in various AI techniques, which may only be readily available to some users [174]. Therefore, there is a need for research that focuses on developing more efficient and cost-effective methods for training and deploying hybrid AI models.

Adversarial attacks can also have serious consequences, as incorrect predictions can lead to suboptimal decision-making and potentially harmful outcomes [175]. For example, suppose a hybrid AI model used for groundwater management is vulnerable to adversarial attacks. In that case, it may produce inaccurate predictions for essential parameters such as groundwater flow rates, contaminant concentrations, or water availability, resulting in efficient or effective management strategies, negatively impacting water resources and the environment.

While hybrid AI models have shown promising results in various domains, their performance can vary depending on the application and the problem being addressed. Therefore, there is a need for research that focuses on developing domain-specific hybrid AI models tailored to each domain's specific characteristics and requirements. This research can help develop effective groundwater management strategies that balance economic, environmental, and social considerations.

In the field of groundwater sciences, it is also essential to conduct research that delves into the ethical and social implications of hybrid AI models. As these models become increasingly prevalent and powerful, it is crucial to consider their potential impact on society, including their effects on privacy, fairness, and accountability. It is necessary to investigate hybrid AI models' ethical and social implications and develop frameworks and guidelines that ensure their responsible development and deployment in groundwater management.

Standardisation and benchmarking frameworks are also required to facilitate the comparison and evaluation of different hybrid AI models across various domains and applications. The complexity and diversity of these models make it difficult to compare and evaluate their performance objectively. Therefore, there is a need for standardisation and benchmarking frameworks that can help in the comparison and evaluation of different hybrid AI models across various groundwater issues.

Addressing these challenges will require further research and innovation in hybrid AI, a collaboration between researchers, practitioners, policymakers, stakeholders, and applicability in various groundwater management scenarios. Guidelines for selecting appropriate hybrid models based on the specific groundwater issues and the available data are also necessary to make decisions and develop effective groundwater management strategies that balance economic, environmental, and social considerations.

5. Conclusions

In summary, this paper aims to review the use of hybrid artificial intelligence models in groundwater quality and management. The selection of appropriate models is crucial since different models have different potentials to address issues with similar characteristics. Identifying the most significant input parameters along with the models is essential for optimal performance. Furthermore, this review paper combines optimisation algorithms with AI models to form a hybrid model, successfully addressing many combinatory optimisation problems. However, there are no standard procedures for developing a hybrid model with a specific algorithm, and information on additive parameters is limited. Future research should focus on improving machine learning and developing new hybrid AI modelling approaches to make groundwater research more exciting, challenging, and rewarding for researchers. It is worth noting that while this review paper aims to cover the most cited techniques in groundwater issues, rapid technological advancements in hydrogeology and other areas that incorporate AI models frequently occur, making it challenging to keep up with the latest updates.

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