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Groundwater-Level Forecasting: Evolution from Conventional to Quantum-Inspired Approaches

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Abstract— **Groundwater is an essential source of fresh water that forms an important part of hydrological model. Ground Water Level (GWL) is dependent on many factors such as meteorological conditions, geographic conditions, and human interactions taking place for the purpose of agriculture, industrial uses and livestock. Forecasting ground water levels is a challenging aspect, due to the uneven, nonlinear behaviour of groundwater. Traditional monitoring methods and analytical methods, which are labour intensive and data-dependent struggle with data gaps and evolving climatic conditions. The review is conducted to identify the best modelling techniques followed and the challenges faced in predicting ground water level. The review compares the data used, its sources, data preprocessing techniques, feature extraction techniques, application of various machine learning techniques and optimization techniques used in GWL prediction. Machine learning and deep learning-based models have consistently performed well in not only accurately forecasting GWL variations, but also mapping groundwater potential, and detecting anomalies. It is also observed in the review that the wavelet transforms, ensemble models, and empirical mode decomposition (EMD) techniques have been successful in handling the complex nature of ground water data. The survey also highlights the significance of model tuning, time-step considerations, and methodological decisions. Future studies may benefit from the use of diverse and widespread data enabling researchers understand the complex interactions better. The study further encourages to integrate approaches that use physical principles with data driven techniques, hybrid models and nature inspired optimization techniques for increased model performance.**

Keywords— **Groundwater Level Forecasting, Machine Learning, Deep Learning, Remote Sensing, Feature Extraction, Optimization Methods, Quantum-Inspired Algorithms.**

I. INTRODUCTION

Groundwater constitutes about 30% of the global freshwater supply. It is a major source of drinking water, irrigation, and industrial use [1]. Unscientific temperament leading to overextraction of Ground Water exceeding the recharge rates is causing aquifer overdraft. Combined with Climatic uncertainties, this has caused significant stress on the world's groundwater resources. Hence, the need for strong and reliable ground water models that regulate water extraction and support human activities through sustainable management have become essential. Additionally, well informed forecasts help in maintaining the balance of regional ecology by preventing ground water overdraft that could result in aquifer depletion, land subsidence, and ecological disruptions [2–6].

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Arid and semi-arid regions benefit greatly from groundwater forecasting models as they allow efficient irrigation schedules to be designed and helps in overcoming drought [7–10]. In coastal areas, the models can be used to regulate the water extraction rates hence decreasing the risk of sea water intrusion into the aquifer that would increase ground water salinity [11]. The widespread use of Advanced machine learning models, have shown to provide high-accuracy, reliability and scalability in groundwater level predictions [12-15]. Complex ground water models depend on many parameters such as meteorological inputs and historical groundwater records. Using multiple types of data together helps the model understand the complex ways groundwater behaves, which allows them to make more accurate predictions [16 -18]. Groundwater forecasting also supports economic growth by ensuring water availability for agriculture, industry, and communities, thereby reducing losses linked with water scarcity [9, 18]. Moreover, accurate forecasts convert uncertainty into actionable insights, enabling informed decision-making for sustainable water management [19- 20].

II. OBJECTIVES OF THE REVIEW

This literature review presents findings of about a hundred peer-reviewed articles published between 2010 and 2025 that give a comprehensive evaluation of the methodological procedures that have been used in the prognostication of the groundwater level (GWL). The first point that is determined in the review is that a vast range of data sources is used to describe the behaviour of groundwater which includes measurements on the ground, satellite surveillance, and climate monitoring. Second, it records the extensive use of preprocessing and feature-engineering steps aimed at alleviating the issues of missing values, measurement noise, non-stationarity, and nonlinear variability. Normalisation, wavelet transforms, empirical mode decomposition (EMD), statistical filtering, dimensionality reduction, and correlation-based feature selection techniques have been mentioned. Third, the literature is compared on the wide range of data-based forecasting techniques versus the classical hydrological models. Fourth, the literature suggests a trend toward optimisation methods aimed at improving the performance of a model, and quantum-inspired optimisation algorithms that are promising faster convergence are of particular interest.

This review gives an insight into different steps of acquisition, processing, construction of the model, model optimisation and emerging computational paradigms that are well illustrated in figure 1.

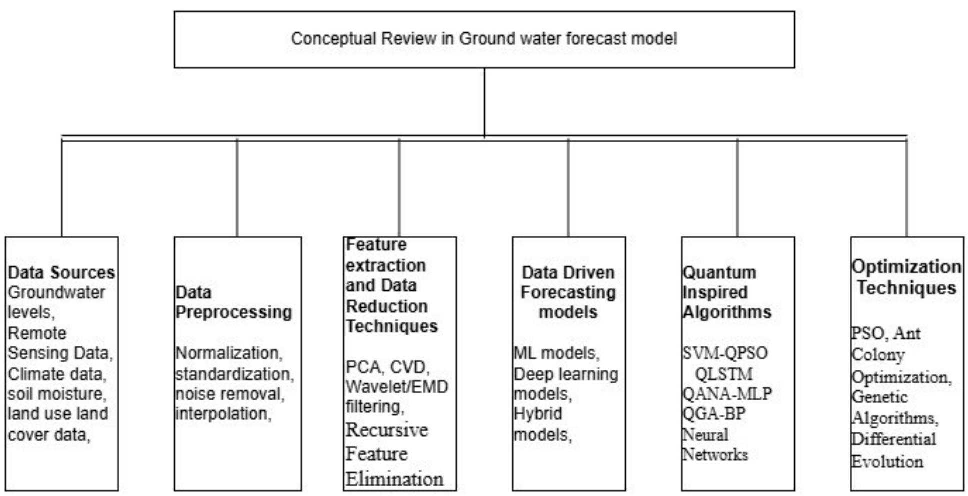

Figure 1. Conceptual Framework of the Reviewed Literature

III. INPUT TYPES, AND DATA SOURCES IN GROUNDWATER RESEARCH

The inputs used in groundwater forecasting models normally vary widely and may include precipitation, temperature, pumping history, satellite-based indices, soil moisture prediction, and previous GWL observations. These parameters are variably measured over time and space by exploiting heterogeneous datasets that combine both the spatially dense monitoring networks and remotely sensed data. The review also mentions that historical GWL observations in monitoring stations form the major source of data used in most modelling processes [21-28]. The addition of these variables to hydro-meteorological data, such as rainfall, temperature, speed of wind, photoperiod, and evaporation rates, has been observed to enhance the accuracy of predictions. [24][27][29]

Remote sensing data cover vast geographic areas, thus providing a wider spatial coverage and more variables that are hard to measure on the ground, like precipitation and ground water storage changes. Sensors on satellites, such as multispectral and radar, are capable of measuring a variety of surface properties, such as soil moisture, land-surface temperature, the normalized difference vegetation index (NDVI), and land-use intensity, and, thus, allow investigators to track the environmental causes of groundwater availability indirectly [30-32]. Other information that is often used includes aquifer properties, pumping and recharge velocities as well as water-quality indicators. [21][23-24][26][33]. Gravity Recovery and Climate Experiment (GRACE) and GRACE-FO satellite-based measurements of the total terrestrial water storage provide aggregate water-storage values and can replace the point measurement of well depth. [36]. Dynamic variables like timestamps, seasonality, lag periods, static variables like geographic coordinates and aquifer properties are also included in studies as covariates [21][23][27][29]. Forecasting can cover various timeframes ranging from short-term (days to weeks) [24] and medium-term (monthly to yearly) [25][36] to long-term forecasts extending up to several years [29][36]. The summary of Data Types, Sources, and Forecasting Timeframes for Groundwater Models reviewed in the study are provided in Table 1.

TABLE I: THE SUMMARY OF DATA TYPES, SOURCES AND FORECASTING TIMEFRAMES FOR GROUNDWATER MODELS

Aspect	Details
Nature of Data	Historical data, hydro-meteorological data, remote sensing data
Types of Data	Groundwater measurements, meteorological data, spatial data, remote sensing data, water quality data
Sources of Data	Monitoring stations, government agencies, remote sensing satellites, state-level databases
Covariates	Dynamic variables, static variables, hydro-meteorological factors, recharge and pumping data, water quality indicators
Tenure of Forecasting	Short-term (1 day to 1 month), medium-term (monthly, annual), long-term (up to 5 years, specific future years)

IV. DATA PREPROCESSING, FEATURE EXTRACTION AND DIMENSIONALITY REDUCTION TECHNIQUES

Any forecasting model relies heavily on effective preprocessing techniques that improve its accuracy. Preprocessing techniques improve the data quality and prepare the dataset for maximum model performance through techniques like standardization and normalization which transforms the non-linear and varied nature of ground water data into a consistent scale thereby reducing bias[37]. Additional data-cleaning procedures such as denoising, imputation, and interpolation helps clean up the dataset and boost forecasting performance [38].

Preprocessing facilitates Machine learning models to extract salient patterns and attenuate noise. The Wavelet Transform is one of the techniques that are commonly used in this regard. It breaks down intricate time series data into clear frequency components, thus separating the long-term and short-term variances to improve the learning ability. Empirical research proves that wavelet-ANN models are more effective in predicting the level of groundwater compared to ordinary ANN models [39][40]. Ensemble Empirical Mode Decomposition (EEMD) can be used to disaggregate data into intrinsic modes, and combined with the Group Method of Data Handling (GMDH), which can find optimal relationships on its own, has demonstrated high predictive accuracy compared to the use of wavelet transforms [41]. When used in ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) models, Multi-Discrete Wavelet Transform (M-DWT) significantly enhances the accuracy of forecasting between a range of different time horizons because it allows the models to identify sudden and seasonal changes [42].

Wavelet Transform has also been cited as an encouraging data-preprocessing method. These approaches reduce noise, record elements in many frequency bands, facilitate training stability and improve time resolution.

The refinement of groundwater-level (GWL) forecasting relies on the feature selection. It involves the determination of the most contributory and relevant predictors. Statistical procedures, including Partial Correlation Analysis and Pearson Correlation allow an initial assessment of variable relevance. Ground-water tables are slow to react to precipitation, existing soil moisture, or recharge conditions. Partial Correlation Analysis is used to identify the factors that affect the level of groundwater and lagged response factors. The more sophisticated methods, such as Maximum Relevance-Minimum Redundancy (mRMR) and Random Forest based importance ranking will identify critical hydrological variables and estimate the degree of individual variable impact on the process [43]. Interpretability techniques like SHAP are able to identify the explanatory weights of each feature and explain that a specific feature was vital in achieving a prediction [44-45]. Other less popular but potential methods include Recursive Feature Elimination, Forward Feature Selection, and evolutionary methods, like Genetic Algorithms, used with statistical filters like SelectKBest. All these ways together can be used to build effective and precise GWL prediction models. A comparison of various feature selection methods used in GWL forecasting models is presented in Table 2.

TABLE II: SUMMARY OF FEATURE SELECTION TECHNIQUES AND THEIR EFFECTIVENESS

Technique	Application Scope	Effectiveness
Partial Correlation Analysis	Groundwater level and lagged values	High
Pearson Correlation Coefficient	Initial screening	Moderate
Maximum Relevance-Minimum Redundancy (mRMR)	Precipitation and lagged values	High
Random Forest -based importance ranking	Artificial recharge and lagged values	High
SHAP	Water quality parameters	Moderate
Recursive Feature Elimination	Groundwater Level monitoring	Low
Genetic Evolutionary Algorithm	Hybrid models	High
SelectKBest	General	High

Dimensionality reduction techniques show increasing use for managing datasets that contain multiple dimensions relating to weather, local topology, historical data or various features extracted from satellite imagery. Principal Component Analysis (PCA) enhances prediction model performance by reducing input features while maintaining variation in the data [49]. Singular Value Decomposition (SVD) is applied particularly for simplifying categorical variables [50]. Convolutional Autoencoders (CAE) and Deep Variational Autoencoders, can provide effective means for representing patterns in data that describe geological and geophysical features [51-52]. Hybrid modelling frameworks frequently incorporate Ensemble Empirical Mode Decomposition to break down unstable, highly fluctuating time-series data into smoother, more meaningful sub-signals [46]. Additionally, probabilistic techniques like Markov Chain Monte Carlo searches within feature space for possible parameter combinations and identifying the most useful ones [49]. Hybrid Approaches like Random Forest with LSTM and CNN-LSTM-MLR can be utilized that combines structured and sequential learning features [53], integrates deep learning models with linear regression for improved predictions [54] and combines data decomposition, genetic algorithm, and deep belief network for multi-time step forecasting [48] respectively. Table 3 provide summaries that show methods for identifying important features and for reducing dimensions in data, areas that apply these methods, and the degree that these approaches show effectiveness.

TABLE III: SUMMARY OF DIMENSIONALITY REDUCTION TECHNIQUES AND THEIR EFFECTIVENESS

Technique	Application	Effectiveness
PCA	General	High [7] [8]
SVD	Categorical variables	High [7]
CAE	Geological data	High [9]
Deep Variational Autoencoder	Geophysical data	High [10]
Hybrid Models	Use specific	High [11] [12]

V. TRADITIONAL METHODS IN FORECASTING GROUND WATER LEVEL:

Numerical models, methods examining time-series data, methods applying geostatistical analysis, and methods using geophysical measures and well inventory can be termed as traditional methods employed in hydrological modelling. Methods such as MODFLOW and FEFLOW which require extensive data on hydrogeological features, provide forecasts by simulating groundwater flow [55-56]. The models show uncertainty that occurs largely from variable inputs and from boundary conditions, and this uncertainty increases with the lack of high-resolution parameters that are calibrated for hydrogeological features [56]. Methods using numerical models often show high computational cost and require substantial resources [57].

Time-series methods provide forecasts by examining observations from the past to find trends, patterns that appear across seasons, and temporal dependencies. Methods such as Auto-Regressive Integrated Moving Average (ARIMA) and Holt-Winters Exponential Smoothing (HWES) are used for forecasting in the short term. ARIMA produces forecasts that are point-based and temporal, so methods for spatial interpolation are required to produce spatially distributed groundwater maps [58]. These methods are effective for predictions in the short term, but they may not include all variables, and this may lead to inaccuracies [59-60].

Sequential Gaussian Simulation use spatial correlation within groundwater measurements to produce spatially distributed groundwater levels maps. However, these methods require is robust understanding of geostatistics and can be intensive in computation [58]. These models may not predict events that are anomalous such as severe droughts [58]. Techniques such as electrical resistivity and well-inventory are used to measure groundwater levels in a direct manner. These methods are often labour-intensive and time-consuming [61-62]. Field-based measures can be expensive, particularly over areas that are large [62].

Traditional methods have been foundational in forecasting groundwater, but limitations in these methods show the need for approaches that are more advanced and integrated. Modern machine learning models and hybrid models are increasingly used to address these challenges and to improve accuracy and efficiency in forecasting [63-65]

VI. Emergence of Data-Driven Approaches

Machine learning models provide strategies that learn relationships between predictors and responses in groundwater. ML methods have proliferated rapidly, due to its capability for modelling non-linear relationships, less physical parameters requirements and ability to collocate the various type of the data such as climate, land use, remote sensing etc., as well as large computational efficiency. Machine learning algorithms especially decision structure-based methods like Random Forest and hybrid models gives good prediction, with reliable results in predicting groundwater level in arid region compared to K Nearest Neighbour models.

Decision Tree models have demonstrated high performance in the prediction of groundwater level based on GRACE, with R^2 and NSE values of 0.95 and 96% during calibration. They also retained prediction stages quite successfully, suggesting their applicability for future groundwater fluctuations [66]. Random Forest models have been applied to simulate groundwater levels from meteorological and hydrological datasets and it was evident that flow volume, distance from the riverbank were vital input variables [67]. Random Forest fused with Wavelet Tranform (WT) enhanced prediction accuracy, especially inter-relation of hydrological frequency content [68].

Ensemble learning techniques such as Boosting and Bagging improve the accuracy of traditional machine learning models up to 22.68% [72]. Hybrid deep learning models like Wavelet Transform Long Short-Term Memory, WT-LSTM, or Wavelet Transform Extreme Gradient Boosting exhibit better results in the real-time prediction of groundwater levels [68]. Support Vector Machine models have also been employed for groundwater potential mapping. These models displayed good predictive performance ranges for AUC as 80.2% [69]. In the groundwater fluctuation modelling GRACE satellite data were also modelled together with SVM models and turned out to be effective [66].

Artificial Neural Networks models, optimized with algorithms like Harris Hawks Optimization (HHO) and Whale Optimization Algorithm (WOA), improved its overall performance [70]. Groundwater level index, which indicates whether groundwater levels are rising, stable, or declining can be forecasted using ANN models. It helps policy makers and the researchers to know how sustainably the water resources has been used [71]. Ensemble learning techniques such as Boosting and Bagging greatly enhance the accuracy of traditional machine learning models, by improving up to 22.68% [72]. Hybrid models that combine deep learning and ensemble methods e.g., Wavelet Transform Long Short-Term Memory, WT-LSTM, or Wavelet Transform Extreme Gradient Boosting show good results in the real-time prediction of groundwater levels [68].

Model performance measures used widely to evaluate the models include accuracy, magnitude of error, and reliability in forecasting.; among them, R^2 measures the variance explained by the model, RMSE reflects the standard deviation of prediction errors, and NSE assesses the overall model capacity for forecasting. The key findings for machine learning models specially in regions with sparse data is that model performance can be improved by combining geological, meteorological, and demographic data [73].

Tactics like SHapley Additive exPlanations (SHAP) dispels the black box nature and brings in openness in interpretation, it clarifies how much each of the parameters contribute, by factoring complexity into calculating the impact towards groundwater level prediction [67-68]. Recent studies have extended from groundwater level prediction, to water demand forecasting, potential zone mapping, anomaly detection, and feature-importance analysis. Also, models need to be designed to specific regional characteristics, considering local climate, human activities, and hydrological conditions for better outcome [68] [70].

Despite the benefits, Machine Learning models often are riddled by challenges. The approaches require substantial computational resources and the models often fail to represent complex nonlinear relationships in data and are data driven [74]. The lack of sufficient and high-quality data can reduce the accuracy and reliability of the models. Deep Learning Techniques can be used to overcome this.

Deep learning techniques are known to have great potential for the prediction of groundwater levels. These methods achieve good prediction accuracy and the models even generalize well to spatial locations in space. Networks consisting of Long Short-Term Memory (LSTM) are particularly powerful for prediction problems on time series. These networks learn long-term dependencies in data. For forecasting the groundwater level, LSTM networks are used in a number of studies and the methods have proved to be highly accurate for different studies [75-80]. Bidirectional LSTM networks, also known as BiLSTM process data forward and backward. Some studies also reveal that such networks outperform standalone simple LSTM models [77-78]. CNNs are the models usually used to process image data for example, but we can also modify the neural network structure to apply in sequence time series prediction problems. These networks discover spatial patterns in data. CNNs have been effectively combined with other models for groundwater level forecast [80-82]. Hybrid model utilizes mixed methods to consider the various features of data. One of the models in this category is ConvAE-LSTM which concatenates a Convolutional Autoencoder (ConvAE) with LSTM networks. This model considers both the spatial and temporal relations of the data, and as an extension to memory network, the approach has demonstrated better prediction accuracy [82]. Ensemble models consist of a number of deep learning models like LSTM, BiLSTM and Gated Recurrent Units (GRU). Studies have demonstrated that integrating these models results in improved predictions. The ensemble approach enables modelling even complex patterns in the data. VMD-iTransformer applies the extension of VMD, known as VMD to non-stationary data. The model is also based on an improved Transformer architecture. This fusion improves the prediction accuracy substantially [83].

Deep learning models, which tends to underestimate GWLs, can introduce bias and future trends can be incorrectly predicted. The deep learning model performance measures cannot be entirely represented by RMSE and R2. Novel evaluation metrics, such as the Wasserstein Distance, can yield insights into details of forecast reliability. It is important to create models that can generalize beyond specific hydrological and climatic conditions.

VII. Use of Quantum Inspired Algorithms

Analysis shows that approaches using principles from quantum computing provide important improvements for predicting levels of groundwater over deep learning models. These approaches allow optimization of parameters in models and increase efficiency in computation. Quantum-Inspired Neural Networks include quantum gates and circuits that augment deep learning models, thereby increasing accuracy in classification, regression and generative modelling tasks.

The Quantum Long Short-Term Memory approach uses principles from quantum computing to improve performance that traditional LSTM networks provide. This approach shows improved performance in predicting groundwater levels when conditions in the environment change in significant ways. The approach provides more accuracy than classical LSTM models [84]. The Quantum-Inspired Recurrent Neural Network approach combines with CNN and with optimizers using gradients to show performance that is more significant for predicting indicators of groundwater quality such as Total Dissolved Solids. This approach can extend to predictions of groundwater levels [85].

The approach that combines Support Vector Machines with Quantum Behaved Particle Swarm Optimization uses Quantum Behaved Particle Swarm Optimization to optimize parameters of Support Vector Machines. This combination provides predictions of groundwater levels that show high accuracy [86]. The Quantum-Based Avian Navigation Optimizer Algorithm improves performance of Multilayer Perceptron models for predicting water levels. This approach produces significant reduction in errors for predictions [87].

The Quantum Genetic Algorithm approach with Back Propagation Neural Networks addresses issues such as overfitting and convergence that occurs in a slow manner. The approach optimizes initial weights and thresholds of BP neural networks. This optimization provides forecasts of groundwater levels that show more accuracy [88]. The comparison of performance of Quantum Inspired Algorithm against traditional models are given in Table 4

TABLE IV: COMPARISON OF QUANTUM INSPIRED ALGORITHMS USED IN GROUND WATER LEVEL FORECAST MODELS

Quantum Inspired Algorithm	Traditional Model	Improvement Area	Key Findings
SVM-QPSO	ANN	Accuracy	Higher reliability and accuracy in groundwater level prediction [86]
QLSTM	LSTM	Environmental Adaptability	Better performance under rapidly changing conditions [84]
QANA-MLP	MLP	Error Reduction	Significant reduction in prediction errors [87]
QGA-BP Neural Networks	BP Neural Networks	Convergence Speed	Solved overfitting and slow convergence issues [88]

Figure 2 illustrates the major research directions and methodological branches connected to Groundwater Level Prediction.

Quantum-inspired algorithms can play an important role in enhancing groundwater prediction models' accuracy and consistency scoring better over the existing deep learning methods. All deep learning and Quantum-inspired algorithms prove to be very strong approaches for groundwater level time series forecasts, while hybrid and ensemble models deliver more accurate results.

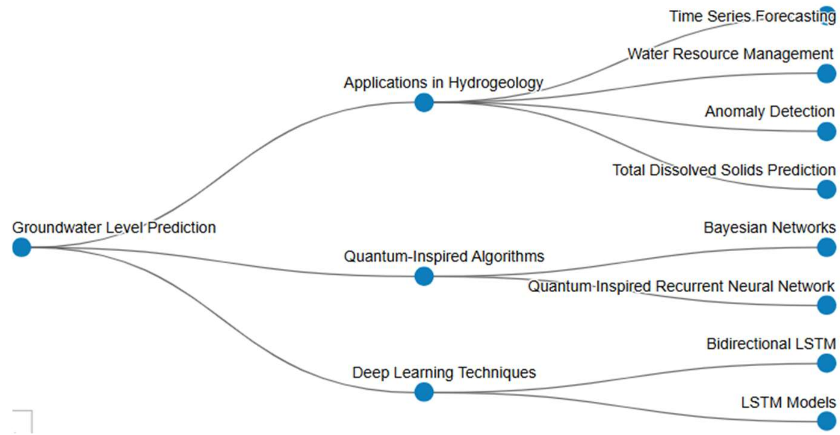

Figure 2: Conceptual map illustrating the major research directions in groundwater-level prediction

VIII. Nature Inspired Optimization Techniques

Nature-inspired optimization algorithms imitate natural processes to learn to extract efficient solutions specially when complex, non-linear and high dimensional data is used, making it an appropriate choice for Groundwater modelling. Some of the use cases of Nature-inspired optimization algorithms in Groundwater modelling can be identified as optimizing model parameters, estimating aquifer characteristics and calibrating groundwater flow models resulting in improved prediction accuracy and robustness of both physical and data-driven models. Hydrogeological system comprises of multiple components and challenging interactions between them, and hence endorses the suitability of Nature inspired optimization algorithms to be employed for maximum optimization. Particle Swarm Optimization (PSO) is frequently utilized for pumping optimization and parameter estimation, consistently delivering near-optimal solutions in challenging groundwater scenarios [89-90]. Ant Colony Optimization (ACO) effectively handles nonlinear hydraulic parameter estimation and monitoring network design problems [89] [91], while Genetic Algorithms (GA) provide a robust global search despite occasionally yielding higher data misfits compared with PSO and GWO in certain modelling tasks [92-93]. Differential Evolution (DE) excels in remediation design and optimal well placement, demonstrating reliable convergence across case studies [94-95]. Grey Wolf Optimizer (GWO) enhances prediction accuracy in groundwater quality forecasting and ML model tuning, making it a strong alternative to traditional optimizers [92] [96]. Other algorithms such as Invasive Weed Optimization (IWO) improve computational efficiency and feature selection quality [97-98], Cuckoo Search has a simple but effective mechanism for solving heterogenous optimization problems [99], and the Honey Badger Algorithm (HBA) has superior accuracy to the other tested algorithms in hybrid models for groundwater-level predictions [100]. Together, these benefits underscore the necessity of optimization as a space that leads to more accurate models and ones that generalize better in spatially diverse areas while also being computationally efficient.

IX. Conclusion

The classical methods of groundwater modelling, though used as an initial source for study or baseline to compare analysis, are limited in many aspects. Traditional data models often require more computational resources, subject expertise and rely on historical data, which is often only partial and not accurate. Furthermore, these approaches have difficulty to deal with uncertain environment changes taking place over time, catastrophic events, and nonlinearities.

The literature review strongly indicates that the use of machine learning and deep learning with extensive data processing enhances the predictions about groundwater levels in terms of accuracy and reliability. These state-of-the-art methodologies facilitate better and more informed decision making to optimize the groundwater systems, that are stressed under climate variability and increased water demand. Inspired by the benefits of quantum algorithms in exploring the solution space more effectively, many quantum-inspired algorithms and

methods have been explored for hydrological purposes indicating the appropriateness for achieving better parameter tuning and searching performance in sparse search spaces.
Any Model's performance is determined and boosted by the Optimization techniques employed. Optimization methods (e.g., GA, PSO, DE, ACO) can be effectively employed for parameter selection and model tuning effectively. Scope for future work lies in combining classical hydrological expertise with advanced Machine Learning and deep learning models, robust Optimization techniques, Quantum Inspired methods in effective Ground Water Modelling.

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