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Integrating Artificial Intelligence, Numerical Methods and Remote Sensing for Advanced Groundwater Modelling: A Comprehensive Review

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ABSTRACT

Groundwater depletion, climate change, and rising water demand are the primary challenges to the sustainable management of water resources in arid/semi-arid areas, such as Iraq. This study evaluates current models for groundwater and their performance and assesses the recent advancements in groundwater modeling techniques. It addresses that currently, numerical models, Artificial intelligence (AI), and remote sensing techniques are being implemented separately. Physically based models are widely used in groundwater modelling due to their reliable performance in simulating groundwater flow and transport processes. It was widely used in Iraqi and international groundwater studies, constituting 62% and 60% of groundwater studies in those regions. In contrast, the application of AI-based tools offers great potential in terms of predicting groundwater dynamics' nonlinear behavior, improved predictive results, and a data-driven assessment of hydrogeological conditions. The use of remote sensing-based techniques such as GRACE and GLDAS has become more popular among researchers as a means of estimating changes in groundwater storage volumes. However, its application in studies is rather limited and amounts to around 28% of studies conducted in Iraq and 23% of international research. It is evident from the review that the use of hybrid approaches can greatly improve predictions and groundwater management.

Keywords: Groundwater modelling, Hydrogeological models, Deep learning, Artificial intelligence.

1. INTRODUCTION

The effects of climate change, excessive pumping, data scarcity, and hydrogeological uncertainty pose serious hurdles to assessing and managing groundwater. The study critically analyzes the progress made in the field of groundwater modeling with special reference to numerical modeling, remote sensing, artificial intelligence (AI), and their hybrid integration. Moreover, groundwater is more widely distributed in the world and is a reliable

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source of water supply **(Khadka et al., 2022)**. Increasing population pressures, the growing need to expand industrial activities, and the impacts of climate change are among the key global pressures on water supply systems **(Alwan et al., 2019)**. Overuse of groundwater resources may cause a substantial reduction in the elevation of the water table, thus reducing discharges to hydraulically connected surface water bodies such as springs **(Wada et al., 2010; Gleeson et al., 2012)**.

Groundwater models are of great importance in the development and management of groundwater resources as well as the prediction of the effects of management measures. Due to the rapid increase in the computational power of computers and the availability of computers and software for modeling, groundwater modeling has become one of the major tools for hydrogeologists to effectively carry out all the tasks related to groundwater resources **(Zhou and Li, 2011)**. Therefore, additional studies are necessary to examine the appropriateness of additional groundwater extraction in some cases. Consequently, groundwater modeling is an effective method of evaluating the effect of groundwater extraction activities on the water table, as well as groundwater availability. The Modular Finite-Difference Groundwater Flow Model (MODFLOW), as well as other prediction tools like the Finite-Element groundwater modeling software, the particle tracking and transport models, and the mass transport models, which are often integrated with MODFLOW, especially when simulating contaminant transport, help in the effective management of groundwater resources through the simulation of the groundwater aquifers **(Bedekar et al., 2016)**. Nevertheless, when these models are used in long-term planning scenarios, they may be confronted with considerable computational burdens. The increase in the number of decision variables in management and optimization studies may impose additional burdens on the processing time, making the execution of the model more demanding, which may limit the efficiency of the model **(Attea et al., 2025)**. Physics-based models, such as MODFLOW, continue to act as the mainstay of groundwater engineering due to their robust representation of groundwater flow and transport processes. Despite their robustness, the efficiency of the model may be limited by the availability of field data, the uncertainties of the parameters, the nonlinear response of the aquifer, and the high computational burdens of the model **(Rojas et al., 2008)**. Recent breakthroughs in data-based modelling have enabled the integration of AI techniques such as Artificial Neural Networks (ANN), Long Short-Term Memory networks (LSTM), and Convolutional Neural Networks (CNN) as additional prediction tools to the conventional groundwater simulation models. ANN uses layers of computational units that can learn the nonlinear relationship between input variables and system responses using observed data as input, which is effective in groundwater prediction problems due to the uncertainty or lack of knowledge regarding the system parameters. LSTM is similar but also takes into consideration the effect of time on the system by using memory units to store the cumulative effect of recharge, abstraction, and climatic factors on groundwater levels **(Sahoo et al., 2017; Wunsch et al., 2021).** CNN is effective in the analysis of spatially distributed variables by identifying patterns within the input data set, which are useful in the analysis of hydrogeological maps and remote sensing images, as well as the spatially varying aquifer properties. Their strength is in dealing with non-linear system responses and identifying patterns in time, enabling them to work with sequential data with great proficiency and achieve highly accurate time-series predictions **(Mohammadi et al., 2018)**.

Recently, advancements in AI have motivated researchers to employ these methods for investigating a wide range of engineering problems **(Khaleel et al., 2023)**. Deep learning has improved computational capabilities by enabling models to make precise predictions based on the patterns of data collected in the past. The practical LSTM model to predict the level of groundwater over short and long periods of time, as well as compare its performance with the conventional neural network model, showed that the LSTM model had significantly higher accuracy in the prediction of groundwater level when compared to the conventional neural network model **(Yokoo et al., 2021)**. In addition, CNNs are increasingly used in civil engineering bidding processes, such as groundwater studies, due to their ability to recognize spatial features and complex data structures **(Demertzis et al., 2023)**. In one of the few studies that used groundwater level data solely as input to the model for simulation, a hybrid model combining CNN and BiLSTM was proposed to simulate hourly changes in groundwater level. The results showed that this type of model is suitable for short interval changes and works well in simulating groundwater time series data **(Khazaeiathar and Schmalz, 2025)**. Simultaneously, remote-sensing technologies such as satellite gravimetric data from the Gravity Recovery and Climate Experiment (GRACE) and Gravity Recovery and Climate Experiment–Follow On (GRACE-FO) missions are widely used to track large-scale variations in subsurface water and groundwater by detecting changes in the Earth's gravity field over time. These observations allow groundwater storage changes to be inferred once the contributions of surface water and soil moisture are separated **(Rodell et al.,2009)**. In parallel, the Global Land Data Assimilation System (GLDAS) uses land surface modeling with satellite and atmospheric inputs to provide estimates of critical hydrologic state variables, including soil moisture, evapotranspiration, and runoff. The joint application of GRACE/GRACE-FO and GLDAS datasets provide a practical means of characterizing groundwater storage behavior and strengthening the calibration and evaluation of numerical and hybrid groundwater models, particularly in regions with sparse monitoring data **(Nigatu et al., 2020)**. Its observations have confirmed capable of capturing large scale changes in groundwater reserves associated with variations in aquifer water levels **(Mohamed et al., 2024)**.

The analysis of data attained through remote sensing represents an efficient and reliable approach for learning physical systems **(Aziz and Alwan, 2021)** and offers significant value in the simulation of a wide range of hydrological methods **(Brunner et al., 2007; Thakur et al., 2017)**. Nevertheless, the main problem in the development of regional groundwater flow models is the lack of data. Geological, hydrogeological, and geophysical surveys are needed to obtain data that is necessary for the construction of a three-dimensional hydrogeological framework and groundwater flow models. Continuous monitoring of the water budget components and groundwater levels is needed to accumulate the database necessary for the analysis of the regional low system and the construction of the regional transient groundwater model. Such models are needed to simulate the effects of human activities on groundwater flow systems, to formulate scenarios of the rational development of groundwater resources, etc. **(Zhou and Li, 2011)**.

Although each of above mentioned methodologies has been extensively reported in prior studies, such as a review of applications for numerical groundwater flow modeling by **(Zdechlik, 2016)**, a review on remote sensing and of Geographic Information Systems (GIS) techniques in water resource development and management with special reference to groundwater by **(Tiwari and Shukla, 2015)** and a review of the AI methods in groundwater level modeling by **(Rajaee et al., 2019)**, their combined use has not been consistently or critically assessed. A substantial contribution to research on groundwater modelling can be made through this review paper that offers a coherent synthesis of numerical modelling,

remote sensing techniques, and AI techniques within one analytical framework. This is done because there is a growing trend in the need for better and more complete modelling strategies to cope with increasing complexities and dynamics of the groundwater systems due to climate change, pumping activities, and lack of data. Methodologically, the main contribution that this paper brings to this field is that it discusses the importance and possibilities of using data-driven approaches that complement physically based numerical simulation approaches rather than replace them. Moreover, this paper tries to evaluate the possibility of using artificial intelligence algorithms in order to improve the predictive power, computational efficiency, and uncertainty management of groundwater simulation models. As such, this paper can also demonstrate how to use remotely sensed information for the calibration and evaluation purposes of groundwater simulation models, which is particularly important for those regions suffering from data deficiency problems.
Thus, this paper offers a comprehensive yet critical discussion of what is missing, what is new, and what is not yet known about the current state-of-the-art technologies of the subject matter. Numerical models, artificial intelligence techniques, and remotely sensed products can individually be of great help in assessing groundwater resources. Numerical models are physically interpretable but depend strongly on field data, boundary conditions, and uncertain aquifer parameters. AI models are efficient in nonlinear prediction but often lack hydrogeological interpretability. Remote sensing provides valuable regional-scale observations but may not sufficiently represent local aquifer conditions. Therefore, hybrid modelling is required to combine the physical reliability of numerical simulation, the predictive strength of AI, and the spatial-temporal coverage of satellite datasets, particularly under climate-change impacts and uncertainty **(Borzi, 2025)**. While each method, numerical modeling, AI, or remote sensing, has played an important role in groundwater studies, the limitations characteristic of applying any of these methods separately cannot be overlooked. The physical plausibility of numerical simulations is associated with a heavy dependence on field data, boundary conditions, and aquifer properties. AI models show high efficiency at predicting nonlinear processes, but their physical acceptability may be questionable. On the other hand, remote sensing helps in observing large regions, yet the information about the local aquifer is limited. Hence, hybrid modeling is needed.

2. METHODOLOGY

The methodology employed by this review is a systematic one that aims at analyzing the current progress in the area of groundwater modeling methods. Special attention is paid to the progress that has been achieved for the purpose of groundwater management and assessment in arid and semi-arid zones, with special consideration of Iraqi groundwater systems. The review process followed a structured, systematic review methodology that ensured the transparency and reliability of research selection and evaluation procedures. Articles related to the topic published during the period between 2000 and 2025 were found through searches in such databases as Scopus, Web of Science, Science Direct, and Google Scholar. Various keywords such as “Groundwater Modeling”, “MODFLOW”, “Artificial Intelligence”, “Deep Learning”, “Remote Sensing”, “GRACE”, “GLDAS”, “Hybrid Groundwater Modeling,”, and “Machine Learning in Hydrogeology” have been used to perform this literature search. Some of the Boolean terms utilized for improving the search process include AND, OR. The inclusion criteria involved:

- Peer-reviewed journal articles and conference papers
- Papers published in English.

- Research related to groundwater flow to simulation, groundwater storage charge, AI applications, remote sensing integration, and hybrid groundwater modeling.
- Studies focusing on arid and semi-arid environments.

The exclusion criteria included:

- Repetitive literature.
- Literature not pertaining to groundwater systems.
- Non-English publications.
- Short abstracts, perspectives, and incomplete reports lacking methodological or analytical details.

Initially, approximately 245 studies were identified through database searching. After removing duplicated and irrelevant studies, 198 articles remained for screening. After going through the title, abstract, and the entire article, only 100 studies made it to the data analysis process.

The research domains analyzed in this review are as follows:

1. Numerical groundwater modelling, specifically MODFLOW and its various modifications, such as MODFLOW-2000, MODFLOW-6, Visual MODFLOW, PMWIN, and GMS.
2. Remote sensing and GIS techniques, such as GRACE, GLDAS, Landsat, and GIS techniques.
3. Deep learning and Hybrid techniques, such as ANN, LSTM, CNN, GRU, PatchTST, and MODFLOW-AI.

The percentages of groundwater modeling categories in Iraq and global studies are shown in **Table 1.**

Table 1. Percentages of groundwater modeling categories in Iraq and global studies.

Modeling Category	Iraq (%)	Global (%)
Numerical Models	62	60
Remote Sensing	28	23
AI & Hybrid Models	10	17

These domains were selected as the dominant groundwater modelling techniques in modern groundwater engineering, and all these techniques are used in a communal manner for simulation, prediction, assessment, and management. The review extracted a steady set of attributes from each study, including the year of publication, authorship, and geographic setting. Information on the modelling approaches adopted, the type of data required, and the calibration procedures were also recorded. Each study was further examined for its objectives, methodological design, results, and reported performance measures such as model performance, usually using the coefficient of determination (R^2), Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), and related error indices. These metrics collectively quantify goodness-of-fit, prediction accuracy, and model efficiency, enabling robust calibration and validation of hydrological, hydrogeological, and AI-based models and various error indices. The major contributions and limitations of every study were documented to establish a clear basis for comparison. The statistical assessment involved several analytical steps, including quantifying the distribution of modelling approaches, for example, the proportion of studies using MODFLOW, AI- based techniques, or satellite-derived data such as GRACE. Arid and semi-arid areas, especially in Iraq, studies were compared with global work to identify differences in methodological development and technological adoption. Temporal trends were also evaluated in order to identify the transition from the traditional numerical models to more recent machine learning and deep learning models. The categories of themes were developed, such as flow simulation, water quality, predictive modeling, vulnerability mapping, recharge estimation, and management scenario analysis. In addition, the bibliometric outcomes, along with the numbers, percentages, and models, were visually represented in order to identify major research trends and gaps in the studies. In the proposed methodological framework, the scientific gap was bridged due to the fact that three major areas were combined, namely, numerical modeling, remote sensing, and AI. By means of the methodological framework, it is possible to clearly assess the technological advancements and deficiencies because the research outcomes obtained from the studies carried out in arid and semi-arid regions were compared with global trends. Furthermore, the emphasis was placed on the limitations and emerging modeling tools, which had not been considered much in the previous reviews and are expected to become major factors in future modeling techniques due to their combination with simulation models.

3. RESULTS AND DISCUSSION

3.1 Numerical Modelling of Groundwater Systems

Numerical groundwater modelling represents the most developed and widely used approach for simulating groundwater aquifer processes, such as Finite-difference models, and in particular, MODFLOW and its associated graphical interfaces. This software was used in Iraq to examine the groundwater status in Karbala. The findings of this investigation show that aquifer recharge was ~21 MCM/year against consumption of ~55 MCM/year, leading to a net depletion of –34 MCM/year. This highlights severe groundwater declines and the need for sustainable management strategies in Karbala **(Al-Shammari et al., 2024)**. To assess groundwater conditions in Erbil, Iraq, the Visual MODFLOW with hydrological data was used to implement a conceptual and numerical model. This model reproduced groundwater flow patterns and storage, providing a reliable tool for evaluating aquifer behavior and supporting sustainable groundwater management in Erbil **(Jwan and Mawlood, 2024)**. To model groundwater flow and assess irrigation water quality in the Turssaq alluvial fan, Near Qazaniyah in Iraq's Diyala Governorate, a 3D five-layer MODFLOW model was developed using 15 pumping and 4 observation wells, scenarios tested 1000 m spacing with 6, 12, and 18 h/day pumping and water samples from 5 wells were analyzed the Optimal operation is 1000 m spacing at 12 h/day (430 m^3/d, 15 m drawdown) and water quality is moderately saline, suitable only for salt-tolerant crops (3,000–7,500 µS/cm) **(Huseen and Abed, 2020)**. Numerical modeling application in the assessment of rates of groundwater depletion include the North China Plain **(Cao et al., 2013)** and Rachna Doab, Pakistan **(Awais et al., 2022).** The accuracy of MODFLOW in simulating surface water and groundwater interaction for connected and disconnected losing streams was examined, and ignoring negative pressure gradients, uniform infiltration under rivers, grid size, and discretization height on infiltration flux results in underestimation and inaccuracy in simulating infiltration **(Brunner et al., 2010)**. Most visual numerical modeling software for groundwater using various processes was developed and highly implemented, such as the Finite Element subsurface FLOW system (FEFLOW) **(AL-Shammari et al., 2024)**.

The temptation is to choose small groups of cells in series and apply the same values to all of the cells in the group. The results in an extreme stair-step condition can slow or even prevent convergence of the numerical solver with the conceptual model approach. It is possible to interpolate values at locations along a linear boundary condition, such as a river **(Zhou and Li, 2011)**. The user ensures that there will be no abrupt changes from cell to cell,

thus minimizing the simple model, which is short, less than 30 min **(Hill, 2006)**, so more time can be allocated for analyzing model results and for investigating alternative models. Reduction of model execution time can be achieved through better representation of hetero genetic contrast and better linearization of water table nonlinearities **(Hill, 2006)**. MODFLOW 6 has enhanced numerical stability and accuracy through the application of a generalized control-volume finite-difference scheme with flexible grid structures. MODFLOW 6 has a modular and object-oriented structure, which enables the simulation of groundwater flow systems in a more reliable manner than previous versions **(Langevin et al., 2024)**.
Important progress in the analysis of the RFS has been achieved with the help of 3D groundwater flow models. The MODFLOW program, released in 1988, has become the industrial standard universal model of groundwater simulation due to the simplicity of its modular structure, completeness of the representation of hydrogeological processes, and free availability in the public domain **(Zhou and Li, 2011)**. Simulations of large groundwater basins are now much simpler thanks to the rapid progress in software engineering, computer science, and the wide application of GIS. Several Windows-based graphic user interfaces were developed in the 1990s for the MODFLOW program. The most commonly used is processing MODFLOW **(Chiang, 2005)**. In the arid regions of the Middle East, North Africa, South Asia, and northern China, groundwater depletion has been extensively reported, mainly due to excessive abstraction for intensive agriculture and low rates of natural recharge **(Doll et al., 2014; Hu et al., 2019)**. These observations are in agreement with the results of the Iraqi case studies **(Wahab et al., 2025; Alshammari et al., 2024)**, where numerical simulations indicate persistent groundwater deficits and declining piezometric levels. The consistency of the results obtained from geographically different arid environments validates that the main cause of groundwater stress in these environments is indeed over-extraction, as opposed to hydrogeological differences. Whilst the robustness of numerical modelling is acknowledged, certain limitations of the technique, especially with regard to parameters, conceptualization, and predictability under non-stationary climatic conditions, have led to the exploration of additional data sources and modelling approaches, especially in data-scarce environments. Overall, numerical groundwater models remain the most established tools for simulating aquifer behavior, particularly under pumping and recharge scenarios **(Harbaugh, 2005; Langevin et al., 2017).**
In comparison with remote sensing and AI techniques, its primary advantage is that it represents the hydrological processes in aquifers physically. Nevertheless, the reliability of numerical modeling heavily depends on conceptual model development, boundary conditions, hydraulic conductivity, recharge assessment, and calibration procedures. The aforementioned constraint becomes especially crucial when dealing with Iraqi aquifers, in which there are insufficient time series for observations. Hence, numerical groundwater modeling cannot suffice and requires the use of satellite imagery together with an AI approach.

3.2 Remote Sensing and GIS-Based Methods

Remote sensing and GIS-based techniques have emerged as essential tools for groundwater assessment in data-scarce arid and semi-arid regions. Satellite data, including GRACE, Landsat, and derived land surface data sets, have become widely applied tools for estimating the variations in groundwater storage, land use dynamics, and other recharge-related parameters at regional to continental scales **(Ibrahim et al., 2024)**. The dynamics of the groundwater system within the Nineveh Plain, northern Iraq, have been analyzed by employing an integrated approach utilizing GRACE data, GLDAS data, and the CMB method. The results showed sustained groundwater depletion from 2002 to 2016, linked to increased withdrawals and reduced recharge estimate results varied widely among methods but showed similar spatial patterns in the south and north. Also, the findings underscore the importance of integrating satellite-based and hydrochemical approaches to improve groundwater recharge assessment and support sustainable water-resources management in arid regions **(Wahab et al., 2025)**. Groundwater basin modelling requires the systematic integration of large and heterogeneous datasets describing the hydrogeological framework, aquifer hydraulic properties, applied hydrological stresses, and observed groundwater heads **(Condon et al., 2021)**. These data commonly occur in a variety of spatial and non-spatial representations, such as thematic maps, graphical profiles, tabulated measurements, digital databases, and, depending on the situation, we have to deal with heterogeneous spatial (and sometimes temporal) resolutions. Sound handling and amalgamation of such widely varying information is a crucial problem in groundwater system analysis **(Gorelick and Zheng, 2015)**. GIS offers an efficient environment for handling spatial datasets, thereby supporting spatial analysis and visualization throughout the modelling workflow **(Gogu et al., 2001)**. Groundwater represents a critical water source in arid and semi-arid environments such as the Jimma and Borena regions of Ethiopia, where surface water resources are scarce **(Dejene et al., 2023)**. The groundwater potential zones are delineated through remote sensing data overlay analysis and GIS using the analytical hierarchy process on the basis of important hydrogeological factors, including geological formations, grade terrain, land-use conditions, drainage, and recharge status **(Tesfaye, 2025)**. Due to the geological structure and hydrological process, over Xinjiang, the groundwater recharge in Xinjiang has complex characteristics **(Ye et al., 2009)**. Specifically, the natural groundwater recharge only accounts for 14% of groundwater recharge in the forms of rainfall infiltration and lateral recharge in piedmont regions, 86% are attributed to horizontal flow across rivers and penetration into the field **(Deng et al., 2015)**. To well interpret the complex hydrological processes in Xinjiang and to support the development of a sustainable balance between water supply and water use, this study examines groundwater dynamics using GRACE **(Zhou et al., 2022)**. However, the GRACE-based GWS (Groundwater Storage) changes estimation still contains large uncertainties caused by the errors in GRACE-derived TWS (Terrestrial Water Storage) changes (e.g., correlated errors in the original GRACE products and the coarse resolution of GRACE) and non-groundwater storage changes from models (e.g., uncertainties in soil moisture) **(Feng et al., 2018; Doll et al., 2014)**. The resulting suitability maps indicated that highly favorable groundwater zones account for approximately 4.6% and 6.2% of the Jimma and Borena areas, respectively, while the majority of each region exhibits moderate to low potential due to structural and topographic limitations **(Assefa et al., 2025)**. Comparison with borehole productivity data confirms the robustness of the proposed framework, demonstrating its effectiveness as a cost-efficient tool for preliminary groundwater assessment and its relevance for guiding sustainable water-resource planning, particularly when complemented by detailed geophysical investigations in structurally complex settings **(Assefa et al., 2025)**. International studies from arid basins in Africa, the Middle East, the western United States, and Central Asia demonstrate that GRACE-derived groundwater storage anomalies reliably capture long-term depletion trends, particularly when corrected for soil moisture and surface-water components **(Long et al., 2017)**.

Similar applications in Iraq verify the suitability of satellite-based monitoring for the detection of large-scale groundwater changes, which places the Iraqi example more as a representative case than as an exception. Applications of the Groundwater Modelling System (GMS), for example, provide a unified environment for data management, conceptual model building, numerical simulation, and spatial visualization of simulation results. Overall, the integration of GIS with groundwater models enhances data handling, improves model interpretability, and strengthens the spatial representation of simulation outcomes, which is essential for robust groundwater assessment and management **(Kumar, 2012)**. Groundwater modeling is a suitable tool for assessing the effects that groundwater abstraction will have on the elevation of the water table and on groundwater availability **(Hussain et al., 2022)**. Some researchers have used GISs to analyze water availability and geographic distribution **(Du et al., 2025)**. There are several advantages of GIS, for example, covering a wide area in the research, which is easier than manually measuring **(Du et al., 2025)**. For example, groundwater storage difference monitoring in mountain and arid regions is not only challenging but also time-consuming through relying on the observation of wells because the well observations are generally incomplete **(Yuan et al., 2022)**. **(Feng et al., 2013)** used GRACE satellite data to estimate groundwater storage changes in the NCP during 2002-2014 and reported that groundwater is being depleted faster. GIS plays a critical role in integrating spatial datasets, supporting interpolation of hydrogeological parameters, and linking remote-sensing outputs with numerical models. Though remote sensing is not adequate for local management decisions on its own, it is important to note that remote sensing is useful for providing spatial and temporal consistency **(Arabameri et al., 2019; Rabie et al., 2025).** However, it is important to note that satellite-based estimates of groundwater are limited by low spatial resolution and problems in discriminating between groundwater storage and total water storage. Consequently, remote sensing should not be seen as an alternative method to ground measurements and numerical models, but as an additional source of data.

3.3 Deep Learning and Hybrid Techniques Frameworks

In recent times, AI and machine learning methods have been identified as important tools in groundwater studies, especially in arid and semi-arid environments where groundwater systems show marked nonlinearity and complex responses to management actions. AI can be used to support decision-making in water resources management through data analysis and the generation of scenarios and suggestions for appropriate actions, and GIS can be used to visualize results obtained from these analyses and thus enhance communication among stakeholders **(Parmar, 2023)**. This branch emphasizes data-driven, deep learning, and hybrid modelling approaches, including ANN, LSTM, CNN, and statistical regression techniques. More attention is being paid to integrated approaches that incorporate physical-based GW models with satellite-derived data, including GRACE data and SWAT-MODFLOW models, to enhance the predictive capabilities of models, alleviate data availability issues, and alleviate modelling uncertainty. Groundwater storage changes in Iraq under climate stress using GRACE data (2002_2023) with GLDAS-based soil moisture correction using GSFC and JPL mascon solutions showed that higher accuracy was obtained using the GSFC mascons (R^2 = 0.92), highlighting spatially varying trends in GW storage depletion and confirming the reliability of GRACE data in regions with limited availability of in situ data

(Mohammed et al., 2025). The hybrid deep learning numerical models developed in the recent Iraqi literature have proven to be more accurate in simulating the accuracy of groundwater level prediction in comparison with the MODFLOW models, as observed in the recent literature on the subject **(Attea et al., 2025)**. Analysis of the groundwater storage on the local scale in the Missan Region, Iraq, using the GRACE satellite and well data, observed the recovery of groundwater in 2023 after continuous depletion **(Mohammed et al., 2025)**. At site and catchment scales, groundwater level is governed by complex, nonlinear, and random processes, including climate-driven recharge and surface water interactions, which increase prediction challenges **(Osman et al., 2022)**.
To evaluate spatiotemporal groundwater recharge variations in the Lesser Zab River basin, northeastern Iraq, a QSWATMOD model was applied and calibrated with hydraulic head and daily streamflow, then compared with SWAT performance for flow simulation. QSWATMOD showed better accuracy, revealing significant recharge fluctuations dominated by wet-season inputs, with lateral and surface flows contributing strongly to water balance and overall stable recharge prediction **(Rahem and Mohammed, 2025)**. Ensemble ANN models were developed using gridded GRACE products and hydrometeorological datasets to forecast monthly and seasonal groundwater fluctuations at wells across the U.S. GRACE data improved ANN performance, particularly under extreme climate events (e.g., Midwest droughts), demonstrating that statistical downscaling can support local water resources planning **(Swain et al., 2022)**. Machine learning has rapidly advanced groundwater prediction **(Hussein et al. 2020; Tian et al. 2018)**, demonstrating that LSTM's ability to simulate rainfall–runoff dynamics is more accurate than conceptual models. A MODFLOW model for the Hutuo River alluvial fan was corrected using RF, XG Boost, and LSTM with observed groundwater levels from 10 wells as benchmarks. LSTM outperformed other algorithms, with the LSTM2 model (using multiple feature variables) significantly reducing RMSE and improving correlation, effectively capturing both long-term trends and seasonal fluctuations in groundwater levels **(Shuai et al., 2024)**. To predict seawater intrusion in coastal aquifers of Fujairah, UAE, using deep learning for sustainable groundwater management, over 14,000 daily TDS records from 16 wells were pre-processed (KNN imputation, outlier removal, normalization) and modeled with FFNN, LSTM, Transformer, and hybrid LSTM-FFNN architectures. Attention-augmented LSTM was found to have the best performance in terms of MAE = 401 mg/L and R^2 = 0.983. It has better spatial and seasonal stability and can be used for real-time salinity risk management in a scalable way **(Kassem et al., 2025)**. Using integrated MODFLOW-2005 for simulating climate changes (RCP 4.5 and RCP 8.5), machine learning algorithms (GPR, SVR, Tree, and ANN), and using groundwater data for calibration, the drawdown of groundwater was ~40-42 m by the year 2100 for the machine learning algorithms. In addition, the best accuracy was obtained by using GPR, with R^2 = 1.0. It was also found that the optimum pumping rates for the Oligocene and Eocene aquifers are ~0.6 M m^3/day and ~10.2 M m^3/day, respectively **(Makhlouf et al., 2024)**. To well forecast groundwater levels, machine learning models have become a principal point in time-series analysis **(Barzegar et al., 2025)**. A key advantage of these models is their capacity to simulate and predict groundwater levels without requiring the wide-ranging topographical and hydrogeophysical data **(Barzegar et al., 2025)**. An extensive array of machine learning models has been applied to groundwater level estimation, including ANNs, deep learning, support vector machines (SVM), neuro-fuzzy, and Bayesian models **(Samani, 2024; Mahakur et al., 2025)**. AI and deep learning models show strong potential for predicting groundwater levels, storage changes, and water quality

variables because they can capture nonlinear temporal patterns **(Khan et al., 2023; Alshehri and Rahman, 2023).** As compared to stand-alone numerical modelling, AI models can be expected to give better results if adequate data sets are available. However, the biggest challenge with AI models is their inability to explain the physics of any system and their reliance on adequate data sets. Hence, the best way forward would be to use hybrid models. The application of AI in Iraq is still limited, but recent hybrid studies point to significant improvements in terms of predictive accuracy. These studies should be interpreted as suggesting that the gap identified is not conceptual but rather methodological, with comparable standards being achievable with better data availability and computing capabilities.

3.4 Spatiotemporal Coverage of Groundwater Studies

The reviewed literature demonstrates a widespread range of spatial and temporal scales in groundwater research, reflecting both localized hydrogeological investigations and larger regional to national assessments. Temporally, the majority of studies published between 2000 and 2015 focused on steady-state or short-term simulations, primarily aiming to characterize aquifer properties, groundwater flow regimes, and water quality conditions using numerical models and GIS-based analyses. From 2016 onward, a noticeable shift is observed toward transient modeling, long-term prediction, and multi-decadal assessments, driven by increasing concerns related to groundwater depletion, climate variability, and increased human-caused pressures.

In Iraq, research activities are focused primarily on site-specific aquifers, for instance, alluvial fans, confined and unconfined aquifers, and urban or agricultural basins (e.g., Karbala, Erbil, Wasit, Diyala, Missan, Simawwa, and Middle Euphrates Basin). In this context, numerical models using MODFLOW, spatial analysis using GIS techniques, and field observations are often used to simulate groundwater flow, evaluate different pumping scenarios, and determine the rates of recharge. The time period considered for this study is usually in the range of a few to medium periods, between 5 and 15 years, due to the limitations in the long-term monitoring data, yet providing detailed information on site-specific hydrological stress and management scenarios. The recent research activities in Iraqi studies have been identified with the extended spatiotemporal scale, using different satellite data, for example, GRACE and GLDAS, to study the changes in groundwater storage on large spatial scales and long time periods, ranging between 2000 and 2023. This has helped in identifying the depletion trends in groundwater on large spatial scales, which are beyond the limitations of the time and spatial scale of the conventional groundwater monitoring activities. Globally, research trends show a wider spatial scope and longer temporal scales. Many global research works cover the entire river basin, coastal areas, national aquifer systems, or multi-catchment datasets, which cover a period of more than 20-50 years or longer. The research works are employing machine learning, deep learning, and hybrid modeling approaches to tackle the complexities of groundwater spatiotemporal variability, including climate change projections, to enhance the predictive capabilities of the models for future scenarios. The availability of monitoring networks with a high density and the ability to observe the globe via satellites make it possible to analyze groundwater variability at the global scale.

In terms of trends, the reviewed literature reveals the evolution of the scale of analysis, which was originally conducted locally with relatively short periods of observation. This made it impossible to conduct an analysis on a large scale. However, modern research tends to employ a combination of remote sensing and numerical modeling to address such problems. This happens because people now realize that the analysis should include the consideration of spatiotemporal variability, which can be important, especially in dry regions, where climate and anthropogenic changes might have adverse impacts. In other words, it appears that a combination of satellite observations, physically-based models, and machine learning algorithms provides higher quality when linking large-scale analysis and prediction to the local scale of observations. However, data consistency, scale, and validation issues are still present, indicating that further refinements are necessary in methodology to achieve robust spatiotemporal groundwater assessment. Consequently, the spatiotemporal comparison indicates that Iraqi groundwater studies are still largely concentrated at local aquifer scales and medium-term periods, whereas international studies increasingly cover basin, national, and continental scales using long-term satellite and climate datasets. This difference reveals an important research gap in Iraq: the limited availability of long-term monitoring networks and integrated multi-scale modelling frameworks. Expanding the temporal coverage and linking local well data with regional satellite observations and AI-based forecasting would improve groundwater assessment under future climate and abstraction scenarios.

3.5 Comparative Analysis of Independent and Integrated Approaches

As illustrated in **Fig. 1**, which compares the modelling practices in Iraq and worldwide, some trends in the development of groundwater research can be identified. Numerical models based on physics, such as MODFLOW, have been widely used in both Iraqi and worldwide modelling practices, accounting for about 62% and 60%, respectively. This is likely due to the long history and successful applications of MODFLOW for simulating various flow and transport processes in groundwater systems. To support the review with a quantitative basis, the selected studies were grouped according to their primary modelling approach, namely numerical modelling, remote sensing applications, and AI-based techniques. The relative contribution of each category was estimated for both Iraqi and international studies. The resulting percentages were used to develop a comparative evaluation.

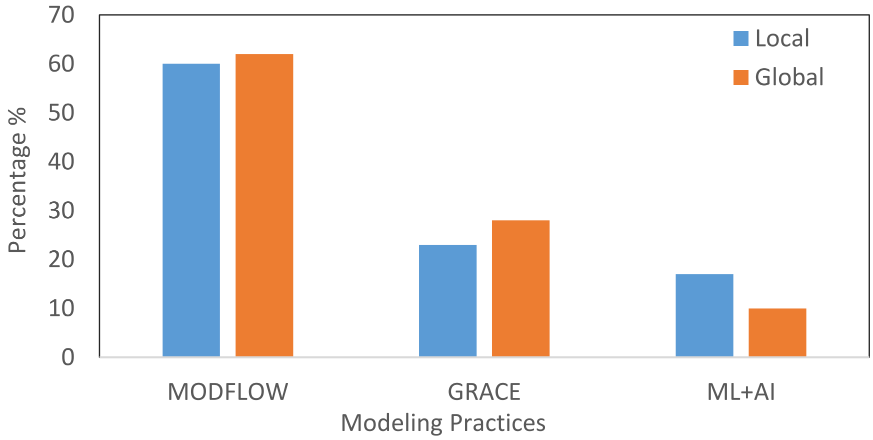

Figure 1. Comparison between Iraqi and worldwide modelling practices.

On the other hand, trends in the application of remote sensing data show a relatively balanced picture, where about 28% of Iraqi and 23% of international studies have utilized GRACE, Landsat, and other satellite data products. Interestingly, there is a noticeable increase in trends related to remote sensing applications from the year 2020 onward. This may be due to a better understanding of its potential for groundwater storage, recharge, and land surface process monitoring, especially where these data are scarce. There is a noticeable contrast between trends related to the application of AI and machine learning, where about 10% of Iraqi and almost 17% of international studies have utilized these techniques. This may be due to the complexity of data integration related to hydrologic, climatic, and socio-economic factors, as well as the lack of multidisciplinary expertise and better computational capabilities in this field. In terms of international research, integrated research that involves numerical modeling, remote sensing techniques, and AI techniques constitutes a significant portion of recent groundwater research that has a high analytical depth and treats uncertainties in a more appropriate manner. This integrated research is still lacking in Iraqi research, and this is indicative of a great potential for methodological improvements in this field. The advantages of the integrated approach stem from its ability to overcome the limitations of the individual methods. In this respect, the numerical methods are physically consistent, while the remote sensing approach provides spatial and temporal completeness.

The AI techniques also enhance the predictability of the methods. Generally, the above results show a research world in which local research is still largely based on traditional numerical approaches, while global research is slowly moving towards the use of a hybrid approach involving the use of AI and integrated modeling approaches. The enhancement of the use of advanced AI approaches, the extension of the use of remote sensing, and the enhancement of the use of integrated modeling approaches would significantly improve the analytical capacity of groundwater research in Iraq. The strength of integrated modeling approaches is that, by combining the strengths of individual approaches, the limitations of each can be compensated for, as the physical consistency of numerical modeling, the spatial and temporal completeness of remote sensing, and the predictive capabilities of AI can all be incorporated into a single approach. Overall, these results show a research environment where local research prefers traditional numerical approaches, whereas global research seems to be trending towards the use of hybrid, AI-enhanced, and integrated models. Enhancing the adoption of advanced technologies in AI, remote sensing capabilities, and integrated modelling will significantly enhance the analytical capabilities of groundwater research in Iraq. The sequential evolution of groundwater flow modeling methodologies from 2000 to 2025, **Fig. 2**, shows how research priorities and technical approaches have evolved. In the early 2000s, analytical models were theoretical basis for groundwater flow.

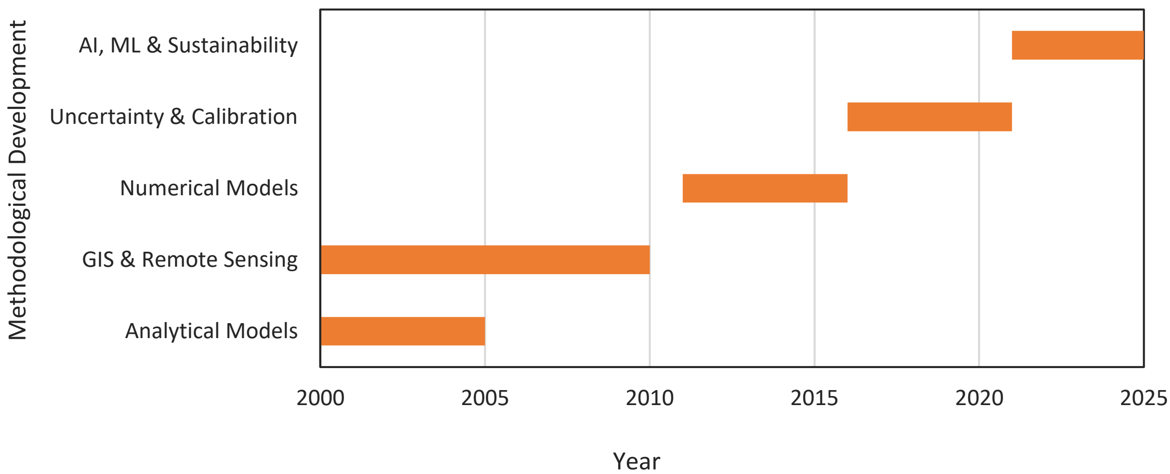

Figure 2. Timeline of groundwater flow modeling developments (2000-2025).

Simplified assumptions were used to describe the flow characteristics, and this allowed for rapid analysis and understanding. However, this meant that spatial heterogeneity and complex boundary conditions could not be adequately addressed. In fact, between 2000 and 2010, there was a marked expansion in the scope of groundwater investigations using GIS and remote sensing technology. This allowed engineers and hydrogeologists to effectively integrate distributed parameters such as land use, topography, and climatic data into groundwater investigations. The development shifted from theoretical modeling to data-oriented approaches. From 2011 to 2015, numerical modeling of groundwater systems became the leading approach. The development of numerical computing technologies made it possible to simulate complex interactions in groundwater systems under various hydrological conditions. Engineers successfully used numerical models to evaluate the impact of groundwater extraction, its recharge, and sustainability. The period of 2016-2020 characterizes the growing attention paid to model calibration and uncertainty assessment. Researchers were aware of the importance of the reliability of a particular model, not only the model, but also of the parameters used in calculations. Thus, sensitivity analysis, uncertainty quantification, and calibration are the key aspects of the research on the modeling of groundwater. As reflected in the figure from 2021, the trend reflects the application of AI, machine learning, and sustainability. The key aspects of the research are the attempt to improve the prediction, handle large data, and make decisions based on the changing conditions of the climate and the increasing demands for water.

The significant increase observed after the year 2020, as depicted in **Fig. 3**, reveals a noticeable trend towards integrated and data-based modelling. Researchers tend to incorporate computational intelligence methods into traditional numerical models in a progressive manner. From the academic engineering point of view, the figure reveals a progressive trend in groundwater research in the last fifteen years. It has progressed beyond the traditional approach of using conventional physics-based models and now incorporates AI-based models to enrich the analytical potential and forecasting ability of the models.

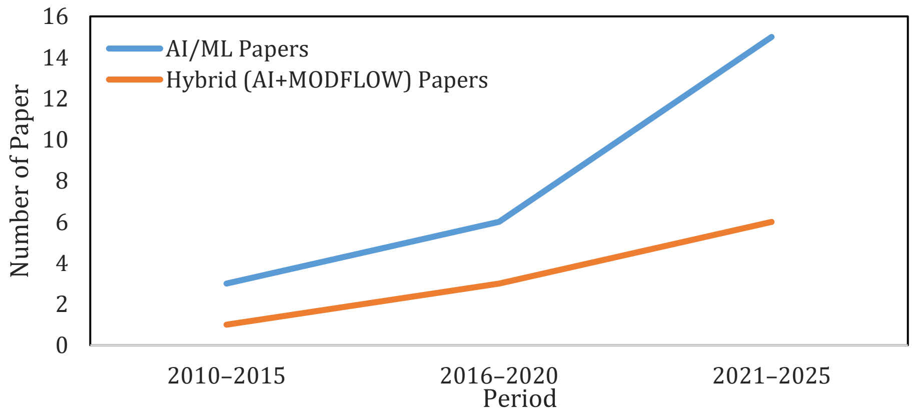

Figure 3. Trend of AI and hybrid groundwater modeling (2010-2020).

The paper helps bridge this important gap in our understanding by providing insight into the role of AI in groundwater studies, not replacing physically based numerical models, but acting as a supporting tool for improving predictive capability, reducing computational effort, and better representing nonlinear system responses. Moreover, this review provides information on how remote sensing data can be effectively used to address monitoring limitations, providing spatially continuous information for improving model calibration, validation, and regionalization. By organizing and comparing existing studies, this work reduces disintegration in literature and provides engineers and researchers with guidance on selecting appropriate hybrid modelling strategies. From a development perspective, this review provides a boost to the development of more robust and flexible groundwater modelling frameworks. This review inspires the development of integrated approaches, which are interdisciplinary in nature. This review provides a practical basis for addressing some of the challenges associated with groundwater modelling, such as physics-informed AI approaches. This review provides a practical basis for addressing some of the challenges associated with groundwater modelling, such as uncertainty-based hybrid approaches.

4. CONCLUSIONS

This review paper emphasizes the tremendous change that groundwater modelling has witnessed in the past two decades due to advancements in numerical modelling, data-based algorithms, and satellite hydrology. Numerical modelling is still the primary tool for simulating groundwater systems; however, the increasing trend of applying AI and deep learning models indicates the importance of such models in simulating groundwater dynamics and overcoming the non-linear characteristics of groundwater systems. The inclusion of remote sensing data from satellites like GRACE and Landsat has increased the scope of groundwater modelling by providing a wide platform for groundwater evaluation, particularly in regions with inadequate groundwater data. The increasing trend of hybrid models that combine numerical and AI models indicates the future direction of groundwater modelling towards a more effective and integrated approach. The above review has demonstrated that the developments in groundwater modelling can be accomplished through the integration of ideas of AI, numerical modelling, and remote sensing instead of using them independently. The innovative feature of the article is that it outlines a coherent framework about how these three methods are complementary to each other in dealing with the limitations associated with the traditional groundwater models due to a lack of data, scale, and uncertainty. In general, the review of existing literature makes it evident that there is a need for the development of integrated models with respect to numerical and remote sensing as well as AI.

Credit Authorship Contribution Statement

Batool Saleh Al-Khafaji: Methodology, Investigation, Formal analysis, Writing - original draft. Mahmoud Saleh Al-Khafaji: Formal analysis, Validation, Writing - review & editing. Ali Hussain Ali: Conceptualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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دمج الذكاء الصناعي والأساليب العددية والاستشعار عن بعد لنمذجة المياه الجوفية المتقدمة: مراجعة شاملة

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الخلاصة

يُعدّ استنزاف المياه الجوفية، والتغير المناخي، وتزايد الطلب على المياه من أبرز التحديات التي تواجه الإدارة المستدامة للموارد المائية في المناطق الجافة وشبه الجافة مثل العراق. تقيّم هذه الدراسة النماذج الحالية المستخدمة في تمثيل المياه الجوفية وأداءها، كما تستعرض أحدث التطورات في تقنيات نمذجة المياه الجوفية. وتشير الدراسة إلى أن النماذج العددية، وتقنيات الذكاء الاصطناعي، وتقنيات الاستشعار عن بُعد تُطبّق حالياً بصورة منفصلة في معظم الدراسات. تُستخدم النماذج الفيزيائية على نطاق واسع في نمذجة المياه الجوفية نظراً لكفاءتها وموثوقيتها في محاكاة جريان المياه الجوفية وعمليات انتقال الملوثات. وقد شكّلت هذه النماذج ما نسبته 62% من دراسات المياه الجوفية في العراق و60% من الدراسات العالمية. وفي المقابل، تُظهر أدوات الذكاء الاصطناعي إمكانات كبيرة في التنبؤ بالسلوك غير الخطي لديناميكية المياه الجوفية، وتحسين دقة النتائج التنبؤية، وتقديم تقييم قائم على البيانات للظروف الهيدروجيولوجية .كما أصبح استخدام تقنيات الاستشعار عن بُعد، مثل GLDAS و GRCE أكثر شيوعاً بين الباحثين لتقدير التغيرات في خزين المياه الجوفية، إلا أن تطبيقها لا يزال محدوداً نسبياً، إذ يمثل نحو 28% من الدراسات المنجزة في العراق و23% من الدراسات العالمية. وتُبيّن نتائج هذه المراجعة أن اعتماد المناهج الهجينة يمكن أن يسهم بدرجة كبيرة في تحسين دقة التنبؤ وتعزيز إدارة المياه الجوفية بصورة أكثر فاعلية واستدامة.

الكلمات المفتاحية: نمذجة المياه الجوفية، النماذج الهيدروجيولوجية، التعلم العميق، الذكاء الاصطناعي.