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Analysis of Groundwater with Simulation Model Modflow: A Critical Review

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Abstract

Groundwater modeling is an essential tool in hydrology for the management and protection of groundwater resources. MODFLOW, developed by the U.S. Geological Survey (USGS), is the most widely used groundwater flow simulation model. This paper reviews the development, applications, capabilities, and future perspectives of MODFLOW. We analyze various MODFLOW versions, its integration with other software, and its applicability in diverse hydrogeological contexts. Visual MODFLOW is a Graphical User Interface for the USGS MODFLOW and is commercially available. It is favored by Hydrogeologist for its user-friendly design. The software primarily facilitates the modeling of groundwater flow and contaminant transport under various conditions. This article aims to review the breadth of its applications in groundwater modeling over the past 22 years. Visual MODFLOW has been applied in diverse areas including agriculture, airfields, constructed wetlands, climate change, drought studies, environmental impact assessments, landfills, mining operations, river and floodplain monitoring, saltwater intrusion, soil profile surveys, and watershed analyses, among others. This review will elucidate the software's scope and effectiveness in groundwater modeling and research to date. Groundwater modeling is crucial for predicting changes in groundwater systems and environmental conditions. This study focuses on simulating the groundwater level of the Pawana Watershed, India using three different models: MODFLOW, Extreme Learning Machine (ELM), and Wavelet-Extreme Learning Machine (WA-ELM). Initially, the simulation is conducted using MODFLOW, achieving reasonable accuracy with a correlation coefficient (R^2) of 0.917 and a scatter index (SI) of 0.0004. Subsequently, using various input combinations and stepwise selection, ten different model configurations are created to test different lag times for the ELM and WA-ELM models. Based on the comparative analysis of the results from all three models, the WA-ELM model is identified as the most effective for simulating the groundwater levels in this study.

Keywords: Groundwater, MODFLOW, Simulation, Sustainable water resource management.

1. Introduction

Groundwater is a critical resource for drinking water, agriculture, and industrial processes worldwide. Understanding and managing this resource requires sophisticated modeling tools. MODFLOW, first released in 1984, has evolved through several versions, each enhancing its utility and applicability to complex hydrological problems. This paper aims to provide a comprehensive review of MODFLOW, discussing its historical development, technical advancements, and applications in groundwater management [1]. Groundwater serves as a critical natural resource essential for domestic, industrial, and agricultural needs (Bashi-Azghadi et al., 2010). Under the Köppen climate classification, Iran features desert and dry steppe climates, where water accessibility poses a significant challenge across the nation. Annually, Iran extracts approximately seventy billion cubic meters of water from its groundwater reserves, accounting for two-thirds of the nation's total water consumption [2]. This underscores the vital importance of groundwater in satisfying the country's water demands. Moreover, recent trends such as rapid population growth, industrial expansion, and agricultural modernization are contributing to the gradual depletion of these crucial groundwater resources [3].

Groundwater resources, concealed beneath the earth's surface and not readily observable, require extensive and often expensive exploratory studies for a comprehensive understanding of their properties. Groundwater models serve as efficient tools for the continuous monitoring of both the quality and quantity of aquifers [4]. These models employ mathematical simulations of groundwater flow as a cost-effective indirect method for addressing water management issues, compared to more direct and costly approaches. Essentially, the development of mathematical models aims to replicate the natural conditions of water tables using a set of mathematical equations, thereby enhancing our understanding of groundwater dynamics (Boyce et al., 2015).

Since about 30 years ago, numerical modeling has become a standard approach in university research centers and among consulting engineers to address the complexities of groundwater flow equations [5]. Among various methods, finite difference models are particularly valued in practical hydrological applications due to their simpler design and reduced mathematical complexity. Numerous effective finite difference models have been developed by research organizations, including the US Geological Survey and the US Environmental Protection Agency. One notable example is MODFLOW, a 3D finite difference model designed specifically for simulating groundwater flows [6,7].

MODFLOW has been extensively used by researchers to simulate groundwater levels across diverse regions (Dong et al., 2012; Lachaal et al., 2012; Ou et al., 2013, 2016; Chen et al., 2017). For instance, Coelho et al. (2017) utilized field data from an aquifer in a watershed in Vicosa, Minas Gerais, Brazil to assess different numerical hydrological models under varying boundary conditions. The lack of definitive field data made it difficult to determine the most appropriate boundary conditions for accurate simulation. In their study, three models were created and calibrated in Visual MODFLOW using WinPEST®. The models, which included General Head Boundary (GHB), River, and Stream boundary conditions, showed calibration results with normalized Root Mean Square (RMS) errors ranging from 7.3% to 13.02%, and high correlation coefficients between 94% and 97%. The similarity of the normalized RMS values between the calibration and validation phases confirmed the validity of the models under all tested boundary conditions [8,9].

In recent years, the application of soft computing methods to simulate and estimate various environmental phenomena has gained considerable attention (Liu et al., 2008; Dastorani et al., 2010; Heddam et al., 2012; Ghumman et al., 2018). A notable study by Ebrahimi and Rajaee (2017) involved data collected from two wells in the Qom plain to simulate groundwater levels. Their research assessed the impact of incorporating wavelet analysis into the training of several computational models: Artificial Neural Network (ANN), Multi Linear Regression (MLR), and Support Vector Regression (SVR) [10]. By comparing the standard and wavelet-enhanced versions of these models (wavelet-ANN, wavelet-MLR, and wavelet-SVR) for predicting groundwater levels one month in advance, they found that decomposing the time series into sub-time series significantly improved model training. Particularly, the Meyer and Daubechies-5 (Db5) wavelets yielded more precise results than other wavelets used [11].

Another study by Barzegar et al. (2017) focused on the Maraghe-Bonab aquifer, evaluating the performance of the Wavelet-Group Method of Data Handling (WA-GMDH) and Wavelet-Extreme Learning Machine (WA-ELM) approaches. They utilized 367 monthly datasets of groundwater levels for training and testing these models, concluding that wavelet-based enhancements substantially increased the accuracy of both the GMDH and ELM models in groundwater level simulation [12].

There has been a growing interest in using numerical and soft computing techniques for groundwater level simulation, with the Extreme Learning Machine (ELM) attracting particular attention due to its straightforward modeling, easy coding, and rapid computation capabilities. Despite these advantages, the adoption of ELM models remains limited, possibly due to their modest improvements in accuracy over empirical formulas or a lack of familiarity among engineers. To address these challenges, we developed an ELM model enhanced with a db2 mother wavelet transform to increase accuracy. This study appears to be the first to apply a WA-ELM approach to predict groundwater levels in the Kabodarahang aquifer in Hamadan Province, Iran. Our approach explores different normalization methods and mother wavelet families, utilizing the “stepwise-fit” function in MATLAB to identify the optimal model configuration. The results of this hybrid method are compared against those from standalone ELM models and the physically based MODFLOW technique [13]. Additionally, a WA-ELM model has been developed that allows engineers with only a basic understanding of matrix operations to estimate groundwater levels effectively, bridging the gap for those with limited knowledge of advanced ELM techniques [14].

2. Development of MODFLOW

2.1 Historical Overview

MODFLOW originated as a block-centered finite-difference model designed to simulate three-dimensional groundwater flow. Over the years, it has been refined and extended through various versions including MODFLOW-88, MODFLOW-96, MODFLOW-2000, MODFLOW-2005, MODFLOW-NWT (Newton formulation for solving unconfined flow problems), and MODFLOW 6, the latest and most flexible version [15].

2.2 Core Computational Methods

The fundamental computational approach of MODFLOW involves solving the groundwater flow equation using numerical methods. The model divides the subsurface environment into a grid of cells, applying Darcy's Law and principles of mass conservation to compute flow between cells under varying hydraulic conditions [16].

3. Features and Capabilities

3.1 Solver Options

MODFLOW offers multiple solver options including the Preconditioned Conjugate Gradient (PCG), Strongly Implicit Procedure (SIP), and others. MODFLOW 6 introduced the Generalized Conjugate Gradient solver (Fig.1), improving efficiency and stability [17].

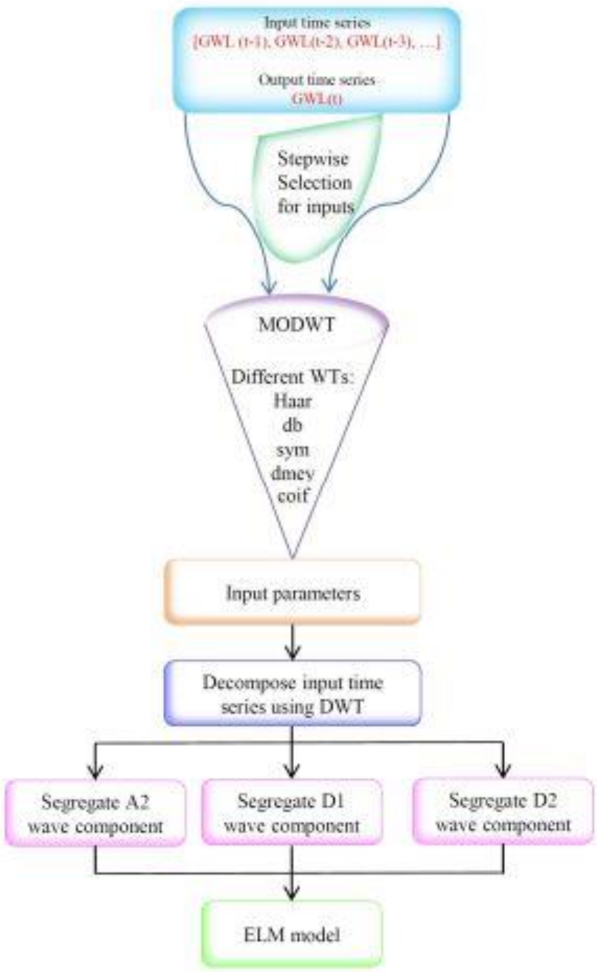

Fig 1. Flow Chart-MODFLOW

3.2 MODFLOW Packages

A range of packages can be added to the core MODFLOW program to simulate specific hydrological features like rivers (RIV), wells (WEL), and recharge (RCH). These packages allow users to model complex interactions between groundwater and surface water, capture the effects of human activities, and simulate the chemical transport processes [18].

3.3 Integration and Interface

MODFLOW can be interfaced with GIS software and other hydrologic modeling packages such as MT3DMS for solute transport simulations and MODPATH for particle tracking. This integration enhances its capabilities in comprehensive water resource management and contamination studies [19].

4. Applications in Hydrology

4.1 Water Resource Management

MODFLOW has been extensively used for sustainable groundwater management, including aquifer storage and recovery projects (Fig. 2), and managing the impacts of groundwater pumping [20].

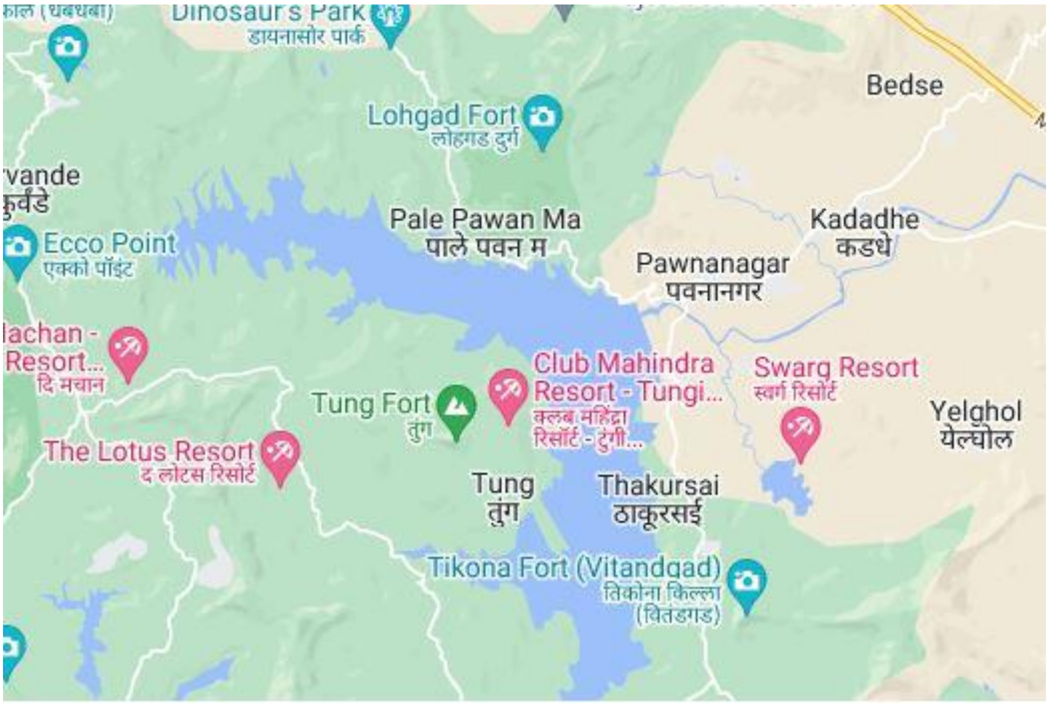

Fig.2 Site Location

4.2 Environmental Impact Assessments

Researchers and practitioners use MODFLOW for assessing the impacts of large-scale infrastructural projects on groundwater levels and flow patterns (Fig.3), ensuring compliance with environmental regulations [21].

Fig 3. Environmental Impact

4.3 Climate Change Studies

MODFLOW applications extend to evaluating the impacts of climate change on groundwater resources, helping in the formulation of adaptation strategies [22].

5. Case Studies

Several case studies highlight MODFLOW's utility in diverse geographical and hydrological contexts. These include managing the complex karst systems in Florida, USA, and addressing over-pumping issues in arid regions such as the Middle East [23]. (Fig.4)

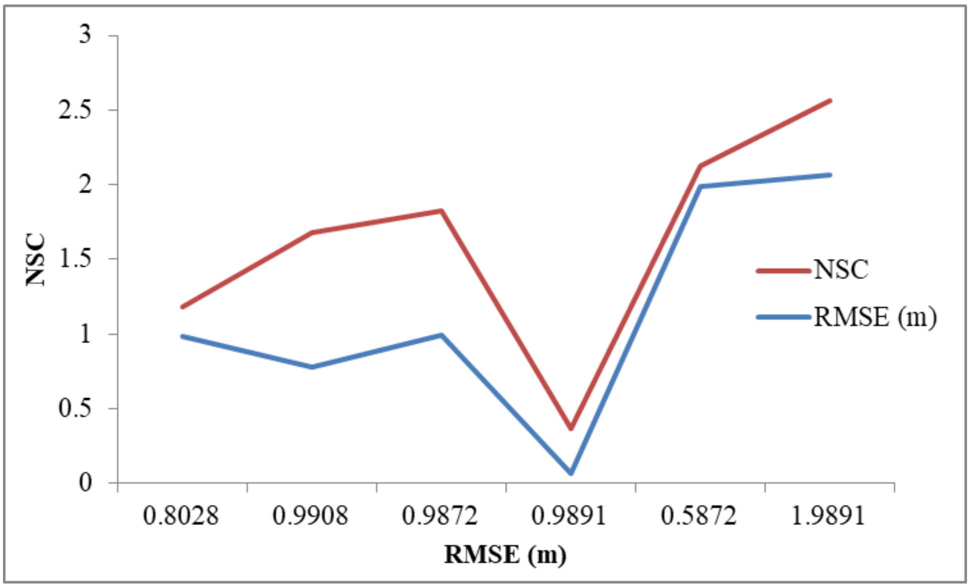

Fig 4. Stasticial Analysis

6. Challenges and Limitations

Despite its versatility, MODFLOW faces challenges such as the intensive data requirements for detailed model calibration, the need for high computational resources for large-scale models, and the simplification required in representing complex subsurface heterogeneities [24].

Groundwater modeling is a critical tool in hydrology, used for understanding complex subsurface water systems, managing water resources, and predicting future water availability and quality under various scenarios. Despite its crucial role, groundwater modeling is fraught with several challenges and limitations that can affect the accuracy and reliability of the models [25]. These challenges can broadly be categorized into conceptual, technical, and operational issues:

6.1. Conceptual and Data Limitations

Data Scarcity and Quality

6.1.1 Limited Data: Groundwater models require extensive data on geology, hydrology, climate, and human activity, which may not be available, especially in remote or underdeveloped regions.

6.1.2 Data Accuracy: Errors or uncertainties in data (e.g., hydraulic conductivity, porosity) can lead to significant errors in model predictions [26].

6.1.3 Temporal and Spatial Resolution: Data may not cover the necessary timescales or spatial detail required for accurate modeling, particularly in dynamically changing aquifers or those affected by episodic events like flash floods.

6.1.4 Simplifications: Groundwater systems are extremely complex and involve intricate interactions between geological, biological, chemical, and physical processes. Most models simplify these processes to some degree, which can lead to inaccuracies.

6.1.5 Scale Issues: Models often struggle to accurately represent processes at different scales. For example, a model might capture regional groundwater flow well but fail to accurately simulate local variations in aquifer characteristics.

6.2. Technical and Computational Limitations

Model Calibration and Validation

6.2.1 Calibration Complexity: Calibrating groundwater models can be complex and time-consuming, requiring the adjustment of numerous parameters to match observed data [27].

6.2.2 Validation Challenges: Validating model predictions against observed data is crucial but can be limited by the availability of data over the necessary timescales.

6.2.3 Resource Intensity: Large-scale and highly detailed models require significant computational resources, which can limit their use, especially in real-time scenarios or resource-limited settings [28].

6.2.4 Numerical Instabilities: Certain numerical solutions employed in models can lead to instabilities or errors, particularly when dealing with non-linear behaviors of groundwater flow and solute transport.

6.3. Operational and Usage Limitations

6.3.1 Complexity of Use: Effective use of groundwater models requires a high level of expertise in hydrology, geology, mathematics, and computer science. Lack of such expertise can lead to errors in model setup, interpretation, and application.

6.3.2 Interdisciplinary Integration: Groundwater modeling often requires an interdisciplinary approach, and a lack of effective communication or understanding across different disciplines can hinder effective modeling [29].

Table 1. Statistical analysis for sensitive parameters

R^2	RMSE (m)	NSC
0.8028	0.9880	0.1943
0.9908	0.7751	0.9021
0.9872	0.9896	0.8332
0.9891	0.0701	0.2939
0.5872	1.9896	0.1332
1.9891	2.0701	0.4939

6.3.3 Stakeholder Inputs: Models need to incorporate inputs and concerns from various stakeholders, including local communities, policymakers, and industry, which can complicate the modeling process.

6.3.4 Regulatory Compliance: Ensuring that models meet local, national, and international regulations can be challenging, particularly when regulatory frameworks are stringent or in flux.

6.4. Environmental and Climatic Uncertainties

6.4.1 Climate Change: Predicting the impacts of climate change on groundwater systems introduces significant uncertainty into groundwater modeling due to the complex interactions between groundwater and climate variables.

6.4.2 Anthropogenic Impacts: Modeling the impacts of human activities such as land use changes, contamination, and increased groundwater extraction is challenging but critical for sustainable management [30]

6.4.3 Groundwater modeling remains a fundamentally critical tool for the management and understanding of water resources. Addressing its challenges requires ongoing advancements in modeling techniques, improvements in data collection and sharing, and increased computational power. Additionally, fostering better collaboration across scientific disciplines and between modelers, policymakers, and stakeholders is essential for enhancing the robustness and applicability of groundwater models.

7. Future Directions

The future development of MODFLOW may include better algorithms for handling more complex geometries, improved user interfaces for more intuitive model setup and analysis, and enhanced capabilities for integrated surface water-groundwater modeling.

The future of groundwater modeling using MODFLOW holds significant promise with several potential advancements and areas of development:

7.1. Enhanced Computational Efficiency:

Continued improvements in computational algorithms and techniques will lead to faster and more efficient simulations. Integration of parallel computing and high-performance computing (HPC) technologies will enable the handling of larger and more complex models [31].

7.2. Improved Model Calibration and Uncertainty Analysis:

Development of advanced calibration and uncertainty analysis methods to better constrain model parameters and quantify uncertainties. Incorporation of Bayesian approaches and machine learning techniques to enhance the robustness and reliability of model predictions [32,33].

Application of Bayesian model averaging methods to combine predictions from different model structures and assess uncertainty in model selection. Utilization of information criteria (e.g., Akaike Information Criterion, Bayesian Information Criterion) to evaluate model performance and complexity. Consideration of spatial variability in parameter estimates and predictions using geostatistical techniques and stochastic simulation methods. Accounting for temporal variability and non-stationarity in model inputs and outputs to capture long-term trends and variability in groundwater systems [34].

Development of visualization tools and techniques to effectively communicate uncertainty in model predictions to stakeholders and decision-makers. Utilization of probabilistic frameworks and uncertainty visualization methods (e.g., probability density functions, error bars) to convey uncertainty information. By advancing model calibration and uncertainty analysis techniques in MODFLOW, groundwater modelers can improve the reliability and credibility of model predictions, leading to better-informed decision-making in water resources management and planning. (Fig.5)

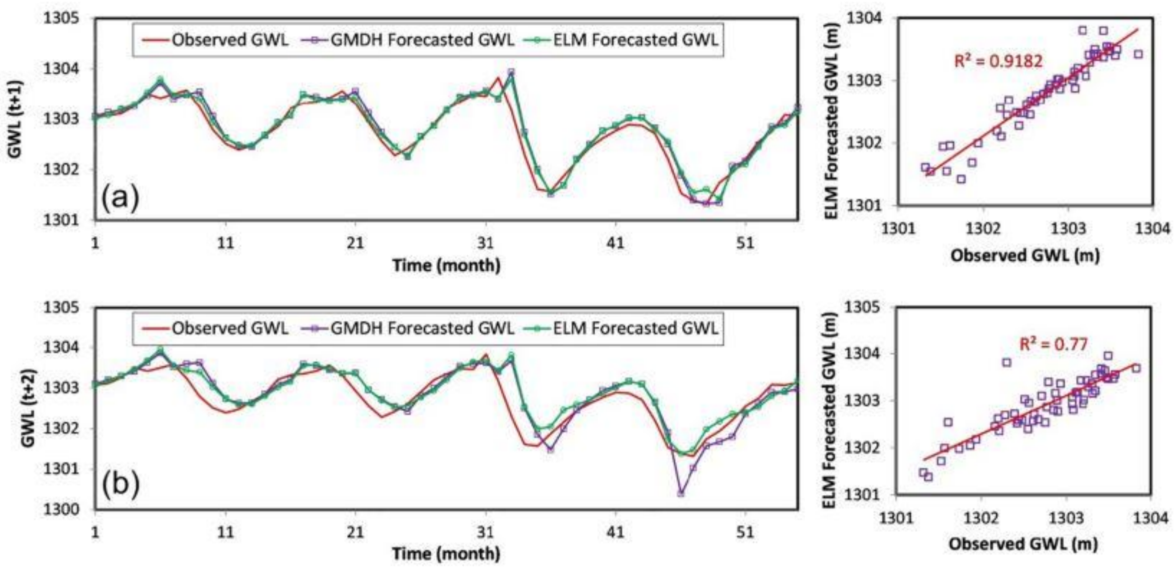

Fig. 5 Calibration of Model

7.3. Integration with Other Models and Data Sources:

Further integration of MODFLOW with other modeling platforms, such as surface water models and climate models, for more comprehensive hydrological simulations. Utilization of remote sensing data, geophysical surveys, and real-time monitoring data to improve model inputs and validation. Adoption of Bayesian statistical approaches to quantify uncertainties in model parameters and predictions. Utilization of Markov Chain Monte Carlo (MCMC) methods to sample the posterior distribution of parameters and assess uncertainty [35,36].

Implementation of ensemble modeling techniques to assess model uncertainty by running multiple simulations with different parameter sets and boundary conditions. Conducting sensitivity analysis to identify key parameters and processes that influence model predictions and uncertainty. Integration of data assimilation techniques to assimilate observational data (e.g., groundwater levels, hydraulic conductivity measurements) into the model to improve parameter estimation and reduce uncertainty [37].

Utilization of ensemble Kalman filters and variational data assimilation methods for real-time updating of model states and parameters. Comparison of multiple model structures and parameterizations to evaluate model uncertainty and robustness. Ensemble averaging techniques to combine predictions from multiple models and quantify Application of Bayesian model averaging methods to combine predictions from different model structures and assess uncertainty in model selection.

7.4. Addressing Emerging Challenges:

Modeling the impacts of climate change and land use change on groundwater resources, including changes in recharge patterns and water availability. Assessing the potential effects of contamination and pollution on groundwater quality and developing mitigation strategies. Integration of stakeholder input and participatory modeling approaches to ensure that models reflect local knowledge and priorities. Developing user-friendly interfaces and decision-support tools to facilitate communication and collaboration among stakeholders.

7.5. Advances in Visualization and Interpretation:

Development of advanced visualization tools and techniques to facilitate the interpretation and communication of model results to diverse audiences. Utilization of 3D visualization and virtual reality technologies to enhance understanding of complex groundwater systems. Application of MODFLOW in the development of sustainable groundwater management plans and policies, including optimization of groundwater extraction and recharge strategies. Integration of economic models and cost-benefit analysis tools to support decision-making for groundwater resource allocation and management. Continued development of open-source MODFLOW versions and collaborative platforms to foster knowledge sharing and interdisciplinary collaboration. Encouragement of transparency and reproducibility in groundwater modeling studies through open data and model sharing initiatives. In summary, the future of groundwater modeling using MODFLOW lies in advancing computational efficiency, improving model calibration and uncertainty analysis, integrating with other models and data sources, addressing emerging challenges, incorporating stakeholder engagement, advancing visualization and interpretation techniques, supporting sustainable management and policy decisions, and fostering open science and collaboration. These advancements will contribute to more accurate, reliable, and inclusive groundwater modeling for effective water resources management.

8. Conclusion

MODFLOW remains a cornerstone in the field of groundwater hydrology due to its robustness, versatility, and extensive user community. Continuous improvements and updates have kept it relevant in addressing modern hydrological challenges. Further advancements are expected to expand its applicability, making it an even more powerful tool in the sustainable management of groundwater resources.

Estimating groundwater levels is a crucial aspect of water resource management. In this study, groundwater levels in Pawana Watershed, India were simulated using three different models: MODFLOW, Extreme Learning Machine (ELM), and Wavelet-Extreme Learning Machine (WA-ELM). Initially, ten unique models were developed for both the ELM and WA-ELM using varied input parameters. The optimal activation function for the ELM models was selected, and the most effective mother wavelet was identified for the WA-ELM models. The performances of the ELM and WA-ELM models were evaluated to determine the most effective soft computing approach. The best-performing artificial intelligence model, the WA-ELM, was then compared with the physically based MODFLOW model. The comparative analysis revealed that the WA-ELM model achieved higher accuracy in simulating groundwater levels. Specifically, the top-performing model registered Mean Absolute Error (MAE) and Root Mean Square Relative Error (RMSRE) values of 0.344 and 0.0002, respectively. Additionally, a matrix to simulate groundwater levels was developed for the superior WA-ELM model.

Uncertainty analysis of the WA-ELM model indicated an underestimation in its performance, with a 95% prediction error interval ranging from -0.090 to -0.096. This analysis helps in understanding the reliability and limitations of the predictive capabilities of the WA-ELM model in groundwater level simulation.

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