A Systematic Review of Neural Network Applications for Groundwater Level Prediction

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Abstract

Physical models have long been employed for groundwater level (GWL) prediction. Recently, artificial intelligence (AI), particularly neural networks (NNs), have gained widespread use in forecasting GWL. Forecasting of GWL is essential to enable analyze, quantify and manage groundwater. This systematic review investigates the application of NNs for GWL prediction, focusing on the architectures of the various NN models employed. The study utilizes the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) methodology to screen and synthesize relevant scientific article. Various NN architectures, such as artificial neural networks (ANNs), feedforward neural networks (FFNNs), backpropagation neural networks (BPNNs), long short-term memory (LSTM), and hybrid models, were analyzed. The results from the systematic review indicates a growing preference for hybrid models, which are effective in capturing hidden relationships between GWL and environmental factors. The root mean square error (RMSE) emerges as the predominant performance metrics, highlighting its significance in evaluating NNs. Results from the review also highlights the significance of comprehensive, long-term datasets covering a decade for a robust trend analyses and accurate predictions. The findings, contribute to a deeper understanding of new trends in groundwater research such as the application of neural networks for prediction problems in groundwater research. In conclusion, hybrid metaheuristic algorithm produced more efficient results emphasizing their efficacy. In addition, lagged values were essential input for GWL prediction. The paper, addressed both technical nuances and broader environmental implications

KEYWORDS: Review, Neural Networks (NNs), Artificial Neural Networks (ANNs), Groundwater Level (GWL) Forecasting, Climate Variables

1.0 Introduction

Assessing and analyzing groundwater level (GWL) variations in aquifers is essential for effective management and quantification of groundwater resources [1]. It allows for informed decision-making in managing groundwater resources, helping to prevent over exploitation or depletion. groundwater is its depletion due to various human activities. These activities encompass a wide range of practices, including industrial processes, urbanization, and agricultural practices. Insufficient research on the consequences of various human activities such as heightened irrigation on groundwater has necessitated a renewed interest in understanding the dynamic nature of groundwater [2].

Groundwater, a critical global water source, is becoming more vulnerable to overexploitation. In recent times, there has been a rise in the excessive withdrawal of groundwater, resulting in the overuse of this vital resource [3]. The escalating demand for water in developing countries, driven by rapid population growth and intensified irrigated agriculture, has led to a surge in groundwater extraction [4]. [5] demonstrated the impact of climate variations in Iran, revealing a decline in groundwater levels (GWL). This has led to a significant deterioration in groundwater systems [6]. Therefore, precise quantification and effective management become imperative to ensure sustainable water usage and conservation of this vital resource for present and future generations. Accurate modeling and prediction of groundwater behavior offer valuable insights into the dynamics of underground aquifers [7]. This knowledge is essential for optimizing extraction strategies, preventing overexploitation, and ensuring a sustainable water supply for various purposes [8].

In groundwater level (GWL) prediction, two primary methods are explored: the use of physical models and data-driven models [9]. Both approaches face limitations that affect their applicability and accuracy. Physical models encounter challenges such as insufficient data, susceptibility to uncertainties including random and systematic errors and the need for fine-tuning through trial-and-error [10]–[12]. The presence of inadequate data introduces uncertainties in model parameterization, hindering the accurate representation of hydrogeological characteristics and generalization [13]. Conversely, having ample high-quality data enables detailed and accurate model development. Comprehensive datasets on groundwater levels, water quality, and geological properties enhance the calibration process, resulting in a more reliable representation of the aquifer [11].

In contrast, data-driven models like machine learning excel in handling complex relationships and sparse data, providing accurate predictions without a deep understanding of the physical processes [14]. While they may lack interpretability compared to physical models, these approaches offer valuable insights in situations where traditional physical models face challenges due to data limitations [15]. Machine learning models are easy to use, and most researchers are employing them in groundwater modelling [1]. Recently, there has been an upsurge in the use of data-driven models with different algorithms in predicting groundwater level [9], [16]. [17] reported the use of a number of data-driven techniques for forecasting groundwater level. It was found that, Adaptive Neuro-Fuzzy Inference System (ANFIS) using the bell membership function successfully predicted GWL level for 1-month and 2- month, achieving a Coefficient of determination (R2) of 0.95 and 0.93 respectively. [18] utilized Artificial Neural Network (ANN) model in predicting groundwater level using total monthly evaporation, average temperature, aquifer recharge, and discharge as inputs. Results showed that ANN models demonstrated acceptable performance in predicting GWL.

Neural networks have been successful in accurately predicting GWL. [19] demonstrated that a Feed Forward Neural Network model trained with Levenberg-Marquardt (LM) algorithm accurately predicted ground water fluctuation at Tikri Kalan well, India. Moreover, [20] compared the performance of Multilayer Regression and ANN in predicting groundwater level. It was observed that the ANN models showed a better agreement between the observed and predicted groundwater levels. Neural networks are cost effective since they need fewer data and less human interference to produce better results. [21] Reported on how neural network is able to capture the spatio-temporal behavior of complex dynamic systems with less computational time. ANN one of the most used neural networks for predicting groundwater level, is capable of efficiently representing non-linear systems [22]. Neural networks may handle complex problems because they can learn and generalize from sufficient data [23], making it capable of revealing hidden patterns from limited data.

Neural networks, like any other machine learning algorithm, have their constraints, including drawbacks like overtraining, limited generalizability, the potential risk of incorporating unrelated data, and the possibility of incorrect modeling through inappropriate methods [1]. Given the growing enthusiasm for applying Artificial Intelligence (AI) models to groundwater-related studies, numerous review papers have emerged, extensively exploring their potential and applications within this domain, for example, for hydrological modeling [24], GWL modeling [25], and groundwater flow [26]. However, to the best knowledge of the authors, there is not yet a systematic review paper evaluating the application of neural network methods in GWL modeling and forecasting.

This study, therefore, seeks to systematically review publications that have utilized neural networks for the prediction of groundwater level. The primary focus is on the evolution of neural networks and the model configuration which can lead to an optima level of model performance and consideration of variables exhibiting robust correlation with groundwater level, thereby guiding us in the judicious selection of those variables to be incorporated into future modeling framework.

2.0 Methodology

A meticulous systematic review was conducted, leveraging diverse databases. The search, executed on July 1, 2023, involved a refined search string, ensuring a comprehensive exploration of the literature. Recognizing the inherent limitations of individual databases, a multi-database approach was used to reduce the risk of oversight. For this reason, a robust framework was used for the review process to reduce research bias. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [27] was used for this investigation. This framework helps identify the various stages in a systematic review.

We conducted an extensive search for relevant literature on the topic, focusing on English-language journal articles from major electronic databases such as Scopus, Science Direct, and Google Scholar. A total of 452 articles were retrieved, and their distribution over the various databases is shown in Table 1.

Table 1. *Databases and the number of items identified from the databases*

Database	Number of articles
SCOPUS	300
Science Direct	108
Google scholar	44
Total	452

After thorough screening, duplicate articles, review articles, technical reports, books and conference papers were excluded from the scope, this thorough screening process was carried out to ensure that our systematic review is centered on primary research studies, providing a more focused and relevant exploration of the topic and a total of 272 publications were realized. The remaining publications were then evaluated by three independent assessors too identify those that satisfied our eligibility criteria for further analysis. A total of 187 articles were settled on for this study. Figure 1 shows the diagrammatic flow of the screening process.

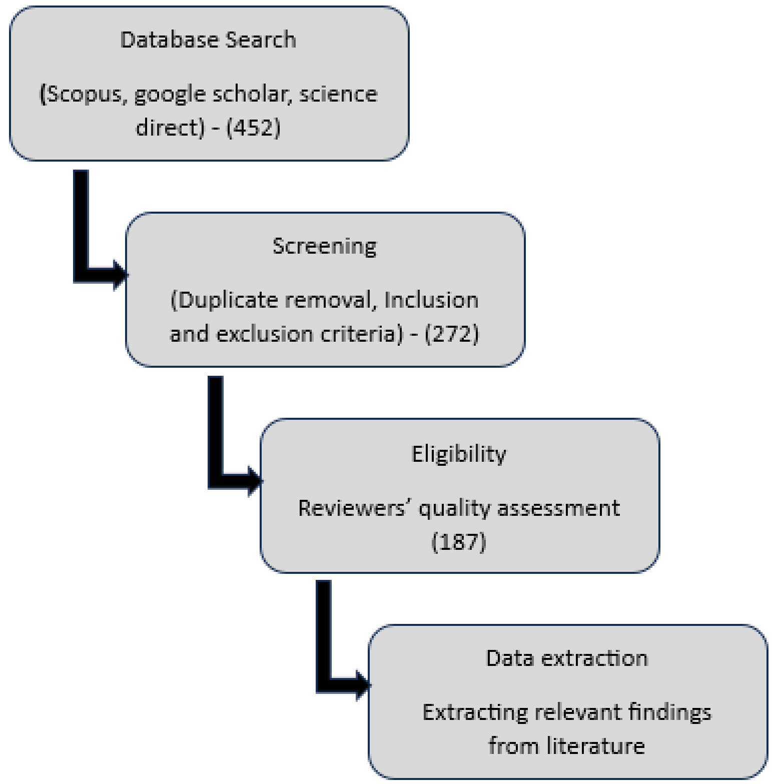

Figure 1: *systematic flowchart for the data screening*

3.0 Results

In this section, we outlined significant findings derived from the examination of the 187 papers under review. These findings encompass diverse elements, such as the progression of neural networks in groundwater level prediction, the most employed input variables and validation metrics in reviewed studies. Our review further encompasses an in-depth analysis of performance metrics predominantly employed for evaluating the effectiveness of neural network model. Our scrutiny also extends to various facets of neural networks, including the scope and quality of datasets employed for model development.

3.1 Publication distribution

In the years covered by the review, we observed an expansion in the volume of scholarly articles dedicated to the utilization of neural network techniques for forecasting changes in groundwater levels (GWL). Figure 2 shows the yearly distribution of publications on neural network techniques for forecasting changes in groundwater levels (GWL). It was observed that the publications span between year 2000 to 2023, with the highest percentage of published papers occurred in the year 2022 (14.87%) with 2001, 2005 and 2007 having the least published papers of 0.51%.

Furthermore, no papers for review were published in the years 2002, 2003, and 2004 per the extracted articles. Overall, an increase is observed in the number of papers in recent years.

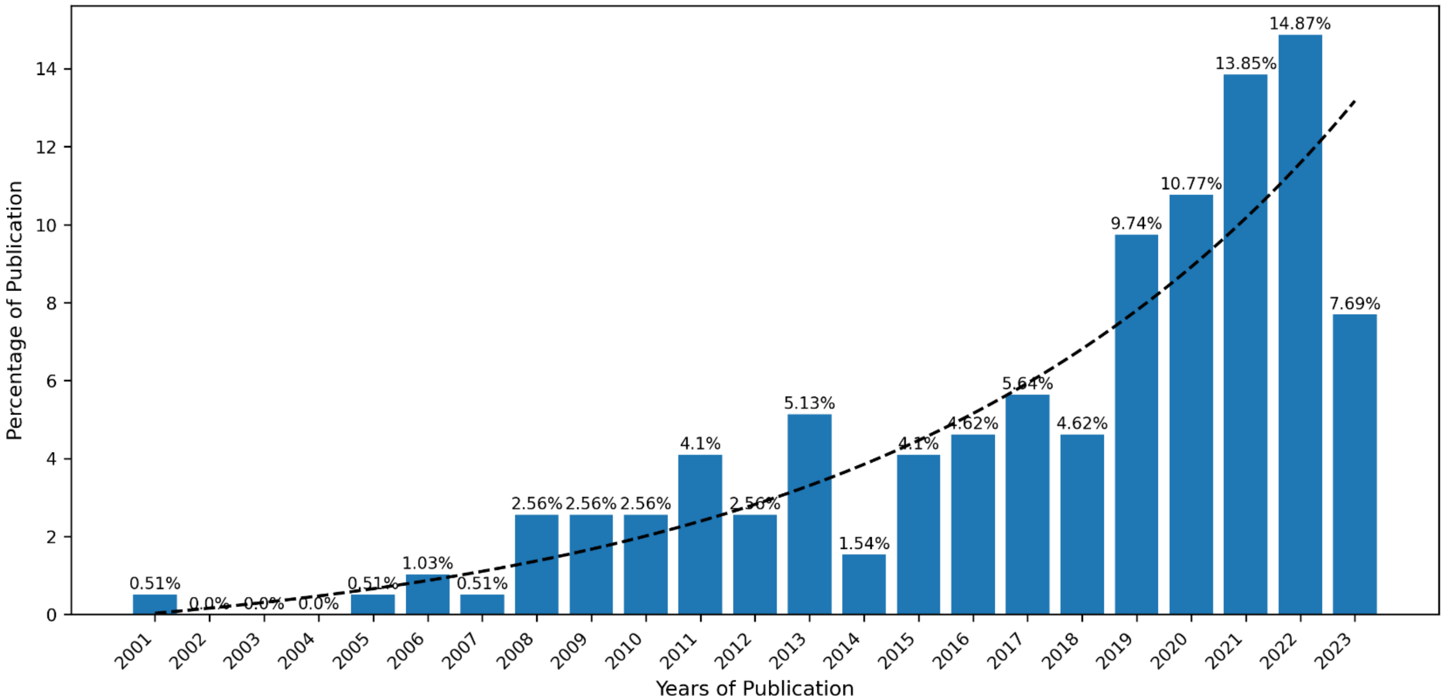

Figure 2: *Yearly trends of publication of neural network algorithms used in groundwater prediction.*

3.2 Geographic distribution

The geographic distribution of papers is illustrated in Figure 3 spans 26 countries. Iran (26.92%), India (17.69%), China (15.38%), and the United States (7.69%) were the top four countries that contributed the highest number of publications constituting about 76.68%. The remaining 22 countries contributed varying percentages of publications totaling 32.32%. Korea, accounted for 5.38%, Bangladesh and Japan each contributed 3.08%, while Germany and Taiwan had of 2.31% each. Italy, Malaysia, South Africa, and Turkey each represented 1.54%. Australia, Azerbaijan, Burkina Faso, Canada, Denmark, France, Greece, Indonesia, Kuwait, Luxembourg, Nigeria, Pakistan, and Tunisia each contributed 0.77%.

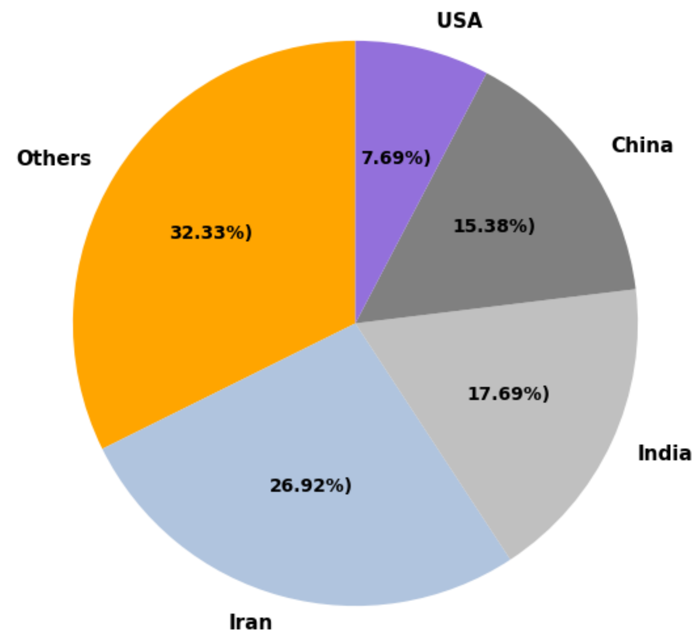

Figure 3*: Geographic distribution on neural network for GWL*

3.3 Artificial Neural Network (ANN) algorithms for GWL prediction

Artificial neural networks are a class of machine learning (ML) that mimics how the neurons of the brain process information [28]. Artificial Neural networks possess great strength as models that can reveal hidden representations from vast and intricate datasets, a task that might take human expertise a longer time to accomplish [29]. Artificial neural networks can be used to find the relationship between nonlinear input features [30]. The application of Artificial neural networks for GWL prediction has undergone a transformative evolution. Beyond traditional feedforward networks, the field of machine learning encompasses various other types of neural networks, each tailored to specific tasks [31] and several of them have been used for GWL prediction.

The study revealed a host of widely used ANNs such as back-propagation neural network (BPNN), feed-forward neural network (FFNN), long short-term memory (LSTM) and hybrid model were used for GWL prediction as shown in Table 1.

Table 1: Types of ANNs observed during our review.

ANNs	Reference
FFNN	[18]–[20], [32]–[53]
BPNN	[11], [18], [25], [54]–[60]
LSTM	[46], [61]–[66]
Hybrid	[5], [67]–[83]

3.4 Artificial Neural Network (ANN) models

In the early 20th century, the conceptualization of artificial neural networks (ANN), inspired by the human brain [84], marked a significant milestone. Comprising interconnected nodes organized into layers, ANNs learn complex patterns through weighted connections and activation functions, enabling applications in varying tasks [85].

Figure 4a shows the general architecture of an artificial neural network (ANN). ANN models typically comprise three or more interconnected layers: the input layer, hidden layer(s), and the output layer. The input layer receives features into the model, and the subsequent extraction of hidden patterns is a crucial phase facilitated by the hidden layer [57]. The output layer represents the processed output data, where this could be a binary value or continuous values depending on the activation function. Neurons within layers perform a weighted sum of inputs, passing the result through an activation function to introduce non-linearity [86].

During model training, weights (w) and biases (b) are adapted based on the input (x), and an activation function is applied to the model to produce an output (y). This helps minimize the difference between predicted and actual outputs, improving the model's accuracy. Figure 4b provides an illustration of how the weights and biases adapt during the training of a model. The optimization process, driven by algorithms like Gradient Descent [87], updates these parameters.

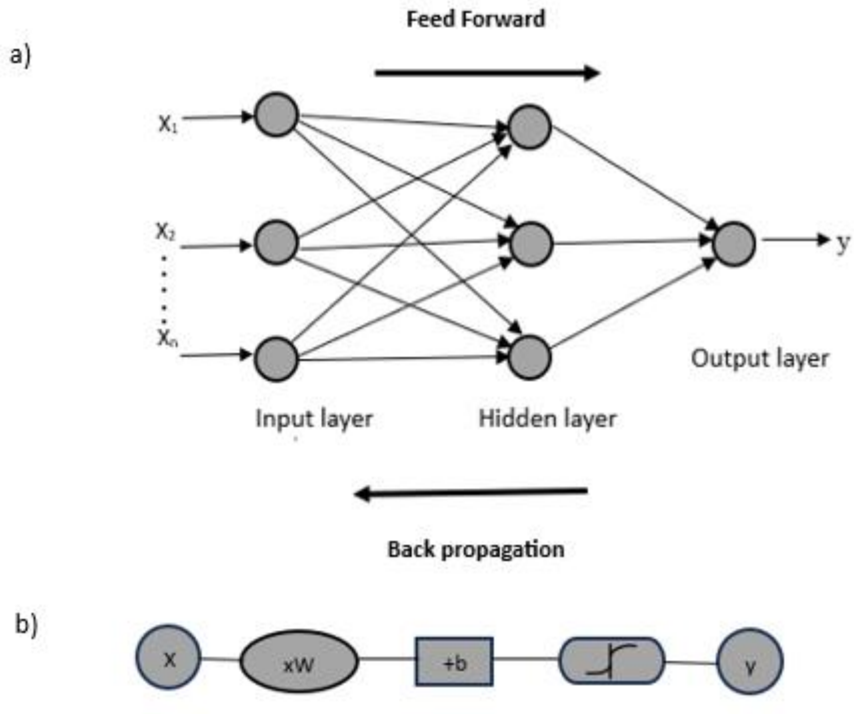

Figure 4: *a) General architecture of an artificial neural network b) Activation function of an artificial neural network*

Feed-forward neural network (FFNN)

A Feedforward Neural Network (FFNN) or multilayer perceptron neurons (MLPs), as outlined by [85] and [52], represents a neural network architecture wherein information flows unidirectionally from the input layer to hidden layer(s) and subsequently to the output layer. The absence of feedback into the network after reaching the output node characterizes this model, and its depth is determined by the number of layers, as depicted in Figure 4a.

FFNN using Levenberg Marquardt (LM) algorithm was used to model GWL for a short term in the Andhra Pradesh, India. The model was calibrated using lag values and current values. Using various correlation analysis, the input was selected. Using trial and error method the number of neurons were chosen. The author noticed FNN accurately simulated GWL for a short term [45].

[20] compared the predictive performance of Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) techniques in forecasting transient water levels across 17 sites in Japanese groundwater basins. The study incorporated various input variables, including seasonal factors and lagged environmental parameters. Results indicate that ANN models outperform MLR models in predicting spatio-temporal groundwater levels, as evidenced by statistical metrics.

Numerous investigations have explored the capability of Artificial Neural Networks (ANNs) in forecasting Groundwater Levels (GWL) across various locations. For instance, studies conducted by [53] and [36] demonstrate the effectiveness of these networks in predicting GWL. The latter investigated spatial nonlinearity in groundwater depletion, proposing the utilization of ANNs to discern water table patterns, showcasing diverse severities over time and space. ANNs decode complexities, facilitating accurate forecasting and precise water resource management.

The ANN model designed by [33], using a single-layer architecture and LM algorithm for training, incorporates a linear function in the hidden layer to forecast groundwater levels. Input parameters for the model include groundwater extraction, surface water supply, temperature, rainfall, and initial groundwater level. The efficacy of the ANN model in predicting groundwater levels demonstrates its potential as a valuable decision-making support system in research endeavors.

The evolution of groundwater level prediction methodologies through artificial neural networks (ANN) has seen a continuum of research, each study building upon the insights and methodologies of its predecessors. Initiating this progression, [37] laid the foundation by employing the Levenberg-Marquardt algorithm and emphasizing key predictive variables like monthly total precipitation, stream flow, temperature, evaporation, and groundwater level (GWL). This approach set a precedent for subsequent studies, inspiring investigations like [40] focusing on monthly GWL prediction with an extended set of input variables, achieving notable model performance with a coefficient of determination (R^2) score ranging from 0.92 to 0.97.

[42] underscored the effectiveness of the LM algorithm in predicting GWL at specific well locations. Their emphasis on variables such as precipitation, temperature, evaporation, discharge, and recharge marked a transition towards a more location-specific approach. [52] further advanced the field by examining a Feedforward Neural Network (FFNN) with LM, achieving a commendable R^2 of 0.93 and emphasizing variables like rainfall, temperature, evaporation, and relative humidity. [19] reported the use of the LM algorithm, achieving notable R^2 values for both training and testing.

[47] selection of the FFNN model and consideration of lagged parameters demonstrated a refinement in model selection and input variable optimization. [34] expanded the scope by modeling groundwater level variations using ANN with streamflow and accumulated rainfall, showcasing the integration of additional hydrological factors. Also, [88] brought attention to the importance of higher-resolution daily data for better prediction accuracies, introducing a finer temporal granularity into the modeling process. [39] exploration of climate change impacts and the incorporation of wavelet transform denoising showcased a shift towards addressing broader environmental contexts.

The quest for optimal input combinations, highlighted by [32], emphasized the importance of predicting monthly GWL up to 4 months while employing constrained input variable selection. However, this study also identified challenges associated with increasing lag time. In addressing these challenges, [41] strategically focused on optimizing ANN architectures. Specifically, they opted for a streamlined approach by utilizing a single hidden layer with 24 neurons, complemented by a tangent sigmoid activation function. This deliberate configuration signals a nuanced exploration of neural network settings tailored to the intricacies of groundwater level forecasting. The choice of a single hidden layer with a specific number of neurons and activation function reflects a careful consideration of model simplicity and effectiveness.

[43] evaluated the short-term predictive performance of Multilayer Perceptron (MLP), achieving optimal outcomes through a composite input set. The most effective combination included the groundwater level from the previous month, current temperature, evapotranspiration, present precipitation, and precipitation from the preceding month. Similarly, [49] utilized FFNN to predict monthly GWL in Iran, from the period 2021–2040 based on sixth Intergovernmental Panel on Climate Change (IPCC) report emission scenarios. Input variables included monthly temperature, precipitation, and the water table of the previous month from 2000 to 2019. Data were divided into training, validation, and testing sets, with an optimal hidden layer having 8 neurons determined through trial and error. The results suggest an increasing trend in groundwater depth, indicating improvement, while all piezometers project a gradual decrease in groundwater depth over the next two decades due to climate change.

The study [38] analyzed changes in groundwater level in villages in Jaipur district, India. utilizing eight years (2012–2019) of groundwater data. ANN model was used in the accurate prediction of groundwater level. The model achieved a high R^2 value by modeling spatio-temporal variation of GWL using various ANN models with different combinations of hidden neurons and layers. Results highlighted the superior accuracy of the ANN model in describing groundwater level. The projections for 2023–2024 indicated no significant rise in water level (>4.0 m), but a drop of more than 6.0 m.

The research by [35] investigated the comparative performance of ANNs and support vector machines (SVMs) in predicting transient groundwater levels within a complex system, accounting for variable pumping and weather conditions. Multiple prediction horizons, ranging from daily to bimonthly intervals, were considered. Despite generally similar modeling performance between ANNs and SVMs in terms of prediction accuracy and generalization, the study reveals notable differences. Particularly, ANNs exhibit challenges, especially for longer prediction horizons with limited data events for model development. Additionally, the study emphasizes the consistency between the training and testing phases in SVM models compared to ANNs. The relative error of mean square error in the ANN model significantly increases, approximately seven times higher during the testing phase compared to the training phase, indicating potential limitations in the generalization ability of ANNs, especially in conditions with fewer data points available for model training.

[51] implemented a three-layered Artificial Neural Network (ANN) optimized through the Levenberg-Marquardt (LM) algorithm for predicting GWL. By integrating diverse meteorological variables and lag-time inputs, this ANN model exhibited impressive accuracy, particularly excelling in forecasting GWL one month ahead. Complementing this, [33] conducted an in-depth examination into GWL simulation utilizing a Multilayer Perceptron (MLP) model. With a structured 5-60-1 configuration, featuring a hidden layer with 60 neurons generated randomly until reaching the mean square error threshold, their model consistently achieved an R^2 exceeding 0.80 for all well locations. The accuracy assessment spanning from 2008 to 2018 underscored the

model's high proficiency in predicting GWL, affirming its success in forecasting groundwater levels within each well location.

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[44] investigated the impact of six input variables on GWL using an ANN. A trial-and-error approach was employed for layer selection, and the LM algorithm was utilized. Results indicated that in urban areas, GWL is primarily influenced by river stage changes, while rural areas are affected by ground permeability. The study introduced the moving average as a beneficial component, underscoring the importance of identifying site-specific factors for accurate GWL prediction using ANN. The length of training data impact was found to be less significant. Incorporating river stage and moving average into the ANN input significantly improved prediction performance in urban and rural areas, respectively.

[48] employed a MLP model to predict the impacts of climate change on Groundwater Level (GWL) in the Mashhad aquifer, Iran. Climatic variables were derived from the ACCESS-CM2 model, operating under the Shared Socio-economic Pathways (SSPs) 5–8.5 scenario. The model was trained using historical data spanning the period from 1992 to 2021 to discern patterns between climate changes and GWL. During the model configuration, the determination of the suitable number of hidden layers was achieved through a trial-and-error approach. Subsequently, the MLP model was utilized to forecast GWL fluctuations under climate change conditions for the future period of 2022–2064. The observations indicate a projected decrease in GWL attributable to long-term alterations in weather patterns. This comprehensive analysis establishes a coherent framework for understanding the anticipated impacts of climate change on groundwater dynamics in the Mashhad aquifer.

Back Propagation Neural Network (BPNN)

Backpropagation is an algorithm employed in the training of artificial neural networks. It entails adjusting the connection weights based on the difference between predicted and actual outputs, fostering the network's learning and performance improvement over iterations. Within the context of modeling and forecasting, Backpropagation Neural Networks (BPNN), as described by [89], prove to be a powerful tool, iteratively propagating errors from the output layer to the hidden layer and, ultimately, to the input layer. Figure 4a shows how errors between predicted and actual values are sent back into the model for weights to be adjusted.

Researchers like [57] delve into the robustness of BPNN for monthly GWL predictions, employing a three-layered architecture with a backpropagation algorithm and emphasizing the importance of input variables such as air temperature, rainfall, and GWL. Moreover [42] adopted a comprehensive input selection approach by considering various variables such as total monthly evaporation, mean temperature, aquifer recharge, discharge, and the water table from the previous month. They utilized an ANN with a backpropagation algorithm for predicting GWL, achieving a Pearson's Correlation Coefficient (R) value of 0.76. The findings indicated a notable and swift decline in GWL.

A time series model was developed by [60] to predict GWL fluctuations, with a specific focus on evaluating the performance of an ANN. The ANN, trained using a backpropagation algorithm, demonstrated satisfactory performance within the range of input variables covered by the dataset from a coastal aquifer in Jeju Island, South Korea. However, outside this range, the ANN exhibited abnormal prediction results, marked by oscillations. This underscores the significance of incorporating a diverse set of input and output variables in the model building

[54] explored the application BPNN with three distinct input parameters. Cross-correlation analysis was conducted to identify the most effective input parameters. Three scenarios, each involving a different input combination, were examined, and the performance of the proposed models in predicting groundwater levels was assessed. The input combination incorporating a 1-day rainfall delay demonstrated optimal performance during both the training and testing stages.

[55] investigated preprocessing techniques and how their influence on prediction accuracy provides valuable insights into data preparation methodologies. This research focused on the diminishing groundwater levels, employing a machine learning-based approach. Through the utilization of singular spectrum analysis (SSA), mutual information theory (MI), genetic algorithm (GA), and an ANN based on the backpropagation algorithm, the approach effectively predicted monthly fluctuations in GWL. The integration of data pre-processing techniques significantly improves prediction accuracy ($R > 85\%$), particularly benefiting 66% of the monitored wells.

[56] employed a feed-forward backpropagation neural network (FFBPNN) for predicting groundwater level (GL) in the next hour, incorporating previous precipitation data to capture short-term temporal dynamics. The study focused on GL and groundwater level fluctuation (GLF) as output variables, with GLF showing greater accuracy in prediction. The model was tested in the landslide-prone area downstream of Wu-She Reservoir, Taiwan, using data from Sinlaku and Jangmi typhoons. Results indicated that GLF prediction yielded a smaller root-mean-square error compared to GL prediction, suggesting its superiority in capturing real-time fluctuations.

[59] research aimed to estimate groundwater levels using innovative modeling methods. The study implemented two distinct soft computing techniques, a multilayer perceptron neural network (MLPNN) and an M5 model tree (M5-MT), to analyze monthly groundwater levels in a shallow unconfined coastal aquifer near Ganjimatta, India. Utilizing data from observation wells spanning 1996 to 2006, [59] incorporated input parameters such as monthly rainfall, mean temperature, and historical groundwater level observations. Through a series of trial and error stages, the efficiency of each model was assessed. Ultimately, the M5-MT model emerged as more adept at accurately estimating groundwater fluctuations.

[82] also recognized the complexity of the relationship between GWL and influencing factors. They successfully utilized a BPNN to discern the nonlinear nature of this relationship, achieving low root mean square error (RMSE) values of 0.25 for training and 0.41 for testing. This study

further demonstrated the ability of BPNNs in capturing the intricate temporal patterns associated with GWL prediction.

[58] explored the versatility of different backpropagation variants by employing the Levenberg–Marquardt algorithm within a BPNN framework for GWL prediction. By utilizing this algorithm, the study showcased the potential of different optimization techniques in enhancing the accuracy of GWL forecasts. This highlights the importance of selecting appropriate training algorithms when developing BPNN models for GWL prediction. Also [11] contributed to the body of research by utilizing a backpropagation neural network for GWL prediction in Hebei Province, China. Their study reflected the widespread use of this approach across diverse geographical contexts, reinforcing the efficacy of BPNN models in capturing the temporal dynamics of GWL fluctuations.

Long Short-Term Memory (LSTM) models

Long Short-Term Memory (LSTM), a type of ANN, was designed to overcome the problem of vanishing gradients seen in traditional sequential models [90]. [91] introduced a method to address long-term dependencies in sequential data. The key elements of LSTM are the memory cell (C_t) and three gates: input gate (i_t), forget gate (f_t), and output gate (o_t) ([91]

Input gate(i_t) determines which information from the current input is relevant to store in the cell state. The formula for computing the input gate (i_t) is given as follows:

$$i_t = \sigma(W_{ix} \cdot x_t + W_{ih} \cdot h_{t-1} + b_i) \qquad (1)$$

Where: σ is the sigmoid function, W_{ix} and W_{ih} are weight matrices, x_t is the input at time *t*, h_{t-1} is the previous hidden state, and b_i is the bias.

Next is the forget gate (ft) which decides which information from the cell state should be forgotten.

$$f_t = \sigma\left(W_{fx} \cdot x_t + W_{fh} \cdot h_{t-1} + b_f\right) \qquad (2)$$

Where: σ is the sigmoid function, W_{fx} and W_{fh} are weight matrices, x_t is the input at time *t*, h_{t-1} is the previous hidden state, and b_f is the bias.

Output gate determines the next hidden state based on the current input and memory cell.

$$o_t = \sigma(W_{ox} \cdot x_t + W_{oh} \cdot h_{t-1} + b_o) \qquad (3)$$

Where: σ is the sigmoid function, W_{ox} and W_{oh} are weight matrices, x_t is the input at time *t*, h_{t-1} is the previous hidden state, and b_o is the bias. The formula for computing the new hidden state generated by the output gate (ot) is expressed as follows:

$$h_t = o_t \cdot tanh\ tanh\ (C_t) \qquad (4)$$

Input gate (i_t), forget gate (f_t), and output gate (o_t) all have output values ranging between 0 and 1 [92]. Figure 5 represents the architecture of a Long Short-Term Memory (LSTM) model

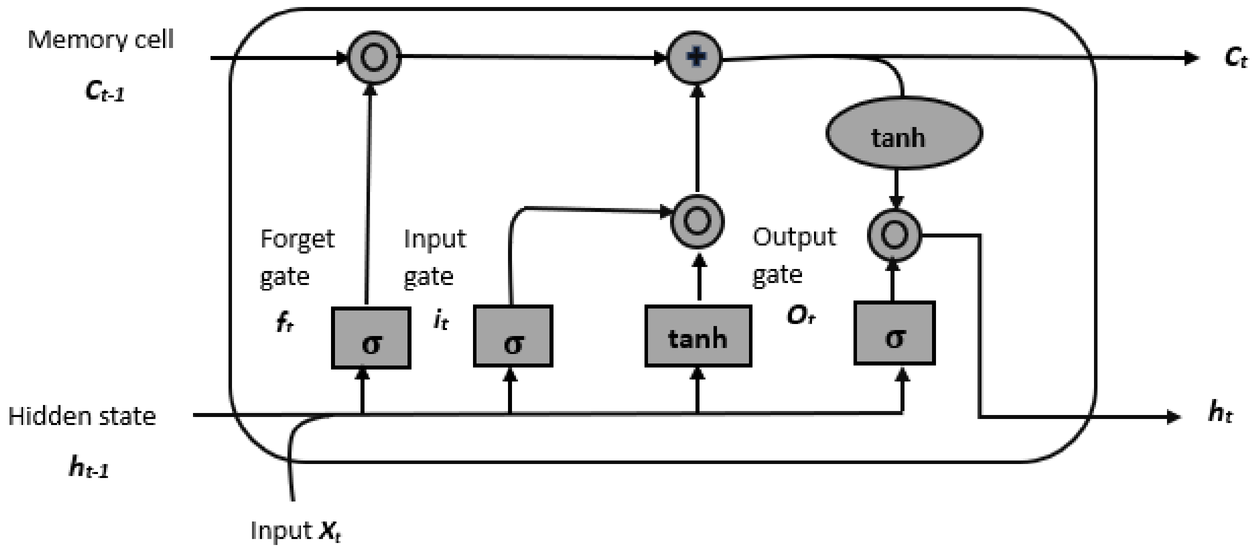

Figure 5: Schematic diagram of the LSTM model

[67] applied a LSTM model to predict GWL. The application of a standalone Long Short-Term Memory (LSTM) model exhibited limitations when confronted with limited data for each series. The inherent challenge arises from LSTM struggling to effectively capture comprehensive patterns from individual datasets when data availability is constrained.

[61] explored the use of LSTM, a NN model, for daily GWL prediction. The LSTM model is trained with selected predictors identified through partial mutual information (PMI) analysis, considering teleconnection patterns. The study includes a case study with two wells in different climate zones, where the LSTM model performs better in humid areas than in arid areas. This observation underscores the significance of considering climatic variations when implementing predictive models for groundwater levels, Also, [46] reported the LSTM for daily GWL The hypermeters for this model were optimized using two surrogate model-based algorithms that are the radial basis functions (RBFs) and the Gaussian process (GP) and a random sampling method. The model was trained on daily GWL, streamflow, precipitation, and ambient temperature. It was observed that with the right hypermeter optimization method models can learn to make accurate forecasts.

[66] Reported the use of LSTM for groundwater level forecasting Two instances were considered here the sequence-to-value(seq2val) and sequence-to-sequence(seq2seq) forecasting scenarios. It was observed that LSTM performed poorly for both scenarios, but including past GWL as inputs strongly improves its forecast accuracy. However, LSTM might perform well with a larger dataset. Similarly, [93] utilized LSTM to predict GWL changes, aiming to identify the factors influencing these changes across five distinct zones. The model demonstrated improved performance during validation, particularly in regions marked by groundwater withdrawal. Training and validation were conducted using a dataset covering the period from 2003 to 2018, with the model achieving

an NSE greater than 0.76 in each zone. The accuracy of the model hinges on both the quality and quantity of the training data.

[9] demonstrated the superiority of using LSTM for GWLs prediction in Victoria, Australia. Using a dataset from the period April 2002 – June 2017. The dataset was divided into 60% for training, 20% for validation and 20% for prediction. The model performed well due to its ability to efficiently capture groundwater characteristics of the region and relate with historical information by learning long-term dependencies. Also, [62] employed LSTM to forecast GWL in the lower Tarim Basin. The model was developed using input data such as s relative humidity, flow volume and distance to the riverbank to forecast GWL. It was observed that GWL is greatly affected by the distance to the reservoir.

[94] utilized LSTM for short-term and long-term groundwater level (GWL) forecasting. The model demonstrated good accuracy, particularly in predicting long-term GWL. Specifically, it predicted GWL one lag, up to four lags, and up to 26 lags ahead with respective accuracies (R2) of at least 99.89%, 99.00%, and 90.00%, over a testing period spanning longer than 17 years of the most recent records. These results substantiate LSTM's superiority and reinforce its efficacy across extended forecasting horizons.

Hybrid models

A hybrid model is a novel technique that combines elements or techniques from two or more different models or methodologies. It takes the outcome predictions produced by one machine learning model and feeds them into another [95]. The goal is to capitalize on the strengths of each constituent model, addressing their individual weaknesses, and achieving improved overall performance

Recent research by [1] observed limitations in neural networks models which have to do with nonlinear and non-stationary processes. This has led to the development of hybrid modeling approaches, incorporating data-preprocessing and combining various Artificial Intelligence (AI) techniques to enhance overall capabilities. Further advancements involve integrating swarm algorithms such as wavelet transform (WT), rat swarm algorithm (RSA), particle swarm optimization (PSO), salp swarm algorithm (SSA), and genetic algorithm (GA) to optimize NN models, enhancing their predictive capabilities [5]. [80] introduced a three-layered Wavelet-Artificial Neural Network (WA-ANN). Leveraging the Levenberg–Marquardt optimization algorithm, the model was designed for predicting monthly GWL using inputs such as groundwater level (GWL), total precipitation (P), total evaporation, and average temperature. The study, conducted over the period June 2003 to December 2010, demonstrated that incorporating previous timesteps and current timesteps resulted in the best model performance, achieving an impressive R^2 of more than 0.96 at each well location.

Applying a hybrid model to predict Groundwater Levels (GWL), [67] demonstrated the effectiveness of this approach in abstracting prevalent patterns from diverse groundwater monitoring time series in the Namoi region. This hybrid model combines the application of unsupervised (Self-Organizing Map, SOM) and supervised (LSTM) models. Unlike LSTM, which may encounter difficulties when dealing with limited data for each series, the Self-Organizing Map (SOM) integrates information across the entire dataset. In a related exploration, [79] applied a genetic algorithm backpropagation neural network (GA-BPNN) to forecast GWL. This study emphasized the model's adaptability to scenarios with abundant sampling data. Notably, a correlation analysis revealed that precipitation from two earlier days and precipitation from three earlier days exhibited a robust correlation with groundwater. This finding underscored the importance of considering temporal precipitation patterns in GWL predictions.

[96] compared the performance of a hybrid Artificial Bee Colony Algorithm and a Back-propagation Neural Network (ABC-BPNN) with a standalone back-propagation neural network (BPNN) for Groundwater Level (GWL) prediction, utilizing nine years of data for both training and testing. The hybrid model, which harnessed the potential of the Artificial Bee Colony optimization algorithm, exhibited improved results compared to the standalone BPNN. By incorporating inputs such as recharge, exploitation, rainfall, and evaporation, the hybrid model, structured with 4-7-3-1 in its two hidden layers, demonstrated resilience against overfitting and achieved robust performance, as evidenced by low mean squared error (MSE) and high R^2.

In a novel integration, [97] combined Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. This hybrid approach adeptly captured temporal relationships between groundwater levels and meteorological data, enabling effective long-term GWL predictions. The study spanned a decade of data, and preprocessing steps were implemented to address outliers and missing values through data imputation. The resulting model showcased impressive predictive accuracy, reflected in a root mean squared error (RMSE) below 0.2 for predicted months.[74] introduced two distinct hybrid models, GA-ANN and ICA-ANN. Genetic optimization and colonial competition algorithms were employed to derive optimal weights for predicting GWL using previous groundwater and rainfall as input variables. The study, based on 70% training data and 30% testing data, exhibited a R^2 value exceeding 0.9 for both training and testing, coupled with an RMSE below 0.6. This highlighted the efficacy of these hybrid models in achieving accurate GWL predictions.

[68] researched into various hydrological setups, optimizing the performance of ANN models by refining hyperparameters. Notably, the study advocated for the synergy of ANN with the Improved Artificial Grey Wolf Algorithm (IA-GWA) to enhance prediction accuracy. Comparative analysis revealed that the hybrid ANN-IA-GWA model outperformed standalone ANN, particularly in achieving a lower Normalized Root Mean Squared Error (NRMSE). Similarly, Incorporating preprocessing techniques, [75] utilized the discrete wavelet transform (DWT) and multi-discrete wavelet transform (M-DWT) in conjunction with ANN to decompose time series into sub-time series. While both preprocessing techniques exhibited similar correlation values, M-DWT showcased a lower RMSE, underscoring its superiority in extracting useful information for GWL prediction.

[72] employed k-means clustering to group aquifers, enhancing the prediction performance of ANN. This clustering strategy involved consolidating similar aquifers into clusters, treating them

as a single observation well. The integration of the evolution algorithm, specifically Particle Swarm Optimization (PSO), optimized and improved the model's prediction accuracy. Also, [76] directed their attention to the Aspas aquifer in Iran, coupling ANN with the Wavelet Transform algorithm. This integration aimed to refine prediction accuracy, with an emphasis on selecting the optimal wavelet. The study revealed a significant increase in the Coefficient of Determination (R^2) from 0.927 to 0.938 after incorporating the wavelet, affirming its positive impact on model accuracy.

In a unique fusion of ANN and Genetic Algorithm, [70] showcased the efficiency, precision, and robustness of the hybrid model. Notably, the study highlighted that utilizing a smaller dataset for model training enhanced accuracy and reduced training time. The accuracy achieved by the model trained on less data was notably high, with an R^2 of 99.8% and low RMSE. Also, addressing short-term groundwater fluctuation, [82] investigated the application of the BPNN algorithm coupled with a genetic algorithm. Calibration of the model, based on 70% training data and 30% testing data, demonstrated the model's ability to overcome convergence challenges and generalize effectively, as evidenced by an RMSE of 0.21 and 0.33 for training and predicting, respectively.

[83] demonstrated the superiority of a hybrid model LSTM and Empirical Mode Decomposition (EDM) in predicting GWL. The architecture utilized approximately 90% of the data for training and 10% for testing, showcasing optimal performance with an LSTM hidden unit of 200. To address gradient explosion, the study set a threshold of 1 and implemented a learning rate reduction strategy. The integration of LSTM with EDM effectively mitigated uncertainties, randomness, and volatility in groundwater, resulting in low relative and absolute errors and establishing the hybrid model's superiority.

[71] explored the integration of Adaptive Neuro-Fuzzy Inference System (ANFIS) with various metaheuristic algorithms. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization for Continuous Domains (ACOR), and Differential Evolution (DE) were employed to enhance the predictive capabilities of ANFIS. The study highlighted the superior performance of the ANFIS-ACOR model among the hybrid variants. In a comprehensive approach, [98] decomposed GWL time series components using the Wavelet Transform (WT). Utilizing an ANN model, the study directly incorporated decomposed approximation and detail series obtained from past GWL values as input variables. The number of components derived from decomposition determined the number of input neurons for the ANN. With an 80% training and 20% testing split, the model achieved a Pearson’s correlation coefficient (R) value exceeding 0.9, accurately simulating groundwater levels. The study underscored the influence of the choice of mother wavelet on the model's outcome.

[5] extended the hybridization paradigm by coupling an ANN model with optimization algorithms such as salp swarm algorithm (SSA), genetic algorithm (GA), rat swarm algorithm (RSA), and particle swarm optimization (PSO). The study incorporated input parameters based on rainfall and temperature for GWL prediction. This diverse hybridization approach showcased the versatility of integrating ANN with different optimization algorithms. Also, [69] compared performance of a hybrid ANN model and an ANN model for predicting GWL at two different well locations. The hybrid model consists of a wavelet transform algorithm which decomposes the time series data

into various decomposition times. The hybrid ANN performed better than the ANN, with the average RMSE of the hybrid model at both wells being 0.146.

[77] reported on GWLs in the Ardabil plain aquifer, Iran. Addressing the challenges posed by rapid urban expansion and intensified agricultural and industrial activities, the study applied a wavelet approach to denoise selected input variables, effectively eliminating noise. Approximately 75% of the dataset was allocated for model training, with the remaining portion dedicated to model testing. Emphasizing the critical dependence on both the quantity and quality of utilized data, the study underscored the essential role of data denoising in improving modeling accuracy, particularly in hydrological time series like GWLs.

3.4 Input Variable

To predict GWLs the input variables for the machine learning algorithms need to be carefully chosen. Figure 6 presents input variables used in predicting GWL variation based on the reviewed articles. The most frequently used input variable is groundwater level (GWL) with a percentage of 25.34%. The second most used input variable is temperature having 18.27. Furthermore, precipitation, third most employed predictive variable with 17.58%. Precipitation input variables include rainfall at 12.79%, evaporation at 6.85%, and evapotranspiration at 4.79%.. Additional factors such as humidity (3.653%), water table (2.51%), runoff (1.14%), wind (1.14%), and recharge (1.37%) contribute varying percentages of input variables used for predicting GWL. Others comprises 4.57% of the total input variable employed for GWL prediction. Figure 4 shows the percentage distribution of each input variable discussed.

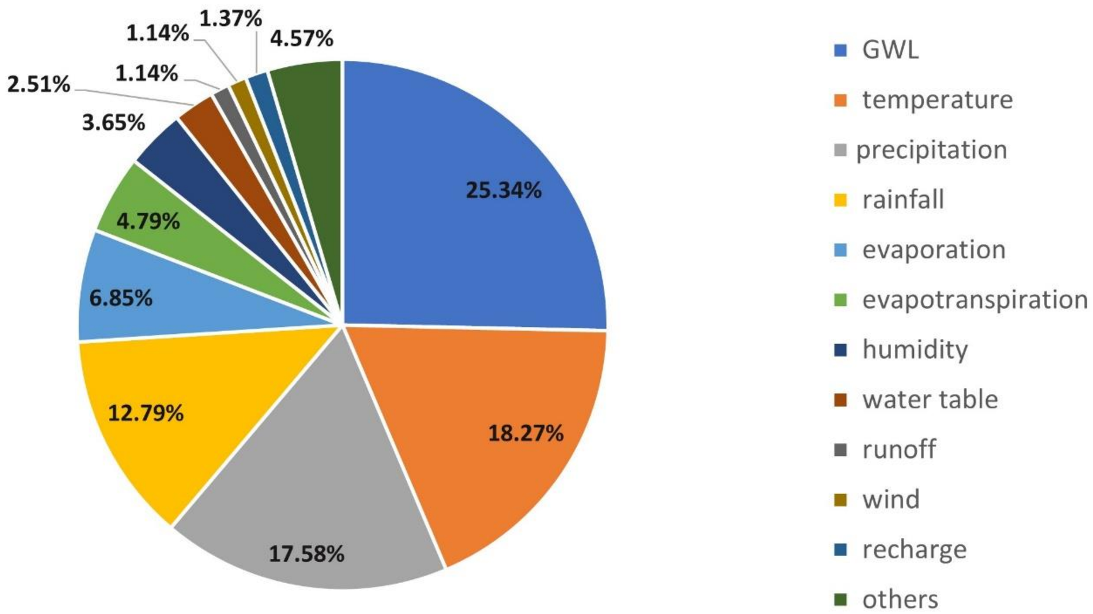

Figure 6: *Pie chart of usage of input variable*

3.5 Performance Metrics

Performance metrics are critical in assessing the accuracy and effectiveness of predictive models in various fields. Different metrics have been used for assessing the performance of the models utilized in the extracted studies. We observed the wide usage of five performance metrics in our extracted studies. Figure 7 presents the distribution in terms of percentages of the most applied performance metrics in GWL prediction. We observe that the most widely used metric is Root Mean Square Error **(**RMSE) accounting for (31%) of the studies, followed by coefficient of determination (R^2), (18%), Nash-Sutcliffe efficiency (NSE) (13%), mean absolute error MAE (11%) and Pearson's correlation coefficient (R) (9%) to measure the performance of neural network `(NN) models. The category "Other" included less frequently used metrics such normalized RMSE, residual error or skill score. Table 3 shows the different performance metrics and their references from our extracted studies. Each of the performance metrics is detailed in the subsequent subsections.

Table 3. *performance metrics employed and their references*

Performance Metric	References
RMSE	[5], [6], [9], [11], [16]–[22], [34], [38], [39], [43], [49], [51]–[55], [60], [66], [72], [76],

	[77], [80], [88], [96], [96], [97], [99]–[145], [145]–[157], [158, p. 201], [159]–[163], [145], [164]–[167]
R2	[5], [6], [9], [11], [16]–[22], [34], [38], [39], [43], [49], [51]–[55], [60], [66], [72], [76], [77], [80], [88], [96], [96], [97], [99]–[145], [145]–[157], [158, p. 201], [159]–[163],[165], [167],[168]
NSE	[5], [16], [18], [20], [32], [38], [43], [51], [53], [59], [68], [69], [71], [72], [74], [75], [80], [83], [93], [98], [99], [104], [108], [110], [113], [116], [117], [125], [126], [131], [134], [136]–[138], [144], [146], [148], [151], [154], [155], [155], [157], [158], [162], [169]–[188],[189],[190]
MSE	[5], [16], [20], [21], [33], [37], [38], [41], [43], [49], [51], [54], [64], [80], [96], [96], [97], [100], [101], [108], [109], [111], [113], [115], [119], [125], [127], [133], [134], [142], [144], [148], [152], [154], [157], [160], [170], [173], [181], [184], [186], [191]–[195],[164], [196], [197]
R	[3], [16], [37], [43]–[45], [49], [51], [55], [59], [74], [75], [80], [86], [103], [110], [116], [123], [124], [135], [136], [138], [142], [144], [150], [152], [153], [155], [155], [157]–[160], [163], [166], [175], [180], [183], [184], [186], [188], [198]–[201], [201],[190], [196], [202]

Pearson's Correlation Coefficient, R:

Pearson's correlation coefficient (R) measures the linear relationship between two continuous variables that is X and Y. It's particularly useful for determining how closely related the two variables are in a linear sense. The value of R indicates how our predicted value correlates well with the observed value, where 1 indicates a perfect positive linear correlation, -1 indicates a perfect negative linear correlation, and 0 means there is no linear correlation. The formula for computing the Pearson correlation coefficient is given as follows:

$$R = \frac{\sum_{i=1}^{n}(X_i - \underline{X})(Y_i - \underline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \underline{X})^2 \sum_{i=1}^{n}(Y_i - \underline{Y})^2}} \qquad (5)$$

n is the number of observations.

Y_i and X_i are individual data points for variables X and Y.

$\underline{X}$and $\underline{Y}$ are the averages of variables X and Y respectively.

Pearson's correlation coefficient enhances its effectiveness in capturing consistent relationships, providing a more accurate depiction of persistent directional trends in diverse datasets [203]. However, it focuses on linear correlation and may not effectively capture non-linear relationship, showcasing its limitation in addressing outliers [204].

Mean Absolute Error, MAE:

The Mean Absolute Error (MAE), is a metric quantifying the average absolute difference between actual and predicted values. The formula for computing the mean absolute error**,** is given as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (6)$$

- n is the number of observations.
- y_i represents the observed values
- $\hat{y}_i$ represents the predicted values

MAE is beneficial for Laplacian errors [205]. MAE is a straightforward measure of average error, making it preferable for evaluating and comparing model performance [206]. However, the influence of outlier data on MAE-based forecast evaluation is notable [207] suggesting that its conservative nature may lead to an underestimation of the model's effectiveness [207].

The autoregressive integrated moving average (ARIMA)-LSTM-salp swarm algorithm (ARIMA-LSTM-SSA) hybrid model, as employed by [154] to forecast GWL, utilized Mean Absolute Error (MAE) as the performance metric. The MAE values for both the training and testing phases were reported as 0.182 and 0.192, respectively, indicating a satisfactory performance in predicting GWL. In a related study by [208], various models were applied for GWL prediction. Among these models, the one demonstrating acceptable performance achieved MAE values of 0.212 and 0.182 for both training and testing.

Coefficient of determination, R^2:

It evaluates the proportion of the total variability in the observed values that is explained by the model's predictions [209]. The formula for computing the coefficient of determination**,** is given as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2} \qquad (7)$$

- n is the number of observations.
- y_i represents the observed values for the dependent variable.
- $\hat{y}_i$ represents the predicted values by the regression model.
- $\underline{y}$ is the mean of the observed values.

R^2 proves useful when evaluating the performance of a regression model across two datasets characterized by varying value scales [210]. The coefficient of determination is applicable when assuming a linear relationship, but it may not be suitable for models exhibiting non-linear. A high coefficient of determination does not guarantee that the selected regression model accurately represents the true relationship [211].

[94] model's performance was evaluated using the R^2 metric. It was found that the model successfully predicted the GWL up to four days in advance with an R^2 exceeding 0.99. For one-week predictions, the R^2 was as high as 0.98. Two-week ahead predictions achieved an R2 above 0.95, while predictions up to 26 days in advance achieved an R^2 of at least 0.9, the model`s performance was considered acceptable and able to accurately forecast GWL. Similarly, [6] adopted the R^2 metric as a performance measure for their models. They established a benchmark of accepting models with an R^2 greater than 0.95 for all well locations. This benchmark ensured that the models exhibited a high degree of accuracy across different sites.

Nash-Sutcliffe Efficiency (NSE)

Nash-Sutcliffe Efficiency (NSE) is a statistical measure commonly used in hydrology. It is used to evaluate the performance of models that simulate natural processes, such as groundwater levels [172]. [75], [185]. The formula for computing the Nash Sutcliffe efficiency**,** is given as follows

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(O_i - \underline{O}\right)^2}{\sum_{i=1}^{n}(O_i - M_i)^2} \qquad (8)$$

where:

- n is the number of observations.
- O_i represents the observed values.
- $\underline{O}$ is the mean of the observed values.
- M_i is the modeled or predicted values.

In simpler terms, the formula compares the squared differences between observed and modeled values to the squared differences between observed values and their mean. The result is then subtracted from 1 to get the NSE value. If the NSE is 1, it means the model perfectly predicts the observed values. If it's less than 1, it implies the model's performance relative to a simple average of the observed values. Models with NSE values greater than 0.7, can be classified as good to excellent [3]. NSE allows for model comparison and evaluates goodness-of-fit between observed and predicted values; Nevertheless, it is sensitive to outliers and neglects uncertainty associated with model predictions [212].

Employing NSE as a performance measure, [72] achieved an average value of 0.96 for both training and testing phases, indicating effective prediction of groundwater levels. Similarly, [154] reported NSE values of 0.96 for training and 0.95 for testing, demonstrating acceptable model performance in forecasting groundwater levels.

Root Mean Square Error (RMSE)

RMSE is a widely used metric for quantifying the average magnitude of prediction errors. We sum the difference between the in-situ and the observed values, and then divide by the total number of observations made to obtain the RMSE. The formula for computing RMSE is given:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \underline{y_i}\right)^2} \qquad (9)$$

- $\underline{y}$ is the mean of the observed values.
- y_i represents the observed values for the dependent variable.
- n is the total number of observations

RMSE proves advantageous when errors exhibit a normal distribution, ensuring precision in evaluating models under Gaussian error patterns [206]. However, RMSE is considered inappropriate because it considers other aspects of error in a set, not just the average error [206]. RMSE penalizes larger errors more heavily, making it sensitive to significant deviations between predicted and observed values.

[114] introduced the Double-Gated Recurrent Unit (GRU2+) model, which utilized a GRU2+ architecture with an Addition layer, incorporating seven layers and undergoing hyperparameter tuning. This specific configuration demonstrated a satisfactory RMSE of 0.094 meters for the accurate prediction of groundwater level fluctuations. Furthermore, [149] employed the Self-Adaptive Extreme Learning Machine (SAELM) for modeling GWLs, yielding an acceptable RMSE of 0.1496.

In summary, RMSE and MSE quantify the prediction error, while R and R^2 provide insight into the relationship between the model's predictions and the observed data.

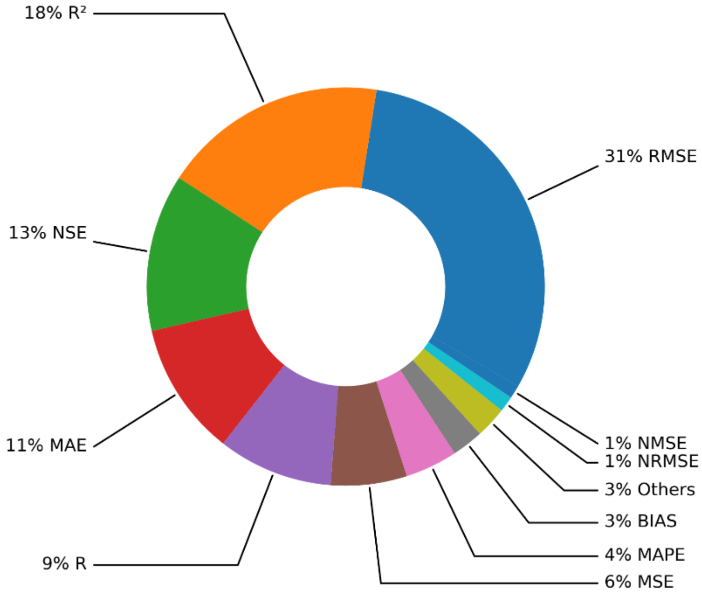

Figure 7*: Performance metrics employed*

3.6 Dataset

In our systematic review of groundwater level prediction studies, the classification of dataset temporal spans reveals diverse frequencies across different intervals. Figure 8 shows the various year span of datasets used for calibrating models for GWL predictions. Dataset spanning 6-10 years (74) and 11-20 years (50), emerge as the most frequently used for model training and testing.

From the review, it was observed that majority of datasets exhibiting these broad ranges spanning over 10 years suggests a deliberate emphasis on capturing and analyzing long-term trends and patterns. [62], [192],[5], [71] and [193] employed datasets exceeding a decade in duration.

In contrast, [117] utilized a shorter dataset with a duration of 4 years, [54] with a 9-month duration and [136] with a 3-year and 4-month duration. These studies using shorter datasets focused on extracting more immediate insights and patterns within a limited timeframe, providing a diverse perspective on temporal coverage.

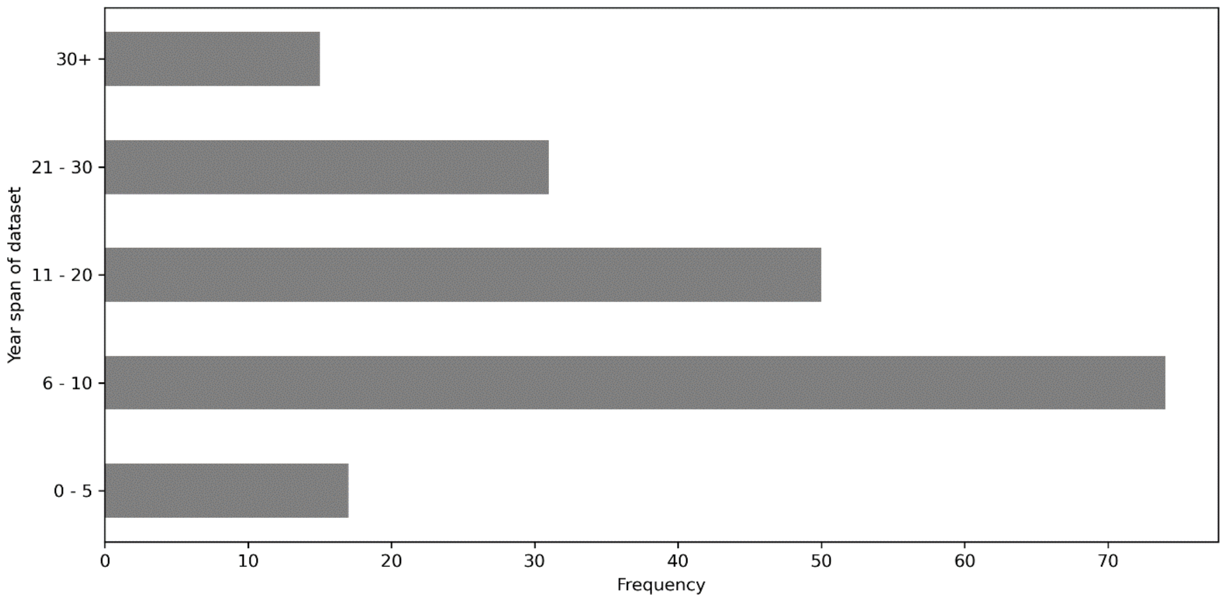

Figure 8: *Year Spans of datasets employed in machine learning studies*

5. Discussion

The main findings from 187 reviewed papers are discussed. This includes selection of input variables, current trends in neural networks, performance metrics, and other relevant aspects.

The analysis of publication trends revealed a surge in research utilizing neural networks for addressing the critical challenge of groundwater depletion over the past two decades. With notable peaks in 2022 and 2021, constituting 14.87% and 13.85% of published papers, respectively. This recent surge suggests a growing recognition of the potential and advantages offered by neural networks in addressing this critical challenge. This trend aligns with broader advancements in artificial intelligence and computational power, further solidifying the potential of neural networks as a robust and effective tool for groundwater level forecasting.

In addition, a significant variation in the distribution of primary studies among various countries was identified, with Iran leading with 26.92% of the published papers on groundwater prediction, followed by India at 17.69%, China at 15.38%, and the USA at 7.69%. This distribution can be attributed to factors such as population growth and escalating water demand, as highlighted by [213]. Moreover, [213] research on the Water Poverty Index (WPI) underscored a critical water scarcity situation, as indicated by a WPI of 41.1, emphasizing the need to address access, capacity, and utilization issues for water poverty improvement. Building on this, [214] explored the correlation between high groundwater consumption countries and the prevalence of neural network applications in modeling groundwater levels. Their findings not only illustrated a higher application of neural network in countries with substantial groundwater consumption but also revealed that the countries with the most published papers are grappling with the depletion of their groundwater resources

The examined literature emphasizes the expanding use of hybrid models for accurate GWL prediction. Numerous studies have effectively coupled Neural Networks (NNs) with a variety of approaches, including Wavelet Transform (WT), swarm optimization algorithms, clustering, and other AI models, regularly outperforming standalone NNs. This trend highlights the potential of hybrid model combining the strengths of various methods while addressing their respective limitations, these hybrid models can achieve higher forecast accuracy compared to individual approaches. Notably, studies have highlighted WT's effectiveness in preprocessing time series data, extracting useful information, and improving NN performance. Optimization strategies such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have shown effectiveness at optimizing NN hyperparameters, improving model accuracy. Furthermore, hybrid models that use Long Short-Term Memory (LSTM) networks have exhibited outstanding capability in capturing temporal relationships and predicting long-term GWL fluctuations

In this systematic review, the use of different types of input variables for groundwater level prediction including climate variables, hydrogeological and geographical parameters were examined. Climate variables like temperature, total precipitation, rainfall, evaporation, evapotranspiration and relative humidity were mostly employed, acknowledging their crucial role in recharge and discharge processes of groundwater. The optimal selection of input variables depends on the specific study area and how their inclusion influences the model's ability to capture details and complexities in groundwater dynamics. Notably, incorporating lagged input variables, representing past values of input variables, has proven to be a valuable strategy for enhancing model performance

During the evaluation of neural network models, multiple performance metrics are commonly employed to assess the performance of a neural network model. Some widely used metrics include the root mean square error (RMSE) coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), mean absolute error (MAE), and Pearson’s correlation coefficient (R). Although these metrics are sometimes used individually in reviewed literature, the simultaneous use of multiple metrics ensures a comprehensive evaluation of the neural network model's performance. One key reason for employing a variety of metrics is to obtain a detailed understanding of the model's strengths and weaknesses.

It is also apparent that a substantial portion of the datasets used in GWL prediction cover a timeframe of over 10 years. This observation suggests the potential years of dataset needed for conducting comprehensive, long-term trend analyses and prediction. By addressing these aspects of dataset quality and temporal coverage models can produce accurate and precise predictions. Moreover, an extended temporal coverage enables the recognition of seasonal variations, allowing predictive models to incorporate these cyclical changes and enhance their precision. Even in instances of missing values, high data availability greatly facilitates the estimation of data gaps [215], contributing to the overall reliability of the analyses.

The systematic review focused on analyzing literature from three distinct databases. While this method facilitated a thorough review of materials within these databases, it is essential to acknowledge its limitations. Articles from Web of Science, Scopus, and Google Scholar were included for this study. However, by concentrating primarily on these databases, there is a possibility that valuable contributions published in other databases or publications may have been unintentionally overlooked.

The integration of neural networks represents a transformative approach to groundwater level (GWL) modeling, unveiling complex patterns within the relationship between groundwater dynamics and various environmental variables. This research significantly advances our understanding by clarifying the detailed relationship between GWL and associated factors.

However, the effectiveness of such models is dependent on the length and quality of the dataset. The success of using neural networks (NN) for GWL modeling relies on the quality and quantity of accessible data, as well as the availability of ample computer resources. To support this, advanced data gathering technologies and databases capable of storing diverse meteorological and hydrological data relevant to specific geographic regions are indispensable. Moreover, fostering a culture of data sharing among researchers is critical. Establishing databases where researchers can collaborate and share their groundwater data not only improves accessibility but also enhances collaborative initiatives, thereby enriching the overall understanding of groundwater dynamics.

6. Conclusion

This paper is a systematic review which provides summaries on Artificial Neural Networks (ANN)s for GWL forecasting. In recent years, there has been a significant increase in interest in using neural networks for groundwater prediction, with Iran, China, India, and the United States at the forefront of this research, indicating countries with huge populations are driving advancement in this field. The analysis of these papers reveals that hybrid models proved effective in uncovering hidden relationships between groundwater levels and other environmental factors. The most employed performance metric was the root mean square error (RMSE). In terms of input variables, GWL, temperature and precipitation emerged as the most frequently utilized, with lagged values from these inputs demonstrating an improvement in model performance. A key finding underscores the significance of comprehensive, long-term datasets covering over a decade for robust trend analyses and accurate predictions. Emphasizing the importance of addressing data quality and temporal coverage, this review underscores the need for enhancing the reliability of predictive models. Furthermore, researchers can gain valuable insights into the evolving trends in the utilization of Neural Networks (NNs) for modeling GWL, driving the development of methodologies aimed at improving the efficacy of NN applications in predicting groundwater levels.

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