Review Article

Resolving challenges of groundwater flow modelling for improved water resources management: a narrative review

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Saadu Umar Wali,[1] Abdulqadir Abubakar Usman,[1] Abdullahi Bala Usman,[1] Umar Abdullahi,[1] Ibrahim Umar Mohammed,[2] Jamil Musa Hayatu[3]

[1]Department of Geography, Faculty of Social and Management Sciences, Federal University Birnin kebbi, P.M.B 1157, Kebbi State, Nigeria
[2]Department of Water Resources & Environmental Management, National Water Resources Institute, PMB 2309, Mando Road, Kaduna, Nigeria
[3]Department of Training, National Water Resources Institute PMB 2309, Mando Road, Kaduna, Nigeria

Correspondence: Saadu Umar Wali, Department of Geography, Faculty of Social and Management Sciences, Federal University Birnin kebbi, P.M.B 1157, Kebbi State, Nigeria, Tel +234(0)8032596509, +234(0)8065555170, Email saaad.wali@fubk.edu.ng, saaduumarwali@gmail.com

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Abstract

Groundwater flow modelling is critical for managing groundwater resources, particularly amid climate change and rising water demand. This narrative review examines the role of groundwater flow models in sustainable water resource management, focusing on challenges and solutions to enhance model reliability. A key challenge is data limitation—especially in regions like sub-Saharan Africa and South Asia, where scarce hydrogeological data hinders accurate model calibration. The complexity of aquifer systems, such as karst aquifers in North America and fractured-rock aquifers in India, further complicates model development, requiring detailed geological data and complex simulations. Additionally, uncertainties arise from limited knowledge of aquifer properties, variable boundary conditions, and sparse monitoring networks, which can reduce model predictability. Despite these obstacles, groundwater flow models are essential for simulating groundwater behaviour in response to altered precipitation patterns, increasing extraction rates, and extreme events like droughts. For instance, predictive modelling has helped assess potential depletion risks in California's Central Valley and contamination risks in industrial zones of East Asia, guiding sustainable extraction strategies and contamination assessments. To improve model reliability, this review emphasizes the need for enhanced data collection, integration of advanced technologies—such as artificial intelligence and machine learning for predictive accuracy—and the adoption of multidisciplinary modelling approaches. These advancements, improved sensor networks, and regional data-sharing initiatives are critical to reducing uncertainties and increasing model precision. Ultimately, such improvements will support climate adaptation efforts and promote the sustainable management of global groundwater resources, benefiting water managers and policy makers.

Keywords: Groundwater flow modelling; Water resource management; Climate change adaptation;

Artificial intelligence in hydrology

Abbreviations: GIS, geographic information systems; ML, machine learning; TRMM, tropical rainfall measuring mission; GPM, global precipitation measurement; NDVI, normalised difference vegetation index; GRACE, gravity recovery and climate experiment; AI, artificial intelligence; MAR, managed aquifer recharge; EIAs, environmental impact assessments; GDEs, groundwater-dependent ecosystems

Introduction

Groundwater is a crucial resource for millions of people worldwide, particularly in arid and semi-arid regions where surface water availability is limited. In many countries, especially in the Global South, groundwater is the primary source of drinking water, irrigation, and industrial uses.[1,2] However, with increasing population pressures, urbanization, and climate variability, the challenges surrounding groundwater resources have become more pronounced. Effective water resource management is imperative to ensure the sustainability of this vital resource, and groundwater flow modelling has emerged as a critical tool in this endeavour.[3,4] This narrative review explores the challenges associated with groundwater flow modelling and how addressing these challenges can enhance water resource management. Groundwater is the world's largest freshwater reserve, comprising approximately 97% of the accessible freshwater supply. Its significance is underscored by its various roles, including domestic water supply, agricultural irrigation, industrial applications, and environmental sustainability. In many developing countries, groundwater accounts for over 60% of agricultural irrigation, highlighting its importance in food security.[5,6]

Groundwater flow modelling simulates the movement and distribution of groundwater within aquifers using mathematical and computational tools.[7] This modelling is essential for understanding groundwater dynamics, predicting future behaviour, and making informed decisions on resource management.[8] In sustainable water resource management, groundwater models help estimate available groundwater, assess recharge rates, and guide extraction practices to prevent overuse and contamination.[9] By simulating the impacts of varying climatic conditions, land use changes, and extraction rates, these models provide insights critical for developing strategies that protect groundwater sources. The relevance of groundwater flow modelling is particularly significant in developing countries, where groundwater is often a primary drinking water source and essential for agriculture.[8] However, these regions' data scarcity, financial constraints, and technical limitations make modelling challenging.[10] Strengthening modelling efforts in these areas can support equitable and sustainable water access, aiding climate resilience and reducing global water scarcity risks.

The reliance on groundwater has made its sustainable management increasingly critical, particularly as climate change exacerbates water scarcity issues. Groundwater provides a buffer during droughts and maintains base flows in rivers and wetlands, supporting biodiversity and ecosystem services.[11] Despite its importance, groundwater management faces several challenges, including over-extraction, contamination, and insufficient data for effective modelling. Over-extraction occurs when groundwater withdrawal exceeds the natural recharge rate, leading to declining water tables, land subsidence, and reduced water quality.[12] A significant example of this can be seen in many aquifers across India and the United States, where groundwater depletion has reached alarming levels. Contamination is another significant issue, often resulting from agricultural practices, industrial discharges, and inadequate waste management systems. Contaminated groundwater poses severe risks to human health and the environment, making it imperative to develop effective monitoring and remediation strategies. Insufficient data availability and quality further complicate groundwater management.[13]

Many regions lack comprehensive hydrogeological data for accurate modelling and informed decision-making, particularly in the Global South. This data gap often leads to reliance on outdated models and assumptions, ultimately hindering effective resource management.[14] Groundwater flow modelling plays a pivotal role in addressing these challenges by simulating the movement of groundwater through aquifers. These models can predict how groundwater systems will respond to various stresses, such as changes in recharge rates, extraction rates, and land-use practices.[15] Flow models can help inform water management strategies by providing insights into groundwater behaviour, allowing for more sustainable practices. There are several groundwater models, including analytical, numerical, and conceptual models. Analytical models are based on mathematical equations and provide solutions for simplified conditions.[16] Numerical models, on the other hand, use numerical methods to solve complex groundwater flow equations, making them suitable for simulating real-world conditions.[17]

Conceptual models provide a qualitative understanding of the groundwater system and are often used as a starting point for more detailed numerical modelling. The lack of comprehensive, high-quality hydrogeological data poses significant challenges.[18,19] Accurate input parameters, such as hydraulic conductivity, porosity, and recharge rates, are critical for reliable modelling. However, such data is scarce or unavailable in many regions, particularly developing countries. Groundwater systems are inherently complex due to various factors, including geological heterogeneity, varying land uses, and climatic influences. This complexity makes it challenging to create accurate models that account for all relevant variables and processes.[20] Model calibration and validation are critical steps in ensuring the reliability of groundwater flow models. However, these processes can be challenging due to limited data and the need for expert knowledge. Without proper calibration, models may produce misleading results, leading to poor management decisions. Uncertainty in groundwater flow models can arise from various sources, including data limitations, model parameterization, and inherent variability in the groundwater system. Understanding and quantifying uncertainty is crucial for effective decision-making and risk assessment.[21]

Effective groundwater management requires collaboration among various stakeholders, including government agencies, local communities, and private sector actors. However, engaging stakeholders in the modelling process can be challenging, particularly in regions with diverse interests and varying knowledge about groundwater issues.[22] Several strategies can be employed to improve groundwater flow modelling and enhance water resource management. Developing comprehensive data collection and monitoring programs is essential for improving the quality and availability of hydrogeological data. This may involve remote sensing technologies, citizen science initiatives, and collaboration with local communities to gather relevant information.[23] Developing robust models that account for regional characteristics and complexities is crucial. Collaboration among hydrologists, geologists, and local stakeholders can facilitate the creation of more accurate models.[24] Employing modern calibration techniques, such as data assimilation and machine learning, can enhance model reliability.

Conducting uncertainty analyses can help identify the most significant sources of uncertainty in groundwater flow models and inform decision-making processes. This may involve using probabilistic modelling techniques to quantify uncertainty and evaluate its impact on management decisions.[25] Building the capacity of local stakeholders, including government agencies, water managers, and communities, is essential for effective groundwater management. This may involve training programs, workshops, and knowledge-sharing initiatives to enhance understanding of groundwater issues and modelling techniques.[26] An integrated water resource management (IWRM) approach can facilitate more holistic groundwater management. This approach emphasizes the interconnectedness of groundwater and surface water systems and promotes stakeholder collaboration to address competing demands.

Groundwater is a vital resource crucial in sustaining livelihoods, supporting agriculture, and maintaining ecosystems. However, the challenges associated with groundwater management are significant and require practical solutions. Groundwater flow modelling is valuable for understanding and managing this resource, but several hurdles must be overcome to enhance its effectiveness.[15] As a result of addressing data limitations, improving model calibration and validation, quantifying uncertainty, and engaging stakeholders, we can create more reliable groundwater flow models that support informed decision-making. Ultimately, effective groundwater management will be essential for ensuring the sustainability of this critical resource in the face of growing pressures from population growth, climate change, and environmental degradation.[11] Through continued research, collaboration, and innovation, we can resolve the challenges of groundwater flow modelling and improve water resource management for future generations.

Importance of groundwater flow modelling

Groundwater flow modelling is an essential tool in the management and sustainable use of groundwater resources, particularly in regions where freshwater availability is critical for agricultural, industrial, and domestic purposes.[27] The significance of groundwater flow modelling lies in its ability to simulate the behaviour of groundwater systems under various conditions, facilitating informed decision-making for water resource management.[28] Understanding groundwater flow dynamics becomes increasingly vital as the world grapples with increasing water scarcity, climate change impacts, and rising demands for freshwater.[29] Groundwater is a crucial lifeline for billions of people, particularly in arid and semi-arid regions with limited surface water sources. In many developing countries, groundwater constitutes the primary source of drinking water and irrigation. Effective management of this resource is essential to ensure water security and sustainability.[30] Groundwater flow modelling provides a framework to understand how aquifers respond to various stresses, such as changes in recharge rates, extraction rates, and land-use practices. By simulating groundwater flow, these models offer insights into the potential outcomes of different management scenarios, enabling stakeholders to make more informed decisions.[31]

One of the primary benefits of groundwater flow modelling is its capacity to predict water movement within aquifers over time. This predictive capability is crucial for assessing the sustainability of groundwater resources.[32] For instance, models can simulate how land-use changes, such as urbanization or agricultural expansion, affect groundwater recharge and discharge patterns. This information is vital for policymakers and water managers aiming to implement sustainable practices that protect and preserve groundwater resources.[33] In addition to sustainability assessments, groundwater flow modelling is instrumental in identifying potential contamination risks. As urban areas expand and agricultural practices intensify, the risk of groundwater contamination increases. Modelling can help evaluate the potential pathways for contaminants and assess their impact on groundwater quality. Water managers can prioritize monitoring and remediation efforts by identifying vulnerable areas and ensuring drinking water supplies remain safe and uncontaminated.[34]

Calibration and validation of groundwater flow models are critical processes that enhance their reliability and applicability. Calibration involves adjusting model parameters based on observed data to ensure that the model accurately represents the real-world system.[35] This process is essential for building confidence in model predictions, as stakeholders rely on these models to make significant decisions about water management. Conversely, validation assesses the model's performance by comparing its outputs against independent datasets. A well-calibrated and validated model enhances the credibility of groundwater flow modelling, allowing for more robust and defensible management strategies.[36] Despite the strengths of groundwater flow modelling, several challenges can hinder its effectiveness. One notable challenge is the availability and quality of data. Many regions, especially in the Global South, suffer from insufficient hydrogeological data, limiting the ability to develop accurate models.[37] Inadequate data can lead to uncertainty in model outputs, which can, in turn, undermine confidence in the predictions made by these models. Addressing this data gap through comprehensive monitoring and data collection programs is vital to improve the reliability of groundwater flow models.[38]

Another challenge is the complexity of groundwater systems themselves. Aquifers can vary widely regarding their geological characteristics, recharge rates, and interactions with surface water bodies. This complexity necessitates the development of sophisticated models that can accurately represent groundwater flow dynamics.[20] Moreover, incorporating climate change scenarios into modelling efforts adds a layer of complexity, as changing precipitation patterns and temperature can significantly influence groundwater recharge and availability.[20] Uncertainty is an inherent aspect of groundwater flow modelling, stemming from various sources, including data limitations, model parameterization, and natural variability in groundwater systems.[39] Understanding and quantifying uncertainty are crucial for effective decision-making. Probabilistic modelling techniques can help characterize uncertainty in predictions, providing stakeholders with various possible outcomes rather than a single deterministic result. This approach allows for better risk assessment and management, enabling water managers to develop adaptive strategies in response to changing conditions.[40]

Stakeholder engagement is another critical aspect of groundwater flow modelling. Effective groundwater management requires collaboration among various stakeholders, including government agencies, local communities, and the private sector.[41] Engaging stakeholders in the modelling process can foster a shared understanding of groundwater issues and enhance the relevance of model outputs. Participatory modelling approaches, where stakeholders contribute their knowledge and insights, can improve model accuracy and promote consensus on water management strategies.[42] The application of groundwater flow modelling extends beyond local and regional scales; it is also essential for addressing transboundary aquifer management issues. Many aquifers extend across national borders, creating challenges for coordinated management. Groundwater flow modelling can facilitate discussions among nations by providing a common framework for understanding shared resources.[43] By simulating different management scenarios, countries can assess the potential impacts of various strategies, promoting collaboration and cooperation in groundwater management.

Therefore, groundwater flow modelling is paramount for the sustainable management of this vital resource. By simulating groundwater behaviour, these models offer critical insights that inform decision-making for water resource management. Despite the challenges associated with data limitations, model complexity, and uncertainty, the benefits of effective groundwater flow modelling are undeniable.[44] As water scarcity and environmental pressures continue to mount globally, investing in groundwater flow modelling will ensure water security, safeguard public health, and promote sustainable development.[45] Ultimately, a more comprehensive understanding of groundwater dynamics will enable stakeholders to implement strategies that balance the competing demands on this precious resource, ensuring its availability for future generations.

Challenges in groundwater flow modelling

Data availability and quality

Groundwater flow modelling is essential for understanding and managing groundwater resources effectively. However, one of the most significant challenges faced in this field is data availability and quality. The accuracy and reliability of groundwater models heavily depend on the data used to parameterize and calibrate them.[46] Inadequate or poor-quality data can lead to erroneous predictions, undermining the purpose of the modelling exercise and potentially leading to misguided management decisions. Data availability is a multifaceted issue influenced by various factors, including geographical location, socio-economic conditions, and technological advancement in data collection and monitoring.[47] Comprehensive hydrogeological data are often lacking in many regions, especially in the Global South. This absence of data can stem from historical neglect of groundwater resources in favour of surface water, insufficient funding for research and monitoring programs, or even political instability that hampers systematic data collection efforts.[14] As a result, many groundwater flow models are developed with limited information, relying heavily on assumptions and generalizations that may not accurately reflect local conditions.

The quality of data is equally crucial. High-quality data must be accurate, consistent, and representative of the hydrological processes occurring in a specific region. However, in many instances, available data suffer from issues such as inconsistency in measurement techniques, variations in data collection methods, and insufficient temporal and spatial coverage.[48] For example, groundwater level measurements might be taken at irregular intervals or in locations that do not adequately represent the overall aquifer system. Such discrepancies can lead to significant uncertainties in model predictions. One common issue related to data quality is the use of outdated information.[49] Many groundwater models rely on historical data, which may no longer represent current conditions due to changes in land use, climate, or groundwater extraction rates. For instance, agricultural expansion, urban development, and changes in climate patterns can dramatically alter groundwater recharge and discharge dynamics.[50] A model based on outdated data may not accurately predict future scenarios, leading to inadequate water management strategies.

Another challenge is the limited understanding of the hydrogeological characteristics of aquifers. Groundwater systems can be highly heterogeneous, exhibiting significant variability in properties such as hydraulic conductivity and porosity.[51,52] Inadequate characterization of these properties can result in oversimplified models that fail to capture the complexity of groundwater flow. This complexity can be particularly pronounced in regions with diverse geological formations, where the interaction between different strata can influence groundwater movement significantly.[53] A multi-pronged approach is necessary to address data availability and quality challenges. First, there is a need for enhanced data collection efforts, particularly in under-researched regions. Governments, research institutions, and international organizations should invest in comprehensive groundwater monitoring networks to gather essential hydrogeological data.[54] These efforts could include using modern technologies, such as remote sensing and geographic information systems (GIS), to improve data collection and analysis.

Collaboration among stakeholders can help improve data quality.[55] Involving local communities in data collection can enhance understanding of groundwater systems and ensure data reflects local conditions. Community-based monitoring initiatives, where residents are trained to gather and report data, can provide valuable insights while fostering a sense of ownership over groundwater resources.[56] Standardization of data collection methods is also crucial for improving data quality. Establishing uniform protocols for measuring groundwater levels, water quality parameters, and other critical variables can enhance the consistency and reliability of data across different regions.[57] This standardization is essential for creating comparable datasets that can be used to calibrate and validate groundwater models effectively.

Moreover, integrating data from multiple sources can enhance model reliability. Combining hydrological data with other relevant information, such as land use and climate data, can provide a more comprehensive understanding of the factors influencing groundwater flow.[58] This holistic approach can help refine models and improve their predictive capabilities. Uncertainty quantification is another critical aspect of addressing data challenges in groundwater flow modelling.[44] Recognizing that data limitations can lead to uncertainty in model outputs is essential for effective decision-making. Probabilistic modelling techniques can help characterize uncertainty and provide a range of possible outcomes rather than a single deterministic prediction. This approach allows decision-makers to consider potential risks and uncertainties when developing management strategies.[59]

Capacity building in data management and analysis is essential for improving the quality of groundwater data. Training programs for researchers, water managers, and local stakeholders can enhance skills in data collection, interpretation, and modelling.[3] By building local capacity, regions can better understand their groundwater systems and improve the overall effectiveness of groundwater management strategies. In summary, the challenges associated with data availability and quality pose significant obstacles to effective groundwater flow modelling. Limited data and poor-quality information can lead to inaccurate models and misguided management decisions, undermining the potential benefits of modelling efforts.[60] Enhanced data collection initiatives, stakeholder collaboration, standardization of measurement protocols, integration of diverse data sources, and uncertainty quantification are essential to overcome these challenges. By addressing these issues, groundwater flow modelling can become a more reliable tool for informing sustainable water resource management, ultimately contributing to the long-term sustainability of groundwater resources worldwide.

Improving data accuracy in groundwater modelling requires robust government, research, and private collaboration.[14,61] Governments can initiate standardized data collection protocols and invest in nationwide monitoring networks, particularly in underserved regions. They can support studies that yield refined aquifer data and site-specific groundwater parameters by partnering with research institutions. Research organizations contribute expertise in advanced technologies[14]—such as remote sensing, artificial intelligence, and IoT sensors—that can improve data collection and real-time monitoring capabilities. The private sector, particularly companies involved in water-intensive industries, can share data from groundwater extraction activities, contributing to a more comprehensive dataset.[62] Additionally, joint funding initiatives among these stakeholders can support open-access databases, enabling data-sharing and minimizing duplication of efforts. This collaborative approach enhances data accuracy and enables more effective and sustainable water resource management, benefiting communities, ecosystems, and industries alike.[63]

Model calibration and validation

Groundwater flow modelling is a crucial component in the management and sustainable use of groundwater resources. Although these models provide invaluable insights into the behaviour of aquifers, they also face significant challenges, particularly in model calibration and validation.[15] Calibration refers to adjusting model parameters to align the model's predictions with observed data, while validation involves assessing the model's accuracy against independent datasets. Both processes are essential for ensuring groundwater flow models yield reliable predictions that inform decision-making. One of the primary challenges in model calibration is the inherent complexity of groundwater systems.[64] Aquifers are often characterized by heterogeneous geological formations, varying hydraulic properties, and complex interactions with surface water. These characteristics can complicate the calibration process, as multiple parameters may influence the model's output.[65] Determining the optimal values for these parameters can be difficult, mainly when dealing with sparse or inconsistent data. Moreover, the interdependence of parameters can lead to equifinality, where different combinations of parameter values yield similar model outputs. This situation makes it challenging to pinpoint the most accurate parameter set for the model.

Data availability and quality significantly impact calibration.[66] Many regions, particularly in developing countries, suffer from insufficient hydrogeological data, making it difficult to establish a robust calibration framework. Lack of data can lead to over-reliance on assumptions or generalized values, which may not accurately reflect local conditions. Consequently, the model may produce misleading groundwater management predictions.[67] Efforts to enhance data collection through monitoring networks and remote sensing technologies can help mitigate these challenges, but they require time, resources, and expertise. Calibration also requires a careful balance between model complexity and usability.[68] Although more complex models can capture intricate groundwater dynamics, they may also increase the difficulty of calibration due to the more significant number of parameters that need to be adjusted. In contrast, simpler models may be easier to calibrate but may not adequately represent the complexities of the groundwater system.[69] Striking the right balance between model complexity and accuracy is a fundamental challenge that modellers must address.

Once a model is calibrated, validation is the next critical step. Validation involves comparing the model's predictions with independent observational data to assess its predictive capability.[70] This step is vital because a calibrated model may fit historical data well but may not perform accurately when predicting future scenarios. Ensuring robust validation requires high-quality data that spans different temporal and spatial scales.[71] However, obtaining such data can be particularly challenging in regions with limited monitoring infrastructure. Consequently, many models may suffer from validation biases due to the unavailability of diverse datasets, leading to uncertainty in model predictions. Uncertainty is an inherent aspect of groundwater flow modelling and can stem from various sources. Parameter uncertainty arises from the inability to accurately measure specific parameters, leading to calibration variability.[32] Structural uncertainty can occur when the model fails to capture the essential processes governing groundwater flow. Additionally, uncertainty can be introduced through the assumptions made during model development. Understanding and quantifying uncertainty are critical for effective decision-making, mainly when groundwater resources are under pressure.[72]

Modellers can employ several strategies to address calibration and validation challenges. One practical approach is to use a systematic calibration process that involves multiple iterations.[73] This process may incorporate optimization algorithms that search for the best-fitting parameter values, providing a more robust calibration framework. Sensitivity analysis can also identify which parameters significantly influence model outputs, allowing modellers to focus on calibrating the most critical parameters.[74] By systematically refining the model through iterative calibration and sensitivity analysis, modellers can improve the accuracy of their predictions. Incorporating uncertainty analysis into the calibration and validation process is another effective strategy. Probabilistic approaches can help quantify uncertainty in parameter values and model outputs, allowing stakeholders to assess possible outcomes.[40] This information is crucial for making informed decisions, mainly when groundwater resources are scarce or at risk. By embracing uncertainty analysis, modellers can enhance the credibility of their predictions and promote more adaptive management strategies.

Engaging stakeholders in the calibration and validation process can also improve the reliability of groundwater flow models.[75] Collaboration with local communities, water managers, and policymakers can provide valuable insights into regional conditions, helping to identify relevant data sources and improve the overall understanding of the groundwater system. Stakeholder engagement fosters a sense of ownership and encourages using model outputs in decision-making, ultimately leading to more effective groundwater management.[76] Therefore, the challenges associated with model calibration and validation in groundwater flow modelling are significant and multifaceted.[77] The complexity of groundwater systems, data limitations, and inherent uncertainties all pose challenges that can undermine the reliability of model predictions. However, by employing systematic calibration processes, incorporating uncertainty analysis, and engaging stakeholders, modellers can enhance the robustness of their models. Addressing these challenges is essential for ensuring that groundwater flow models effectively manage and conserve vital water resources in an increasingly uncertain future.[41] Through ongoing research, collaboration, and innovation, the groundwater modelling community can continue to advance state of the art, contributing to more sustainable water management practices globally.

Calibration and validation are essential in groundwater modelling, ensuring that models accurately reflect real-world conditions. Machine learning (ML) has become an effective tool for calibrating complex groundwater models by analyzing large datasets to optimize model parameters.[17] For example, in Central Valley, California, ML algorithms have been used to improve calibration by identifying relationships between recharge rates and groundwater levels, enhancing predictive accuracy under variable climatic conditions.[78] However, different modelling approaches present unique challenges. Numerical models, which solve equations for fluid flow, are highly accurate but require substantial data and computational power, making calibration difficult in data-scarce regions.[66] In contrast, conceptual models simplify aquifer systems and are easier to calibrate but may oversimplify dynamics and limit predictive power.[79] Both approaches can benefit from more refined calibrations by integrating ML techniques, though each requires tailored strategies to overcome inherent challenges and improve reliability.

Uncertainty and sensitivity analysis

Groundwater flow modelling is a critical tool in managing water resources, providing essential insights into the dynamics of aquifers and the movement of groundwater.[27,80] However, the effectiveness of these models is often compromised by challenges associated with uncertainty and sensitivity analysis. Understanding and addressing these challenges are vital for enhancing the reliability of groundwater flow models and informing effective management strategies. One of the primary challenges in groundwater flow modelling is uncertainty, which arises from various sources, including data limitations, parameter estimation, and inherent variability in the groundwater system itself.[81,82] Uncertainty can significantly impact model predictions, leading to potential misinterpretations and misguided management decisions. It is crucial to distinguish between different types of uncertainty: epistemic uncertainty, which stems from a lack of knowledge or data, and aleatory uncertainty, which is inherent variability in the system.

Epistemic uncertainty is often linked to the quality and quantity of data used in model development. Many groundwater systems, especially in regions with limited resources, suffer from insufficient or poor-quality data.[83,84] Critical parameters such as hydraulic conductivity, porosity, and recharge rates may be poorly constrained, leading to uncertainty in model outputs. For instance, variations in hydraulic conductivity can profoundly impact flow rates and groundwater levels. When such parameters are based on sparse data, the resulting models may fail to capture the actual behaviour of the groundwater system.[85] In addition to data-related uncertainties, model structure and assumptions introduce another layer of uncertainty. Groundwater flow models rely on simplifying assumptions to represent complex systems. While these assumptions are necessary for practical modelling, they may not accurately reflect real-world conditions.[86,87] For example, assuming homogeneity in aquifer properties can lead to significant discrepancies between modelled and observed behaviours. As such, model structure should be carefully evaluated, and alternative structures should be considered to assess the impact of these assumptions on model predictions.

Sensitivity analysis addresses uncertainty in groundwater flow modelling.[88] Sensitivity analysis identifies which parameters influence model outputs most by systematically varying model parameters. This process allows modellers to prioritize data collection efforts and focus on parameters significantly affecting model performance. For instance, if a model's predictions are highly sensitive to hydraulic conductivity, targeted field studies can be conducted to improve the estimation of this parameter, thereby reducing uncertainty.[89] There are various methods for conducting sensitivity analysis, including local sensitivity analysis, which examines the effect of small changes in parameter values on model outputs, and global sensitivity analysis, which simultaneously evaluates the impact of varying multiple parameters.

Global sensitivity analysis is particularly useful for complex groundwater models, as it captures the interactions among parameters and provides a more comprehensive understanding of model behaviour.[90] As a result of identifying key parameters, sensitivity analysis aids in model calibration, guiding the selection of parameters that should be refined to improve model accuracy. Despite the benefits of sensitivity analysis, challenges remain in its implementation. Determining the appropriate range for parameter variation can be difficult, especially when lacking empirical data. The computational cost of running multiple model simulations can also be significant, especially for large-scale or complex models.[91,92] Advanced techniques, such as surrogate modelling and machine learning, are increasingly being utilized to alleviate these challenges, allowing for efficient sensitivity analysis without requiring extensive computational resources.

Uncertainty and sensitivity analysis are essential for model calibration, validation, risk assessment, and decision-making. By quantifying the uncertainty in model predictions, water managers can evaluate the likelihood of different outcomes and develop more robust management strategies. For example, when assessing the sustainability of groundwater resources under various extraction scenarios, understanding the uncertainty in model predictions enables managers to make informed decisions that minimize risks to water availability and quality. Furthermore, stakeholder engagement is crucial in addressing uncertainty and sensitivity analysis in groundwater flow modelling.[75,93] Effective communication of model uncertainty to stakeholders can foster a shared understanding of model predictions' limitations and potential risks. Involving stakeholders in the modelling process can provide valuable local knowledge that enhances data collection efforts and helps to identify critical parameters for sensitivity analysis. As a result of fostering collaboration between modellers and stakeholders, more resilient groundwater management strategies can be developed that account for the complexities and uncertainties inherent in groundwater systems.[94]

Therefore, uncertainty and sensitivity analysis present significant challenges in groundwater flow modelling that must be addressed to enhance the reliability and effectiveness of these models. Understanding the sources of uncertainty, conducting rigorous sensitivity analyses, and engaging stakeholders are crucial steps in improving model performance and informing effective groundwater management.[44,95] As the demand for water resources continues to rise and the impacts of climate change become more pronounced, addressing these challenges will be essential for ensuring the sustainability of groundwater resources and protecting them for future generations. By prioritizing efforts to quantify uncertainty and understand model sensitivity, water managers can make more informed decisions that balance competing demands and promote the long-term health of aquifer systems. Figure 1 illustrates an example of a calibrated model.

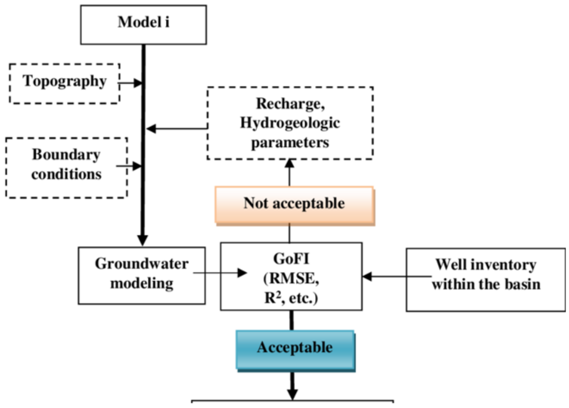

Figure 1 Groundwater modelling flow chart.[96]

The diagram illustrates the iterative process of groundwater flow modelling, highlighting parameter estimation and model validation challenges. Key inputs, such as topography, boundary conditions, recharge rates, and hydrogeological parameters, are essential but often complex to estimate accurately due to data scarcity and variability. After a model is built, its performance is evaluated using statistical goodness-of-fit metrics (e.g., RMSE, R^2), comparing model outputs with real-world data, such as boreholes inventories. If the model's performance is deemed unacceptable, adjustments are made to parameters before re-running the model. Challenges include accurately estimating recharge rates, representing complex hydrogeological conditions, and validating models with limited observational data. Additionally, the iterative process of refining models to achieve acceptable accuracy can be time-consuming and computationally intensive. This process underscores the difficulty in capturing the full complexity of groundwater systems, particularly in regions with sparse data or where groundwater interacts with surface water and human activities.[96]

To enhance groundwater flow modelling for effective water resource management, model calibration and validation are essential for aligning model predictions with real-world data.[97] Including successful applications of machine learning (ML) in model calibration can significantly improve model accuracy and reliability. For instance, neural networks and ensemble learning methods have effectively calibrated complex groundwater models, especially in areas with limited data.[17] ML can adaptively improve model precision by automating parameter tuning, as demonstrated in regions with variable aquifer characteristics and data gaps. Moreover, addressing challenges across different modelling approaches—such as numerical models (finite difference, finite element) versus conceptual models (e.g., lumped parameter models)—is critical.[98] Numerical models, while accurate, are computationally intensive and may require extensive data for calibration, whereas conceptual models are often limited in capturing spatial variability but are more accessible to calibrate with limited data. Highlighting these distinctions can guide modellers in choosing and calibrating the most appropriate model based on resource constraints and data availability, ultimately supporting more resilient and adaptive water resource management strategies.[66]

Innovations and advances in groundwater modelling

Integration of remote sensing and GIS

Integrating remote sensing and Geographic Information Systems (GIS) into groundwater modelling has revolutionised how groundwater resources are studied and managed. Traditionally, groundwater modelling relied on field data collection, often limited by the cost, time, and logistical constraints of monitoring large, heterogeneous areas.[99,100] However, recent remote sensing and GIS technology innovations have expanded the capacity to gather, analyse, and interpret data at unprecedented scales and resolutions. These advances have greatly enhanced groundwater models' accuracy, efficiency, and scope, making them more reliable tools for water resource management in developed and developing regions. Remote sensing provides a way to obtain spatially extensive data about the Earth's surface and subsurface through satellite or aerial sensors.[101,102] It has proven invaluable in monitoring parameters relevant to groundwater systems, such as land use, vegetation cover, soil moisture, precipitation patterns, and changes in water bodies.

One of the most significant contributions of remote sensing to groundwater modelling is its ability to estimate groundwater recharge and discharge over large areas. For example, precipitation data derived from remote sensing platforms, such as NASA's Tropical Rainfall Measuring Mission (TRMM) or the Global Precipitation Measurement (GPM) satellite, can be integrated into models to predict recharge rates with greater precision than was previously possible through ground-based monitoring alone.[103] In arid and semi-arid regions, where groundwater is a critical resource, estimating recharge has traditionally been challenging due to the scarcity of surface water and precipitation variability.[104,105] Remote sensing addresses this challenge by providing continuous, large-scale data that can identify subtle changes in surface conditions related to groundwater recharge. For instance, vegetation indices, such as the Normalised Difference Vegetation Index (NDVI), derived from satellite imagery, can be used as proxies for soil moisture levels directly linked to recharge processes.[106] Using incorporating this type of remote sensing data into groundwater models, hydrologists can improve the spatial and temporal resolution of recharge estimates, leading to more accurate predictions of groundwater availability.

Groundwater discharge, particularly from springs and wetlands, can also be monitored using remote sensing techniques. Thermal infrared sensors, for instance, can detect temperature anomalies in surface water bodies that may indicate groundwater-surface water interactions.[107,108] This approach identifies discharge zones over vast areas that would otherwise be difficult to monitor through conventional methods. Integrating these remote sensing observations into groundwater models, researchers can refine their understanding of aquifer dynamics and more accurately simulate the behaviour of groundwater systems under various environmental conditions. Geographic Information Systems (GIS) have further transformed groundwater modelling by providing a powerful platform for integrating, visualising, and analysing spatial data.[109,110] GIS enables the overlay and analysis of multiple data layers, such as topography, geology, land use, and hydrological parameters, which are all essential for constructing accurate groundwater models. The spatial analysis capabilities of GIS allow for the identification of patterns and relationships within complex groundwater systems, which can then be incorporated into models to improve their predictive accuracy.

One of the critical strengths of GIS is its ability to handle large datasets and link them with groundwater models through spatial interpolation techniques.[111,112] This capability is significant for regions with sparse direct data on groundwater characteristics, such as aquifer properties or groundwater levels. Using GIS to interpolate between known data points, modellers can generate continuous surfaces representing groundwater levels, hydraulic conductivity, or recharge rates across an entire study area.[113] These interpolated datasets can then be used as inputs for groundwater models, allowing for more detailed and comprehensive simulations. GIS-based groundwater modelling allows for the development of more sophisticated decision support systems [114] By combining groundwater models with spatial analysis tools in GIS, water resource managers can simulate different management scenarios and visualise their potential impacts on groundwater systems. For instance, integrating land-use change models with groundwater flow models in a GIS environment allows for assessing how urban expansion, deforestation, or agricultural practices may affect groundwater recharge and quality.[115] This type of scenario-based modelling is critical for sustainable water management, as it provides decision-makers with a clearer understanding of the long-term consequences of different land-use and water management strategies.

Another significant innovation from integrating GIS and remote sensing into groundwater modelling is the ability to assess groundwater storage and depletion at regional and global scales. For example, the Gravity Recovery and Climate Experiment (GRACE) satellite mission has been used to monitor changes in terrestrial water storage, including groundwater, by measuring Earth's gravity field variations.[116] GRACE data has provided critical insights into groundwater depletion in northern India and California's Central Valley regions, where intensive irrigation has led to significant groundwater declines. Via integrating GRACE-derived water storage data into groundwater models, researchers can track the long-term trends in groundwater availability and evaluate the sustainability of current extraction practices. Integrating remote sensing and GIS into groundwater modelling has advanced the development of real-time monitoring systems.[117] With the increasing availability of near-real-time satellite data, it is now possible to continuously monitor critical variables affecting groundwater systems, such as precipitation, soil moisture, and land use. This real-time data can be fed into groundwater models to provide up-to-date predictions of groundwater levels and recharge rates, which is particularly useful for regions experiencing rapid environmental changes or water scarcity crises.

Real-time monitoring systems also enhance the ability to manage groundwater resources adaptively, as water managers can adjust extraction rates, land-use policies, or conservation measures based on the latest model outputs.[4] While integrating remote sensing and GIS into groundwater modelling offers numerous advantages, it also presents some challenges. For instance, remote sensing data must often be calibrated and validated with ground-based measurements to ensure accuracy, especially when estimating subsurface parameters.[118,119] Additionally, the resolution of satellite data may not always be sufficient for modelling small-scale groundwater processes, such as localised recharge from infiltration basins or small springs. Furthermore, the computational demands of processing and integrating sizeable remote sensing datasets into groundwater models can be significant, requiring specialised software and expertise.

Despite these challenges, the continued advancement of remote sensing technologies and GIS tools promises to further enhance groundwater models' capability.[117] As sensors become more accurate and capable of detecting finer spatial and temporal details, integrating these technologies will allow for more precise and dynamic simulations of groundwater systems. Moreover, the growing availability of open-access remote sensing data and the development of cloud-based GIS platforms will democratise access to these tools, enabling more widespread adoption of advanced groundwater modelling techniques worldwide.[120] Integrating remote sensing and GIS into groundwater modelling has brought about significant innovations that have improved these models' accuracy, scope, and applicability. By enabling the collection and analysis of large-scale spatial data, these technologies have enhanced our ability to monitor, understand, and manage groundwater resources sustainably and informally.[121.122] As groundwater plays a critical role in global water security, these innovations will be essential for addressing the complex challenges posed by increasing water demand, climate variability, and environmental degradation.

Advanced groundwater modelling technologies, including machine learning, numerical models, and remote sensing, have greatly enhanced predictive capabilities but present distinct challenges, especially in data-scarce regions.[123] One key constraint is the high cost of deploying advanced technologies, such as high-resolution sensors and specialized modelling software, which can be prohibitive for low-resource settings.[124] Additionally, while remote sensing is invaluable for broad-scale groundwater assessments, its accuracy is often limited in regions with sparse ground-based data.[125] Remote sensing may struggle to capture localized groundwater variations without adequate on-site calibration data, leading to potential inaccuracies in model predictions.[126] Furthermore, advanced models often require extensive computational resources and expertise, which may not be readily accessible in many data-limited areas.[127] These factors underscore the need for context-specific approaches that effectively balance technological capabilities with practical constraints to support water resource management in data-scarce regions.

Machine learning and artificial intelligence applications

Groundwater flow modelling has long been recognized as a valuable tool for understanding subsurface hydrological processes and managing groundwater resources.[15] However, as the complexities of aquifer systems, data limitations, and evolving environmental pressures increase, traditional modelling approaches face several challenges. These challenges include insufficient data availability, high computational demands, and difficulty accurately representing complex hydrogeological systems.[20] In recent years, the emergence of machine learning (ML) and artificial intelligence (AI) technologies has opened new avenues for addressing some of these challenges, offering the potential to enhance groundwater flow models' accuracy, efficiency, and applicability.

One of the primary challenges in groundwater flow modelling is the lack of sufficient and reliable data. Accurate models depend on hydrogeological data, including information on aquifer properties, hydraulic conductivity, recharge rates, and boundary conditions.[128] In many regions, particularly in the Global South, such data is scarce, outdated, or difficult to obtain. ML and AI can help address this issue by analyzing existing datasets to fill gaps and generate predictions in data-poor regions.[129] For example, machine learning algorithms can be trained on limited datasets to infer missing parameters or predict aquifer behaviour based on patterns observed in other, better-studied areas. This ability to generate data-driven insights from sparse datasets can significantly improve the initialization and calibration of groundwater flow models.[130]

AI and ML also offer solutions to the challenge of model complexity. Groundwater systems are inherently complex due to their heterogeneous geological structures, variable recharge conditions, and interactions with surface water bodies. Traditional modelling approaches, such as numerical methods, require significant computational resources to represent these complexities accurately. ML techniques can reduce the computational burden by developing surrogate models that approximate the behaviour of more complex physical models.[131,132] These surrogate models, often called "emulators," can provide quick and reliable predictions of groundwater flow, making them valuable for real-time decision-making in water resource management. AI-based models can thus serve as effective alternatives to high-fidelity numerical models, particularly when rapid simulations are required for large-scale or time-sensitive applications.

The incorporation of machine learning into groundwater modelling also addresses the issue of model calibration and optimization, both of which are critical steps in ensuring that a model accurately represents the real-world system.[17] Traditional calibration methods can be time-consuming and computationally intensive, especially when dealing with highly parameterized models that require numerous iterations to achieve optimal performance. AI algorithms, such as genetic algorithms, neural networks, and reinforcement learning, can optimize model parameters more efficiently by automating the calibration process.[133] These approaches can quickly explore a wide range of potential parameter values, identifying the optimal configuration that best fits the observed data. By streamlining the calibration process, AI can enhance model accuracy while reducing the time and computational resources required.

Another critical challenge in groundwater flow modelling is the inherent uncertainty that arises from data limitations, model assumptions, and the natural variability of groundwater systems.[15,81] Uncertainty can undermine the reliability of model predictions, making it difficult for decision-makers to assess the risks associated with different water management strategies. AI and ML techniques can help quantify and reduce uncertainty by incorporating probabilistic methods and uncertainty analysis into the modelling process. For example, Bayesian networks and Monte Carlo simulations can be integrated with machine learning models to provide probabilistic forecasts of groundwater flow, offering a range of possible outcomes rather than a single deterministic prediction.[134] This approach enables water managers to better understand the likelihood of different scenarios and make more informed decisions under uncertainty.

However, several challenges remain despite the potential advantages of machine learning and artificial intelligence in groundwater flow modelling. One primary concern is the "black-box" nature of many AI models, intense learning models, which can make it challenging to interpret the underlying processes driving the model's predictions.[135,136] In groundwater modelling, where understanding the physical processes of aquifer systems is crucial for effective management, the lack of interpretability can be a significant drawback. While AI models may provide accurate predictions, their inability to explain the results transparently can limit their acceptance among hydrologists and water resource managers who rely on physical insights to make decisions. Addressing this issue requires the development of more interpretable machine learning models or hybrid approaches that combine AI with traditional physical models to balance predictive accuracy with process understanding.[137]

Another challenge is the potential for overfitting in machine learning models, where the model becomes overly complex and tailored to the training data, leading to poor generalization to new or unseen data. This is particularly problematic in groundwater modelling because the limited availability of high-quality data can increase the risk of overfitting.[138,139] Careful selection of model architecture, cross-validation techniques, and regularization methods are essential to avoid overfitting and ensure that AI models generalize well to different groundwater systems. Moreover, integrating domain knowledge from hydrogeology into machine learning models can help constrain the models and prevent overfitting by incorporating physically meaningful relationships. Data quality and representativeness also challenge AI applications in groundwater flow modelling.[140] Groundwater datasets are often noisy, incomplete, or biased, and machine learning models trained on such data may produce inaccurate or unreliable predictions. Ensuring the training data represents the entire groundwater system is critical for producing robust AI models. Additionally, as machine learning models are susceptible to the quality and quantity of data, continuous data collection and monitoring efforts are necessary to provide accurate and up-to-date information for model training and validation.[141] This can be a significant limitation in data-scarce regions, where the costs and logistical challenges of collecting groundwater data may be prohibitive.

Finally, there is the issue of stakeholder engagement and the practical implementation of AI-driven groundwater flow models in water resource management. While AI offers powerful tools for improving model accuracy and efficiency, its integration into existing decision-making frameworks can be challenging. Many water managers and policymakers may lack the technical expertise to understand or apply AI models, leading to scepticism or resistance.[142,143] Bridging the gap between AI research and practical water management requires targeted capacity-building efforts, including training programs for water managers and developing user-friendly AI tools that can be easily integrated into decision-making processes. Furthermore, collaboration between hydrologists, data scientists, and local stakeholders is essential to ensure that AI-driven groundwater models are grounded in real-world needs and priorities.[144,145]

In a nutshell, machine learning and artificial intelligence offer promising solutions to many of the challenges faced in groundwater flow modelling. By improving data analysis, model calibration, computational efficiency, and uncertainty quantification, these technologies can significantly enhance the accuracy and applicability of groundwater models.[140] However, challenges related to model interpretability, overfitting, data quality, and stakeholder engagement must be addressed to fully realize AI's benefits in groundwater management. Continued research and collaboration across disciplines will be critical in overcoming these obstacles and unlocking the potential of AI to contribute to more sustainable and effective water resource management strategies.

Applications of groundwater flow modelling

Water resources management

Groundwater flow modelling is a critical tool in water resources management, offering a structured approach to understanding and predicting the behaviour of groundwater systems.[146,147] As water becomes an increasingly scarce resource due to population growth, urbanization, and climate change, effective groundwater management is essential to ensure sustainable use. Groundwater flow models provide valuable insights into the dynamics of aquifers, allowing water managers, policymakers, and researchers to make informed decisions regarding the allocation, protection, and preservation of this vital resource.

One of the primary applications of groundwater flow modelling in water resources management is its use in predicting groundwater availability under different scenarios.[15,148] Groundwater models simulate water movement through aquifers and help estimate the quantity of water that can be sustainably extracted without depleting the resource. This predictive capability is essential for long-term planning and ensuring groundwater remains available for future generations. For example, models can simulate different pumping rates and predict how these activities will impact water levels over time. This information helps to avoid over-extraction, which can lead to adverse consequences such as declining water tables, land subsidence, and reduced water quality.[149]

In regions where groundwater is the primary water source for agricultural irrigation, groundwater flow models significantly optimize water use. By simulating how groundwater levels respond to different irrigation practices, models can inform decisions on water allocation to maximize agricultural productivity while ensuring the sustainability of the aquifer.[150,151] This is particularly important in arid and semi-arid regions, where groundwater is heavily relied upon during dry seasons. The ability to model the interaction between groundwater and surface water also provides insight into how irrigation practices affect nearby rivers, lakes, and wetlands, helping to maintain ecological balance.

Another critical application of groundwater flow modelling is managing groundwater contamination.[152] As human activities—such as industrial operations, agriculture, and waste disposal—pose a risk to groundwater quality, models are used to track the movement of contaminants within the aquifer. This allows water managers to identify areas where groundwater is at risk of contamination and to predict the spread of pollutants over time. For instance, models can simulate the transport of contaminants like nitrates from agricultural runoff or hazardous chemicals from industrial spills.[153] By predicting the movement and concentration of these contaminants, groundwater flow models help inform remediation strategies and prevent further water quality degradation.

Groundwater flow modelling is also crucial for managing the conjunctive use of groundwater and surface water resources.[154] In many regions, groundwater and surface water are closely interconnected, with groundwater contributing to river base flows, wetlands, and springs. Groundwater flow models can simulate these interactions, helping assess groundwater extraction's impact on surface water bodies. This is particularly important in areas where surface water is scarce and groundwater is relied upon to maintain the flow of rivers and streams during dry periods.[155,156] Understanding these interactions enables water managers to develop integrated water management strategies that balance the needs of surface and groundwater systems, ensuring that one is not depleted at the expense of the other.

In addition to managing water quantity and quality, groundwater flow modelling supports drought management and climate change adaptation.[20] Climate variability and change can significantly impact groundwater recharge rates, altering the availability of groundwater resources. Models can simulate how different climate scenarios—such as changes in precipitation patterns and temperature—affect groundwater recharge and storage.[157,158] This information is vital for developing adaptive management strategies for future climate conditions. For example, in regions experiencing prolonged droughts, groundwater models can help determine how much groundwater can be sustainably extracted without causing long-term damage to the aquifer. These models provide a foundation for drought preparedness and resilience, enabling communities to respond effectively to water shortages.

Groundwater flow modelling also plays a vital role in managing transboundary aquifers. Many aquifers span political boundaries, making their management more complex.[159] Groundwater flow models provide a common platform for neighbouring countries or regions to assess the state of shared groundwater resources and evaluate different management strategies. By simulating the impacts of groundwater extraction and recharge in different parts of the aquifer, these models help facilitate stakeholder cooperation, enabling more equitable and sustainable management of transboundary water resources.[160] This is particularly important in regions where tensions over water resources may arise due to competing demands or water scarcity.

In urban water management, groundwater flow models are applied to address the growing demand for water in rapidly expanding cities.[161] As urban populations increase, so does the pressure on groundwater resources to meet domestic, industrial, and recreational water needs. Groundwater models help planners assess the long-term sustainability of groundwater extraction in urban areas and identify potential risks such as contamination from urban runoff, industrial waste, or inadequate sewage systems. By simulating the impacts of urban development on groundwater systems, these models inform decisions on water infrastructure, land-use planning, and sustainable groundwater extraction rates.[162]

Another critical aspect of groundwater flow modelling is its application in managing artificial recharge systems. Artificial recharge, or managed aquifer recharge (MAR), involves intentionally increasing groundwater recharge using infiltration basins, injection wells, or excess surface water during wet periods.[163] Groundwater flow models evaluate the feasibility and effectiveness of artificial recharge schemes by simulating how water introduced into the aquifer moves and is stored. These models provide insights into the best locations for recharge, the amount of water that can be recharged, and the potential impacts on groundwater quality.[164] Managed recharge is particularly useful in regions facing water scarcity, as it allows excess water to be stored during periods of high availability for use during dry spells.

Therefore, groundwater flow modelling is a powerful tool for managing water resources in various contexts, from agriculture and urban development to transboundary aquifer management and climate change adaptation.[20,165] By providing a detailed understanding of groundwater dynamics, these models enable more informed decision-making and the development of strategies that promote the sustainable use of groundwater resources. As water scarcity continues to pose significant challenges worldwide, groundwater flow modelling will remain crucial to effective water resource management, helping balance human populations' needs, agriculture, industry, and the environment.

Environmental impact assessment

Groundwater flow modelling plays a crucial role in environmental impact assessments (EIAs), particularly in understanding and mitigating the effects of human activities on groundwater systems.[166,167] As groundwater is a vital resource for drinking water, agriculture, and ecosystems, ensuring its sustainability and protecting it from contamination is essential. Groundwater flow models are used in various environmental and industrial sectors to predict how mining, industrial development, and land-use changes may affect groundwater resources. By simulating groundwater flow and transport processes, these models help assess the potential environmental impacts of proposed projects, ensuring that appropriate mitigation measures can be implemented. One of the most critical applications of groundwater flow modelling in EIAs is evaluating the potential for groundwater contamination. Many industrial activities, such as mining, manufacturing, and waste disposal, pose risks to groundwater quality due to the release of contaminants like heavy metals, chemicals, and organic pollutants.[168]

Groundwater flow models can simulate the movement of these contaminants through aquifers, helping to predict their spread and concentration over time. This predictive capability allows stakeholders to identify areas at risk of contamination and develop strategies to protect sensitive water resources, such as drinking water wells and ecosystems that depend on groundwater.[169] In the context of waste management, groundwater flow models are often used to assess the risks associated with landfills, industrial waste sites, and hazardous waste disposal facilities. These models simulate how leachates—liquids that percolate through waste materials and carry contaminants—may move through the subsurface and reach groundwater.[170,171] By evaluating different waste management scenarios, models help identify the best waste containment and treatment practices, reducing the likelihood of groundwater contamination. In some cases, models can also be used to design monitoring programs to detect early signs of contamination and implement corrective actions before significant environmental damage occurs.

Groundwater flow modelling is also applied to assess the impacts of large infrastructure projects, such as dams, reservoirs, and urban development, on groundwater systems. These projects can alter natural recharge and discharge patterns, potentially leading to changes in groundwater levels, reduced river base flows, and drying up wetlands and springs.[172,173] Using groundwater flow models, environmental assessors can simulate how these projects will affect groundwater dynamics over time, allowing them to predict potential impacts on local water supplies, ecosystems, and agricultural activities. Moreover, groundwater flow modelling in coastal areas is essential for assessing the risks of saltwater intrusion into freshwater aquifers.[174,175] This phenomenon occurs when excessive groundwater extraction near the coast lowers the water table, allowing saltwater to move inland and contaminate freshwater supplies. Groundwater flow models can simulate how changes in extraction rates and sea-level rise might affect the movement of saltwater into aquifers, helping to develop strategies to prevent or mitigate saltwater intrusion. Such strategies might include reducing groundwater withdrawals, enhancing recharge, or installing physical barriers to slow the movement of saltwater.[176]

In mining and resource extraction industries, groundwater flow modelling is critical for assessing the environmental impacts of dewatering and tailings management activities. Dewatering removes groundwater to allow mining operations below the water table.[177] This can significantly lower groundwater levels in the surrounding area, affecting nearby wells, wetlands, and ecosystems. Groundwater flow models help predict how dewatering will affect local groundwater systems and inform decisions on water management practices that minimize environmental impacts.[178] Similarly, models assess the contamination risks from tailings, which are the waste materials left over after extracting valuable minerals. These materials often contain harmful substances that can leach into groundwater. By simulating the transport of contaminants from tailings, groundwater models help develop containment and remediation plans to protect groundwater quality.

Groundwater flow modelling also plays a crucial role in assessing the impacts of agricultural activities on groundwater resources. Agriculture is a significant user of groundwater, particularly in regions with limited surface water supplies. However, intensive irrigation and using fertilizers and pesticides can lead to groundwater depletion and contamination.[179] Groundwater flow models can simulate the effects of different irrigation practices on groundwater levels and assess how agricultural runoff, which contains nitrates, phosphates, and other pollutants, may affect groundwater quality. This helps policymakers and farmers develop sustainable water management practices that balance the need for agricultural productivity with the protection of groundwater resources.[180] In addition to assessing contamination and resource depletion risks, groundwater flow modelling is also used to evaluate the potential impacts of climate change on groundwater systems. Climate change can alter precipitation patterns, increase evaporation rates, and shift snowmelt timing, affecting groundwater recharge and availability. Groundwater flow models can simulate how these changes will impact aquifers over time, helping to identify regions vulnerable to water shortages or increased contamination risks due to declining water tables.[181] This information is valuable for developing adaptive water management strategies for future climate variability.

Furthermore, groundwater flow models are valuable in environmental remediation projects to clean up contaminated groundwater. Whether the contamination is due to industrial spills, agricultural runoff, or legacy pollution from abandoned industrial sites, groundwater models can help design effective remediation strategies.[182] These models can predict the movement of contaminants through the subsurface and evaluate the effectiveness of different remediation techniques, such as pump-and-treat, bioremediation, or the use of permeable reactive barriers. By simulating the behaviour of contaminants and remediation processes, groundwater models provide a scientific basis for selecting the most appropriate and cost-effective cleanup strategies.[171] Groundwater flow modelling is essential to environmental impact assessments, providing critical insights into how various human activities affect groundwater systems. These models help predict the movement of groundwater and contaminants, assess the potential impacts of large-scale infrastructure projects, and guide the development of sustainable water management practices.[20] Whether applied in agriculture, industry, resource extraction, or waste management, groundwater flow models enable informed decision-making that protects groundwater resources and ensures their availability for future generations. As environmental pressures continue to grow, the importance of groundwater flow modelling in environmental assessments will only increase, helping to safeguard one of the planet's most valuable and vulnerable natural resources.

Climate change adaptation

Groundwater flow modelling plays a critical role in climate change adaptation by providing a framework for understanding how climate changes affect groundwater systems and identifying sustainable water resource management strategies.[20,183] As the impacts of climate change become more pronounced, including shifts in precipitation patterns, increased temperatures, and rising sea levels, groundwater resources are likely to face significant challenges. Groundwater flow models offer a powerful tool to simulate the effects of these changes, allowing water managers, policymakers, and researchers to predict potential outcomes and develop strategies to mitigate risks.[184] One of the primary applications of groundwater flow modelling in the context of climate change adaptation is assessing the impact of altered precipitation and recharge patterns on aquifers. Climate change is expected to modify the distribution and intensity of rainfall in many regions, affecting groundwater recharge rates.[20,185] In some areas, increased precipitation may enhance recharge, while prolonged droughts may reduce it significantly in others. Groundwater flow models can simulate these varying scenarios, helping to predict how aquifers will respond to different climate futures. This information is vital for long-term water resource planning, as it enables water managers to anticipate periods of water scarcity or surplus and make necessary adjustments to extraction rates, storage, and usage practices.

Figure 2 illustrates the interconnected impacts of climate change on groundwater systems. It shows two main drivers of climate change: changes in air temperature and changes in rainfall regimes, which directly influence groundwater through various pathways. Higher air temperatures can lead to increases in groundwater temperature, which may affect the chemical reactions in aquifers, potentially altering groundwater quality.[186] Additionally, rising temperatures typically result in higher evapotranspiration rates, reducing the amount of water that infiltrates the ground and thus limiting groundwater recharge. This reduction in recharge can decrease groundwater availability, especially in arid and semi-arid regions where surface water is already scarce. Changes in rainfall patterns, including altered intensity, frequency, and distribution, significantly influence groundwater systems. Increased rainfall can enhance recharge, but climate change often leads to more erratic rainfall, with prolonged droughts followed by intense precipitation events. These shifts can negatively impact groundwater recharge in the long term.

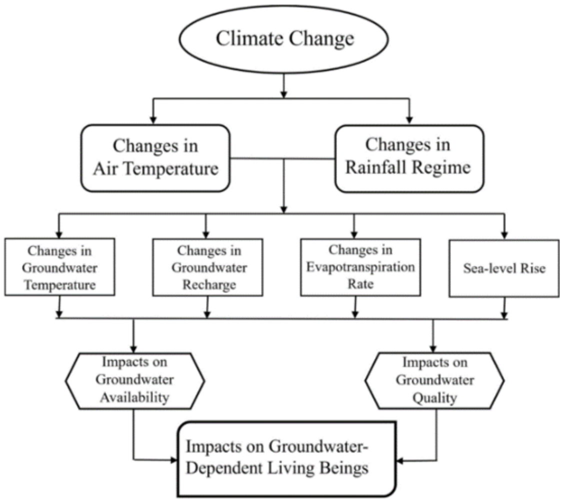

Figure 2 Natural impacts of climate change on groundwater system.[186]

Sea-level rise, another consequence of climate change, threatens coastal aquifers, increasing the risk of saltwater intrusion into freshwater systems and further compromising groundwater quality. The figure highlights that these changes—whether in groundwater temperature, recharge rates, or water quality—directly impact groundwater availability and quality. These shifts, in turn, affect ecosystems and species dependent on groundwater, and human populations rely on this vital resource for drinking water, irrigation, and other needs.[186] Climate change exacerbates challenges in groundwater flow modelling by adding uncertainty to critical variables such as recharge rates, temperature profiles, and contamination risks. Alterations in rainfall patterns can complicate predictions of recharge while rising temperatures and increased evapotranspiration further stress the accuracy of groundwater availability forecasts.

Moreover, saltwater intrusion in coastal areas adds a layer of complexity to modelling water quality, necessitating more sophisticated, dynamic models capable of integrating climatic, hydrological, and geological data.[186] As groundwater flow models aim to simulate these evolving scenarios, they must account for the multifaceted impacts of climate change to provide reliable predictions and inform sustainable water management strategies. Groundwater flow modelling also supports the development of sustainable extraction strategies under changing climatic conditions.[20] As surface water availability becomes more variable due to climate change, groundwater will likely play an even more prominent role in meeting water demands. However, over-reliance on groundwater resources can lead to over-extraction, declining water tables, land subsidence, and water quality degradation. Flow models can simulate the impact of increased groundwater extraction on aquifer systems, providing insights into sustainable withdrawal limits and helping to prevent resource depletion.[187] By simulating future demand scenarios and their interaction with climate-driven changes in recharge, models guide water managers in making informed decisions about extraction policies that balance human needs with long-term sustainability.

Another critical area where groundwater flow modelling supports climate change adaptation is managing the interactions between surface water and groundwater. Climate change is expected to exacerbate the frequency and intensity of extreme weather events, including floods and droughts.[188,189] These events can significantly alter the balance between surface water and groundwater systems. During periods of drought, reduced river flows can lead to increased dependence on groundwater, while in times of flooding, excessive recharge may raise groundwater levels, causing issues such as waterlogging and contamination. Groundwater flow models can simulate these interactions, enabling the assessment of how extreme events influence surface and groundwater resources.[190] This information is essential for designing integrated water resource management strategies that ensure resilience to climate variability and extremes.

Sea-level rise is another dimension of climate change that poses risks to coastal aquifers. As sea levels rise, saltwater intrusion into freshwater aquifers becomes a significant concern, particularly in low-lying coastal areas. Saltwater intrusion can render groundwater resources unusable for drinking water and agriculture, necessitating costly desalination or alternative water-sourcing solutions.[191] Groundwater flow models are crucial in simulating the movement of saltwater into coastal aquifers under various sea-level rise scenarios. By predicting the extent and rate of saltwater intrusion, these models provide valuable insights into areas at risk and allow for developing strategies to mitigate or adapt to these impacts.[192] Potential adaptation measures, such as the controlled reduction of groundwater extraction near coastal zones, the construction of physical barriers, or the implementation of recharge enhancement projects, can be evaluated and optimized using flow models.[193]

Groundwater-dependent ecosystems (GDEs) are also vulnerable to the impacts of climate change, and groundwater flow modelling can assist in their protection and management. GDEs, such as wetlands, rivers, and springs, rely on consistent groundwater contributions to maintain their ecological functions.[193,194] Changes in groundwater availability due to altered recharge patterns or increased extraction can disrupt these ecosystems, leading to biodiversity loss and degradation of ecosystem services. Flow models can simulate the relationship between groundwater levels and the health of GDEs, helping to identify critical thresholds at which groundwater depletion would have detrimental effects on these ecosystems. This allows for implementing adaptive management strategies that prioritize the protection of GDEs while balancing other water uses.

Moreover, groundwater flow modelling can be applied to evaluate the effectiveness of artificial recharge as an adaptation strategy. In regions where natural recharge is insufficient to meet demand, artificial recharge—such as managed aquifer recharge (MAR) projects—can help increase groundwater storage by directing surface water into aquifers.[195,196] With climate change expected to increase the variability of water availability, MAR and other artificial recharge methods are becoming more critical in maintaining sustainable groundwater levels. Flow models can simulate the potential impact of artificial recharge efforts on aquifer dynamics, optimizing recharge rates, locations, and methods to ensure long-term effectiveness. These models provide crucial insights into artificial recharge projects' feasibility and potential outcomes, guiding investment decisions and maximizing the benefits of adaptive water management strategies.[197]

Finally, groundwater flow modelling supports the development of risk management and contingency planning strategies in the context of climate change.[198] As groundwater becomes an increasingly important buffer against the unpredictability of surface water supplies, understanding the capacity of aquifers to provide reliable water during drought is crucial. Flow models can simulate worst-case scenarios, such as prolonged dry periods or increased extraction demands, allowing water managers to assess the resilience of groundwater resources and prepare for future uncertainties.[199] These models can also help identify vulnerable regions where groundwater resources are most at risk, enabling targeted interventions that enhance resilience and protect vulnerable communities from the impacts of water scarcity.

Groundwater flow modelling is a critical tool in climate change adaptation, offering valuable insights into the behaviour of groundwater systems under changing climatic conditions. By simulating the impacts of altered recharge patterns, extraction rates, extreme weather events, sea-level rise, and interactions between surface and groundwater systems, these models inform the development of sustainable water management strategies that ensure resilience in climate change.[200,201] Groundwater flow models provide the data and predictions needed to guide decision-making processes, helping to balance competing water demands, protect vulnerable ecosystems, and ensure the long-term sustainability of groundwater resources. As the effects of climate change intensify, the importance of groundwater flow modelling in adaptation efforts will only grow, making it an indispensable tool for safeguarding water security in the years to come.[202]

Resolving challenges of groundwater follow modelling

Figure 3 presents a conceptual framework for addressing challenges in groundwater flow modelling and highlights its applications for improved groundwater management. At the core, the figure identifies critical challenges in groundwater flow modelling, including data availability and quality, model calibration and validation, and uncertainty and sensitivity analysis. These challenges often limit the accuracy and reliability of groundwater models. The figure emphasizes the importance of incorporating innovations and advances in groundwater modelling to overcome these challenges. This includes the integration of remote sensing and GIS technologies for enhanced data collection and analysis. Machine learning and artificial intelligence techniques can also improve model predictions and decision-making.

The ultimate goal of addressing these challenges and leveraging advancements in groundwater modelling is to improve groundwater management. The figure highlights three critical applications of groundwater flow modelling: water resources management, environmental impact assessment, and climate change adaptation.

By understanding groundwater flow dynamics, decision-makers can make informed decisions regarding water allocation, pollution control, and adaptation strategies to climate change impacts on groundwater resources. The figure emphasizes the need for a comprehensive approach to groundwater flow modelling, incorporating both robust data and advanced modelling techniques, to address challenges and support sustainable groundwater management.

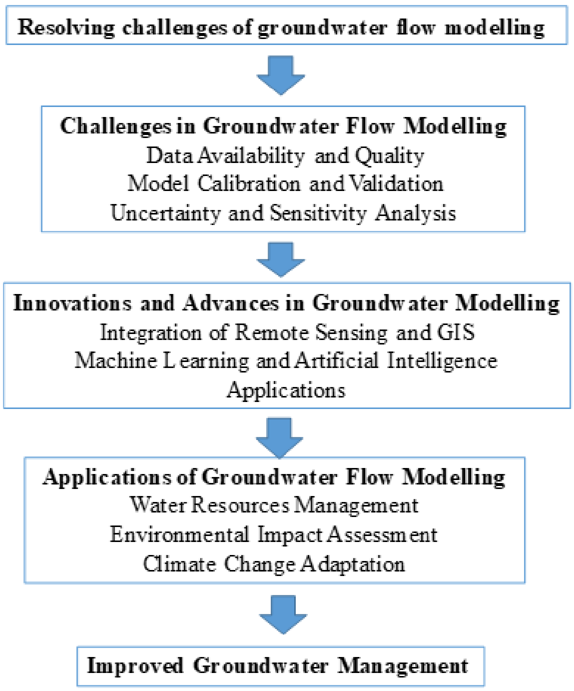

Figure 3 Resolving challenges of groundwater flow modelling.

Conclusion and future directions

Conclusion

Groundwater flow modelling has proven to be an indispensable tool in addressing the complexities of groundwater management, especially in the face of climate change. By simulating the intricate behaviours of aquifers under varying conditions, such as changing recharge patterns, extraction pressures, and contamination risks, groundwater flow models offer critical insights for sustainable water resource planning. The applications of these models in climate change adaptation further demonstrate their significance in predicting and mitigating the impacts of phenomena such as altered precipitation, prolonged droughts, and saltwater intrusion in coastal areas. As water scarcity intensifies across many regions, especially in the Global South, effective groundwater flow modelling will be central to ensuring water security and resilience.

However, despite its many benefits, groundwater flow modelling still faces challenges related to data scarcity, model complexity, and inherent uncertainties. These limitations can hinder the development of accurate models, particularly in regions with limited monitoring infrastructure. Addressing these gaps will improve model reliability and enhance decision-making processes. As the demand for groundwater resources grows due to population pressures and environmental changes, models must evolve to capture better the complexities of groundwater systems and their interactions with surface water and ecosystems. In conclusion, groundwater flow models are pivotal in current groundwater management practices and are crucial for future water resource sustainability. Their capacity to simulate complex groundwater dynamics and inform adaptation strategies makes them invaluable for immediate and long-term decision-making. To fully realize the potential of these models, further research, investment in data collection, and continued innovation in modelling techniques will be necessary to meet the growing challenges of groundwater m**anagement in an era of climate change.**

Future directions

The future of groundwater flow modelling will focus on overcoming existing challenges and enhancing the integration of advanced technologies and methodologies. One key direction is improving data collection through remote sensing technologies, satellite observations, and real-time monitoring networks. These innovations can help fill the data gaps hindering model accuracy, especially in under-monitored regions. Enhanced data availability will improve the reliability of existing models and enable more detailed simulations of complex groundwater systems under varying climatic and anthropogenic pressures.

Another promising future direction is incorporating machine learning and artificial intelligence (AI) techniques into groundwater modelling. AI and machine learning algorithms can assist in optimizing model calibration, improving predictive accuracy, and addressing uncertainty by analyzing large datasets more effectively. These technologies can help overcome the limitations of traditional modelling approaches, enabling more dynamic and adaptable groundwater flow models that can respond to new data inputs and evolving environmental conditions in real time.

Finally, there is a growing need for more comprehensive, integrated modelling frameworks that account for the interactions between groundwater, surface water, ecosystems, and human activities. Integrated Water Resources Management (IWRM) approaches will ensure groundwater flow models reflect the interdependencies between water systems and land-use changes. By incorporating socio-economic and ecological factors into these models, future groundwater flow modelling efforts can provide more holistic insights that support sustainable water management and long-term climate adaptation strategies.

Future directions in groundwater flow modelling must address the pressing climate change needs. First, enhancing model integration with climate projections will enable more accurate forecasts of groundwater availability under diverse climate scenarios, particularly in vulnerable regions. Developing adaptable, real-time modelling frameworks is also critical to respond dynamically to extreme events, like sudden droughts or floods, which are expected to become more frequent with climate change. Additionally, improved data collection methods, including remote sensing and IoT-enabled sensors, can provide high-resolution data to capture better seasonal and climate-driven variations in recharge and discharge patterns. Increased interdisciplinary collaboration will also be essential, merging hydrology with ecology, meteorology, and data science to refine model predictions and broaden their application. Ultimately, these advancements can transform groundwater flow modelling into a more robust tool for sustainable water management in a changing climate, offering resilience and adaptability for future water resource planning.

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Conflicts of interest

The author declares there is no conflict of interest.

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