# Cover Sheet

## Title

This is a preprint. Please note that it has not yet undergone peer-review, and subsequent versions of the manuscript may have different content. It has been submitted to the Journal of Hydrology, Elsevier for review. This is a rapidly evolving and changing field. We welcome feedback and invite you to contact the authors directly to comment on the manuscript (cyrilboat@knust.edu.gh).

## Authors

Jesse Gilbert, Department of Meteorology and Climate Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Cyril D. Boateng, Department of Physics, College of Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana, Caburu Company Ltd, P.O.BOX MD 2046, Madina, Accra, Ghana - cyrilboat@knust.edu.gh

Jeffrey N.A. Aryee, Department of Meteorology and Climate Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Marian A. Osei, Department of Meteorology and Climate Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana, Centre for Ecology and Hydrology, Crowmarsh Gifford, Oxfordshire, UK, School of Earth and Environment,University of Leeds, Leeds, UK

David D. Wemegah, Department of Physics, College of Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Solomon S.R. Gidigasu, Department of Geological Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Akyana Britwum, Department of Physics, College of Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Samuel K. Afful, Department of Computer Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Haoulata Touré, Department of Geological Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Vera Mensah, Department of Geological Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Prinsca Owusu-Afriyie, Department of Meteorology and Climate Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

## Corresponding Author

Cyril D. Boateng - cyrilboat@knust.edu.gh

## Twitter

`@__elHefe`

# A Systematic Review of Machine Learning Algorithms in Groundwater Level Simulations and Forecasting

Jesse Gilbert[a], Cyril D. Boateng[b,g,*], Jeffrey N. A. Aryee[a], Marian A. Osei[a,c,d], David D. Wemegah[b], Solomon S. R. Gidigasu[e], Akyana Britwum[b], Samuel K. Afful[f], Haoulata Touré[e], Vera Mensah[e] and Prinsca Owusu-Afriyie[a]

[a]Department of Meteorology and Climate Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[b]Department of Physics, College of Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[c]Centre for Ecology and Hydrology,Crowmarsh Gifford, Oxfordshire, UK
[d]School of Earth and Environment,University of Leeds, Leeds, UK
[e]Department of Geological Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[f]Department of Computer Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[g]Caburu Company Ltd, P.O.BOX MD 2046, Madina, Accra, Ghana

ARTICLE INFO

*Keywords*:
Machine Learning
Groundwater level simulation
PRISMA
Artificial neural networks
Climate variables
Hyper-parameter tuning

ABSTRACT

Over two billion individuals worldwide rely on subterranean water as their primary reservoir of clean water. Ensuring the sustainable management of this heavily burdened resource necessitates a comprehensive quantitative evaluation of groundwater reserves. This becomes even more critical as water resources face escalating demands resulting from socioeconomic growth, population expansion, and the impacts of climate change. This research paper undertakes an extensive investigation in the context of a special issue dedicated to the utilization of machine learning (ML) algorithms for modeling and predicting groundwater levels (GWL). It offers a concise overview of prevalent Machine Learning(ML) techniques, encompassing their general architecture, key hyper-parameters, methods for fine-tuning, and strategies for optimal feature selection. Drawing insights from the scrutiny of 170 research papers across three prominent online databases, our findings indicate that well-constructed machine-learning models exhibit a commendable capacity for accurately modeling and predicting groundwater levels. Based on our review we realized that the utilization of machine learning to model GWLs is quite common. Typically, past groundwater levels are used as input data, and artificial neural networks (ANN) are a popular choice for this purpose. Our review of existing research provides a useful guide for researchers interested in applying machine learning algorithms for groundwater level modeling and forecasting. We also suggest new methods to improve modeling quality and highlight areas for future research in this field.

## 1. Introduction

A significant portion of the global freshwater resources is obtained from underground sources, representing the primary reservoir of clean water for more than two billion individuals (Famiglietti, 2014). Unfortunately, groundwater reservoirs have experienced significant strain in recent decades, particularly in less economically developed regions, resulting in their unsustainable exploitation. Approximately 20% of the world's groundwater reserve, which serves as a crucial drinking water source for more than half of the global population, is presently subject to over-exploitation. Projections suggest that an escalating number of global aquifers are at risk of over-exploitation by the year 2050 (Piesse, 2020).

Groundwater level (GWL), measured as the vertical column between the Earth's surface and the saturated zone, which is indicated by the thickness of the vadose or unsaturated zone, can be easily assessed using monitoring wells. Monitoring and analyzing GWLs in aquifers hold substantial importance for effective groundwater resource management. Understanding GWL fluctuations is vital for assessing groundwater availability, mainly due to increasing demand, extensive groundwater utilization, and the impacts of climate change. Changes in the groundwater level observed in wells offer direct insights into the impacts of groundwater utilization and provide valuable information about the behavior of aquifers (Butler Jr et al., 2013). It is worth noting that these measurements, often recorded in GWL time series, are occasionally marred by data gaps that can span from several months to multiple years. This makes the study of groundwater dynamics through modeling extremely important.

Traditionally, researchers have predominantly relied on conceptual or physically based models for this purpose. Commonly employed conceptual models for predicting water table levels encompass MODFLOW (Dehghani et al., 2022; Chakraborty et al., 2020), ISOQUAD (Yang et al., 2009), HydroGeoSphere (Brunner and Simmons, 2012), and SIMGRO (Van Walsum and Veldhuizen, 2011). However, these models present practical challenges, notably their demand for extensive datasets and specific aquifer information like transmissivity and specific yield. Unfortunately, such data is often scarce and location-specific.

In recent years, data-driven modeling, particularly through machine learning (ML) algorithms, has emerged as a promising alternative for groundwater modeling (Nourani et al., 2011; Sahoo et al., 2017; Kalu et al., 2022; Maiti and Tiwari, 2014; Kayhomayoon et al., 2022). Nourani et al. (2011) developed a hybrid Artificial Neural Network (ANN) model to predict

*Corresponding author
cyrilboat@knust.edu.gh (C.D. Boateng)

GWL in the East Azerbaijan Province, Iran. The results suggest that the hybrid trained with the Levenberg-Marquardt (LM) optimization algorithm can be successfully applied to predict GWL in the province. Sahoo et al. (2017) developed multi-linear regression (MLR) and ANN models to predict GWL in some specific Japanese sites. The results suggest that both models can be employed to predict GWL and the ANN model outperformed the MLR model. Kalu et al. (2022) developed an ML algorithm based on a Deep Belief Network (DBN) to simulate monthly GWL changes in southern Africa. The results indicated that the DBN was very effective in simulating and forecasting water table levels. Maiti and Tiwari (2014) compared three soft computing techniques, ANN, Bayesian neural networks (BNN), and Adaptive Neuro-Fuzzy Inference system (ANFIS). The study concluded that all models can be employed in simulating GWLs and the ANFIS performs better with noise-free data. Kayhomayoon et al. (2022) employed the ANFIS model to predict GWLs in the Urmia aquifer, Northwestern Iran. The study suggested the ANFIS model was successful in simulating and forecasting GWLs and the ANFIS model coupled with the Ant Colony Optimization for Continuous Domains (ACOR) algorithm outperformed the base ANFIS model.

ML models present advantages in terms of simplicity, computational efficiency, and data requirements compared to traditional models. Utilizing data-driven modeling offers advantages as it eliminates the need for extensive integration of diverse spatial and geological data. Instead, it predicts groundwater levels by discerning intricate relationships between these levels and a specific set of explanatory variables known as covariates. Many researchers have assessed the predictive capabilities of these ML models for groundwater-level modeling and forecasting in different geographical areas around the world. Certainly, these models are not without their imperfections, characterized by inherent limitations such as overfitting, underfitting, and reduced generalizability due to the absence of aquifer-specific data integration, among others.

In the realm of machine learning modeling, several critical steps warrant meticulous examination to attain optimal outcomes. These encompass model selection, data curation, data preprocessing, model training, hyper-parameter fine-tuning, and model evaluation. In the context of forecasting, it's noteworthy that the addition of irrelevant covariates in a model leads to heightened uncertainty and a subsequent decline in overall predictive performance (Kuhn et al., 2013). This, in turn, significantly influences the selection of the most appropriate modeling approach (Mayer and Gróf, 2021). Furthermore, as suggested by Markovics and Mayer (2022), the process of predictor selection holds even greater significance than the choice of the machine learning model itself. Consequently, the judicious selection of predictors emerges as an indispensable prerequisite for effective modeling (Kuhn et al., 2013).

This systematic review paper aims to investigate the methodologies employed across a broad spectrum of literature with the goal of achieving optimal feature selection within the context of machine learning algorithms. We will systematically examine the diverse hyper-parameters utilized within these models, the strategies implemented for their fine-tuning to attain peak performance, and the overall architectural constructs of these models. Numerous prior review articles have delved into the application of ML algorithms in the realm of hydrology (Solomatine, 2006; Afrifa et al., 2022; Rajaee et al., 2019; Nordin et al., 2021; Tao et al., 2022). Additionally, similar explorations have extended to various hydrological and water resource subdomains, such as river variables modeling (Maier et al., 2010) and sphere of water quality modeling (Wu et al., 2014). As far as we know, there has not been a systematic review article yet that thoroughly covers these particular research objectives. While the recent studies by Tao et al. (2022) and Rajaee et al. (2019) touch upon similar aspects, it is important to note that these papers did not consider a crucial aspect—the optimal feature selection procedure. Moreover, these studies are now over a year old, and subsequent publications in the field of ML modeling have proliferated. This study aims to bridge the literature gap concerning novel and efficient feature selection methods that have emerged over the years to achieve optimal model performance in GWL simulation and forecasting. A systematic meta-analysis enables us to compare studies effectively by consolidating individual study findings (Garg et al., 2008). Our current investigation addresses existing research gaps by adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework for conducting a systematic review. By following this framework, we seek to address several key inquiries:

1. What are the most employed ML models in GWL modeling?
2. What are the most effective strategies for achieving optimal feature selection in GWL modeling?
3. How can these models be structured to maximize their performance?
4. Which key hyperparameters are commonly employed in these models?
5. How can these hyperparameters be fine-tuned to optimize model performance?

Through our meta-analysis, we aim to provide valuable insights to researchers regarding established techniques for constructing ML models that yield superior outcomes in GWL modeling.

## 2. Methodology

In this systematic review paper, we employed an extensive review technique to ensure a comprehensive and traceable evaluation of the research literature. By adopting the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram (Liberati et al., 2009) as the guiding framework, we aimed to utilize review methods as the foundation of our review process, minimizing researcher bias and providing an unbiased analysis. Our systematic literature review aimed to achieve several research objectives. Firstly, we aimed to discern the predominant ML models employed ML models for GWL prediction and then we sought to identify the methods commonly employed to determine the best input variables for modeling. Additionally, we focused on understanding the frequently used key hyper-parameters in these models and the techniques utilized to fine-tune them for optimal performance. Through an exploration of these hyper-parameters and a careful analysis of model

**Table 1**
The Detailed Search Query.

| Search Query |
|---|
| TITLE-ABS-KEY ( "groundwater AND level AND prediction" OR "groundwater AND level AND forecasting" AND "machine AND learning" ) AND PUBYEAR >2009 AND PUBYEAR <2024 AND ( EXCLUDE ( LANGUAGE, "Chinese" ) OR EXCLUDE ( LANGUAGE, "Korean" ) ) AND ( LIMIT-TO ( EXACTKEYWORD, "Forecasting" ) OR LIMIT-TO ( EXACTKEYWORD, "Groundwater" ) OR LIMIT-TO ( EXACTKEYWORD, "Machine Learning" ) OR LIMIT-TO ( EXACTKEYWORD, "Groundwater Resources" ) OR LIMIT-TO ( EXACTKEYWORD, "Artificial Neural Network" ) OR LIMIT-TO ( EXACTKEYWORD, "Rain" ) OR LIMIT-TO ( EXACTKEYWORD, "Hydrology" ) OR LIMIT-TO ( EXACTKEYWORD, "Evapotranspiration" ) OR LIMIT-TO ( EXACTKEYWORD, "Temperature" ) OR LIMIT-TO ( EXACTKEYWORD, "Groundwater Level Fluctuation" ) OR LIMIT-TO ( EXACTKEYWORD, "Aquifer" ) OR LIMIT-TO ( EXACTKEYWORD, "Evaporation" ) ) |

performance, our study aimed to offer valuable insights into the factors that impact the accuracy of GWL predictions. To accomplish this, we adhered to the principles specified in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (Page et al., 2021). This systematic review methodology encompassed key stages such as identification, screening, establishment of eligibility criteria, and full-text assessment as shown in figure 1. The PRISMA framework utilized in our systematic review process was to ensure transparency, replicability, and rigor in our study. This methodology provides a standardized approach for conducting systematic reviews, enabling us to comprehensively evaluate the existing literature and draw meaningful conclusions. The specifics of each step of the systematic review methodology are as follows:

1. **Identification**: Following the PRISMA conceptual framework, our systematic review utilized a comprehensive search strategy to capture relevant articles from prominent electronic databases, including Scopus, Science Direct, and Google Scholar. The search was limited to English language publications between 2010 and 2023, aiming to examine the contemporary applications of ML models in predicting groundwater levels and availability. The search strategy employed a carefully designed search string, incorporating specific terms such as "groundwater," "level," "prediction," "forecasting," "machine," and "learning." In total, our search yielded 363 articles across all selected databases, demonstrating the broad scope of literature available on this topic. The details of the search string can be found in table1.
2. **Screening**: Following the identification of relevant publications, pertinent information such as title, keywords, abstract, digital object identifier (DOI), publication year, author names, and additional details were extracted and recorded in a Microsoft Excel spreadsheet. The articles were subsequently imported into a reference management software, Mendeley, known for its ability to streamline reference management workflows (Mendeley, 2022). After removing 37 duplicate records, the screening process commenced with a total of 326 articles. These articles were assessed against predefined inclusion and exclusion criteria. Following the evaluation of titles and abstracts, 156 papers were eliminated. To ensure thoroughness, two independent reviewers were provided with the original titles and abstracts, and they independently evaluated the eligibility of the remaining articles. In situations of uncertainty, article titles were presented to external reviewers with expertise in the respective field for evaluation. The final decision to include or exclude an article was based on consensus between the reviewers or, if necessary, the input from external experts served as the determining factor.
3. Establishment of eligibility criteria
   (a) Inclusion Criteria:
      i. Articles that focus on the utilization of ML algorithms for simulating water table levels and availability.
      ii. Studies that utilize meteorological parameters as inputs in the machine learning models.
      iii. Research articles published in English between 2010 and 2023 to capture contemporary advancements.
      iv. Publications that provide a detailed description of the methodology and model performance metrics.
      v. Articles that present original research findings, including case studies, simulations, or empirical studies.
   (b) Exclusion Criteria:
      i. Articles that do not specifically utilize ML algorithms for simulating water table levels and availability.
      ii. Studies that solely rely on traditional statistical or modeling approaches without the integration of machine learning.
      iii. Reviews, opinions, editorials, conference abstracts, and book chapters that lack primary research content.
      iv. Articles published before 2010 in order to maintain focus on recent developments.
      v. Publications that are not available in English or lack adequate information on methodology and results.

# 3. Results and Discussion

## 3.1. Publication Trends

As evident in Figure 2, the interest in employing ML for GWL prediction experienced fluctuations between 2010 and 2019. However, a notable shift occurred post-2019, marked by a substantial increase in research activity. Since 2019, there has been consistent and rapid growth in publications. In 2022, there was a significant spike in publications, constituting 34 out of the 170 reviewed papers on ML techniques, approximately 20% of the total. Recent review studies (Afrifa et al., 2022; Tao et al.,

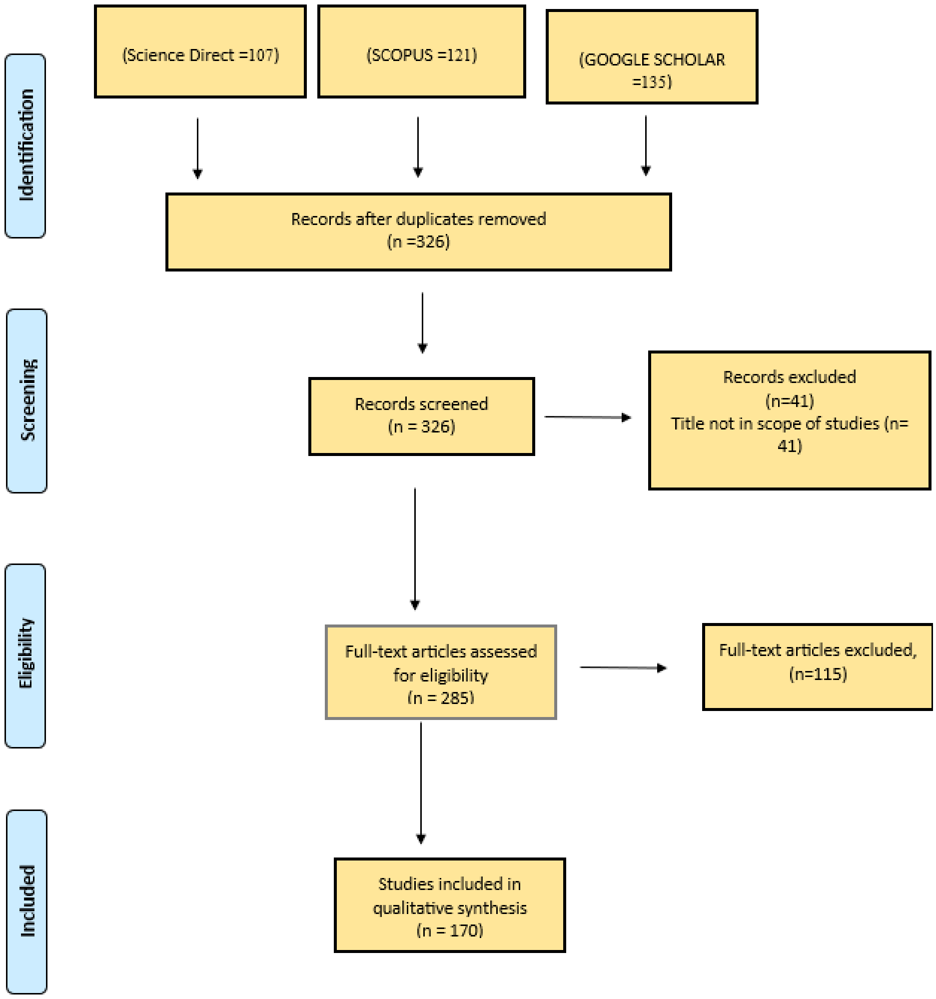


**Figure 1:** The PRISMA workflow diagram.

2022; Ahmadi et al., 2022), also reported such trends in ML models for groundwater modeling. As of our 2023 review, we identified an additional 26 articles, indicating a continued rise in interest in using ML techniques for forecasting changes in groundwater levels. It is noteworthy that the last time we downloaded a paper for this review was in July as indicated in Figure 2. Based on our research findings, it is evident that approximately 76.75% of the 170 articles were published by 3 publication houses. Specifically, Elsevier BV emerged as the leading publisher with 56 articles, constituting approximately 32.64% of the total. Following closely behind is Springer, responsible for 42 articles (24.7%), and the Multidisciplinary Digital Publishing Institute (MDPI) with 33 articles (19.41%). Copernicus Meetings also contributed significantly, publishing 15 articles, which corresponds to around 8.82% of the total as depicted in Figure 3. Intriguingly, these four prominent publishers collectively accounted for 85.57% of the 170 primary articles, indicating their substantial influence in disseminating research in this field. On the other end of the spectrum, the lowest number of articles, 24 in total, were attributed to Taylor and Francis, American Society of Civil Engineers, Wiley Online, IWA Publishing, and IEEE Inc.

In our systematic review, we observed distinct patterns related to authorship and their countries of origin across the 170 articles analyzed. Iran emerged as the leading contributor with 38% of the reviewed papers, followed by China with 21%, and the United States (US) with 11%, as depicted in figure 4. Many of these articles shed light on Iran's challenges in securing surface water, which has led to a heightened reliance on groundwater resources (Sharafati et al., 2020; Motagh et al., 2017; Milan et al., 2023; Arabameri et al., 2019; Moravej et al., 2020). This, in turn, has raised concerns about the rapid depletion of these aquifers. Regarding geographical distribution, Asia notably dominates the landscape, accounting for a substantial 77.64% of the publications (132 out of 170 articles). Zooming into the African continent, it becomes apparent that the utilization of machine learning (ML) for groundwater level modeling remains relatively limited. The existing body of literature on this subject is notably sparse, indicating a notable gap in research endeavors within this domain. This observation prompts the recognition of an unexplored terrain in the application of ML techniques for understanding and predicting groundwater dynamics in the African context. Figure 4 provides a visual summary of this distribution.

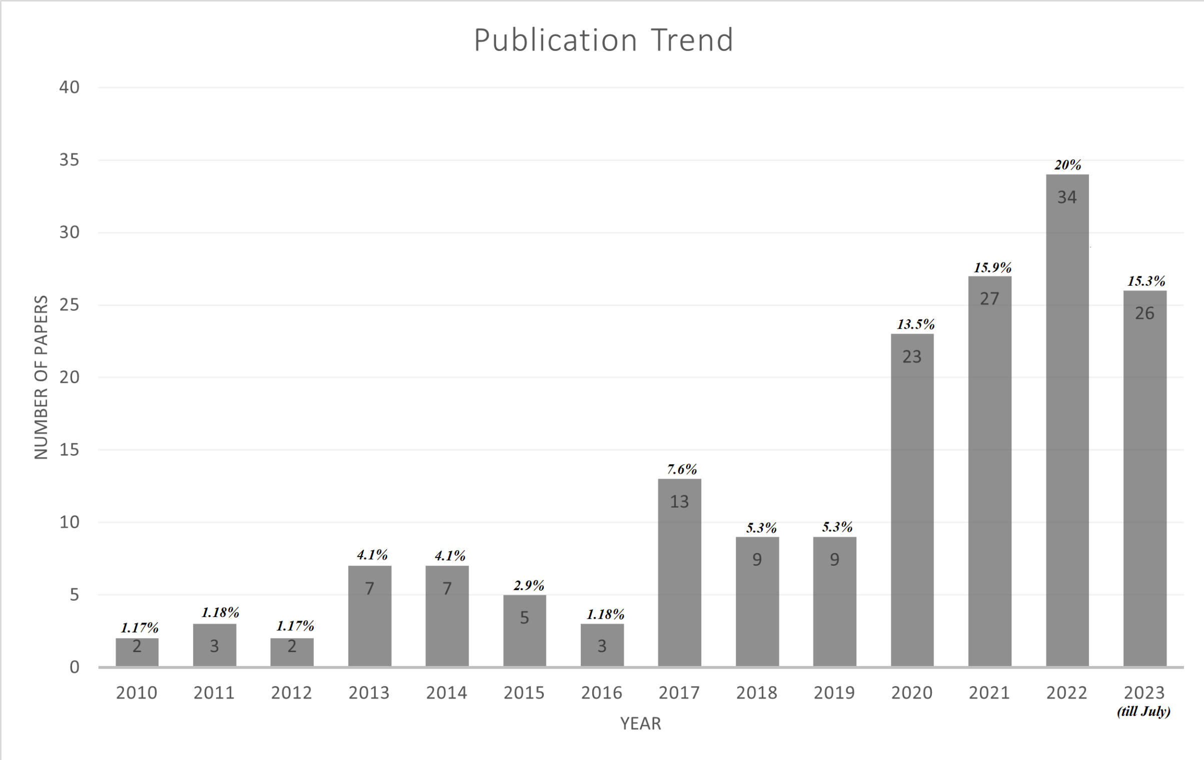


**Figure 2:** Trends in publications within the reviewed articles from 2010 to 2023.

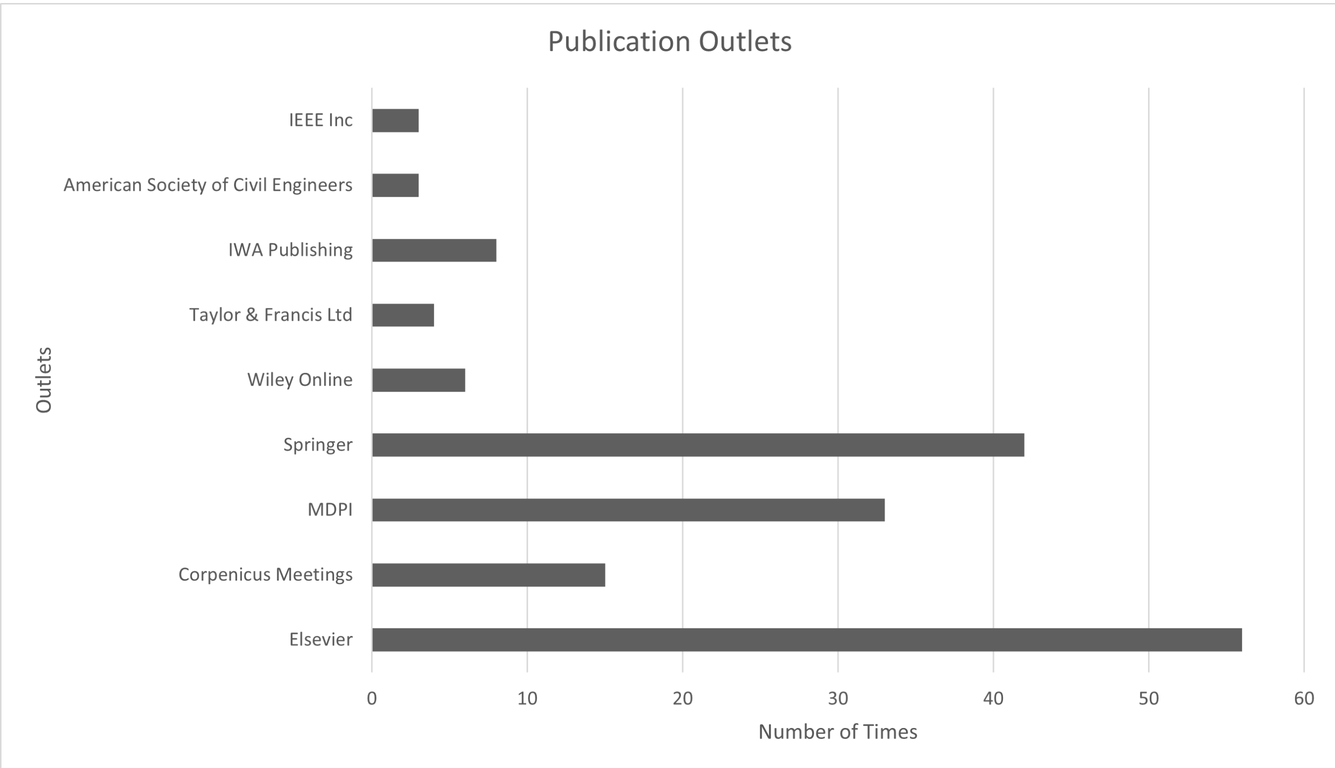


**Figure 3:** Publication outlet of reviewed articles.

## 4. Algorithms Used in Groundwater Level Prediction

GWL modeling and prediction are vital for managing water resources. The effectiveness of ML algorithms in this task relies heavily on the input data's quality and quantity rather than the specific model chosen. In this review, we delve into various techniques used for groundwater level prediction, ranging from established methods like ANN to novel approaches. ANN, ANFIS, Support Vector Machine (SVM), Long Short-Term Memory Networks (LSTM) and Random Forest (RF) were the

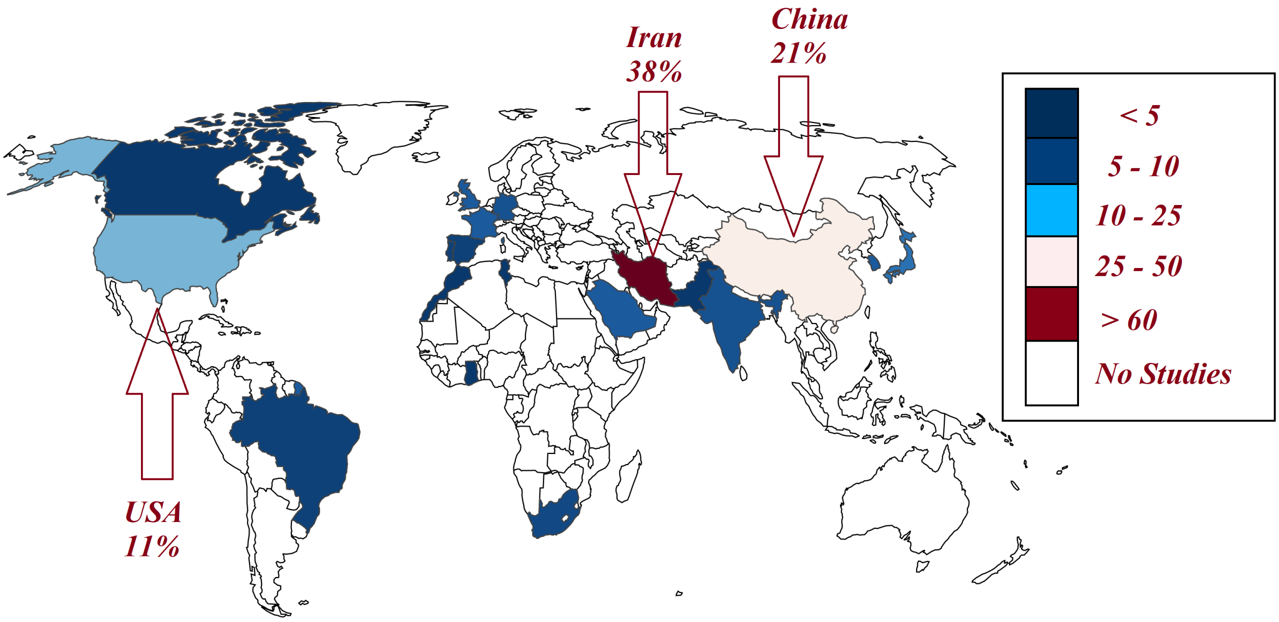


**Figure 4:** Distribution of the reviewed papers based on the country of origin.

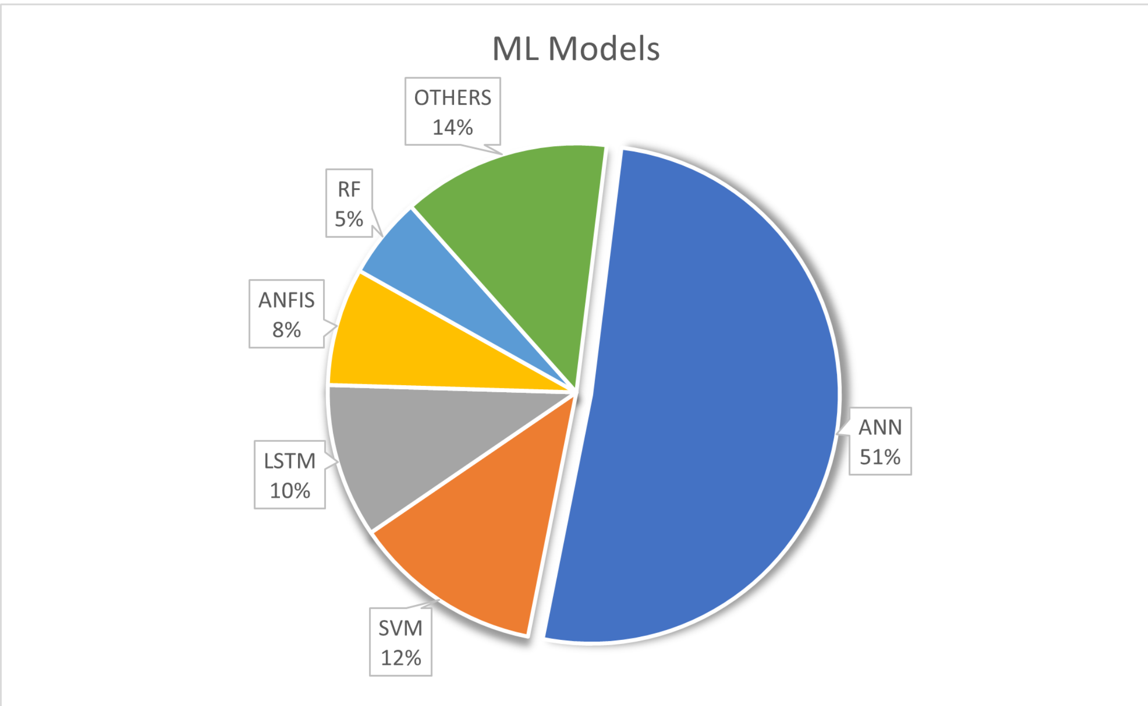


**Figure 5:** ML models utilized in GWL modeling.

most popular ML algorithms used in modeling GWL, accounting for approximately 86% of all the ML algorithms reviewed as shown in figure 5. We critically examine the methods used for optimal input feature selection, model structures, and parameters across some of the most popular ML algorithms used in the reviewed papers. Table 2 summarizes the articles discussing the prediction of groundwater levels using the models reviewed in this study. The details of these models are provided in the sections below.

## 4.1. ANN

### *4.1.1. Overview*

ANNs represent a conventional learning system inspired by the neural networks observed in the human brain. ANNs consist of simple elements known as neurons that work in parallel, and they are widely used for calculating unknown functions or making predictions based on historical categorical or continuous time series data (Nayak et al., 2006; Mohanty et al., 2010). The structure of an ANN neural network, alternatively known as a multilayer perceptron network (MLPN), comprises an input

**Table 2**
Reviewed Papers of various models used in GWL modeling.

| Models | References |
|---|---|
| ANN | Sahoo and Jha (2013), Nourani et al. (2011), Sahoo et al. (2017), El Ibrahimi et al. (2017), Kalu et al. (2022), Kumar et al. (2020), Dash et al. (2010), Choubin and Malekian (2017), Wen et al. (2017), Nourani et al. (2015),Chen et al. (2020), Jeong and Park (2019), Derbela and Nouiri (2020), Guzman et al. (2015), Banadkooki et al. (2020), Lee et al. (2019), Yin et al. (2021), Guzman et al. (2017), Yadav et al. (2020), Wunsch et al. (2018), Collados-Lara et al. (2023), Müller et al. (2021), Panahi et al. (2023), Van Thieu et al. (2023), Aderemi et al. (2023), Mohapatra et al. (2021), Afan et al. (2021), Gharehbaghi et al. (2022) |
| ANFIS | Emamgholizadeh et al. (2014), Jalalkamali et al. (2011), Gong et al. (2016), Seifi et al. (2020), Maiti and Tiwari (2014), Kayhomayoon et al. (2022),Moravej et al. (2020), Shirmohammadi et al. (2013), Naganna et al. (2020) |
| SVM | Yoon et al. (2011), Yoon et al. (2016), Behzad et al. (2010), Suryanarayana et al. (2014), Zhou et al. (2017), Guzman et al. (2019), Hussein et al. (2020), Yin et al. (2021), Yu et al. (2021), Rao et al. (2022), Mukherjee and Ramachandran (2018),Dehghani et al. (2022), Dehghani et al. (2022), Liu et al. (2021), Yadav et al. (2020), Ebrahimi and Rajaee (2017), Kajewska-Szkudlarek et al. (2022), Moravej et al. (2020) |
| LSTM | Kim et al. (2023), Haq et al. (2021), Wu et al. (2021), Zhang et al. (2018), Ao et al. (2021), Vu et al. (2023), Manna and Anitha (2023), Gaffoor et al. (2022), Patra et al. (2023), Solgi et al. (2021), Chidepudi et al. (2023) |
| RF | Gonzalez and Arsanjani (2021), Zhou et al. (2022), Liu et al. (2022), Lendzioch et al. (2021), Pham et al. (2022), Kenda et al. (2018), Mosavi et al. (2021), Rao et al. (2022), Gupta and Kumar (2022), Shi et al. (2023) |

layer, single or multiple hidden layers, an output layer, and a layer containing single or multiple artificial neurons. These layers are interconnected, and it's the connections between neurons that primarily determine the network's functioning. In the context of GWL forecasting, the input layer receives variables such as precipitation, temperature, and GWL time series. These inputs are processed through the hidden and output layers, where all the neurons apply weighted calculations and bias adjustments using specific activation functions to generate results. To train ANNs, sample data is used to optimize the network's performance. This training process involves adjusting the network's adjustable hyperparameters, referred to as weights and biases, to ensure that specific inputs yield accurate target outputs. Various training algorithms are employed in this process, including the backpropagation (BP), Bayesian regularization (BR), Levenberg-Marquardt (LM), and gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithms (Govindaraju et al., 2000). LM is a widely used optimization algorithm in neural network training. It combines elements of the Gauss-Newton method and gradient descent, offering fast convergence and effectiveness in solving complex optimization problems. BP is a fundamental algorithm for training supervised neural networks. It calculates gradients of the loss function and uses them to modify weights, leading to efficient learning from training data. BR is applied to regularize machine learning models, particularly to combat overfitting. It introduces prior probabilities over model parameters, encouraging simpler models and improving generalization. GDX is a comprehensive algorithm that combines gradient descent with momentum and adaptive learning rates during neural network training. It accelerates convergence with momentum and ensures stable learning with adaptive rates. Different types of ANNs are discussed in the various reviewed literature. Feedforward neural networks (FNNs) transmit input signals sequentially through the network, one layer at a time. Multilayer perceptron (MLP) networks, a subtype of FNNs, typically comprise an input layer, single or multiple hidden layers, and an output layer. In contrast, recurrent neural networks (RNNs) loop the outputs of the hidden layer back into themselves, integrating network history. Radial basis function (RBF) networks are also feed-forward but feature a single hidden layer that employs Gaussian transfer functions and Euclidean distances to compute output values. Figure 6 depicts the typical structure of the ANN model consisting of four layers.

### 4.1.2. Bibliographic Review

Experts worldwide have conducted a multitude of groundwater level prediction studies spanning various geographical regions. For example, in a study conducted by Sahoo and Jha (2013), groundwater level prediction was assessed in specific Japanese sites employing two modeling approaches: MLR and ANN. Input features included variables like rainfall, temperature, river stage, seasonal dummy variables, and lagged precipitation, temperature, river stage, and groundwater level. The Levenberg-Marquardt (LM) optimization algorithm was utilized in training the ANN model. The study optimized hidden neuron configuration with a genetic algorithm, using a logistic sigmoid function for the hidden layer and a linear activation function for the output layer. Cross-correlation analysis identified influential variables. Evaluation metrics, including standardized regression coefficient ($\beta$ j), SE, t-test, F-test, $R^2$, R, adjusted p-level, and SEE, favored the ANN model as the top-performing method. In a study by Nourani et al. (2011), a hybrid approach combining ANN and geostatistics to predict GWL in eastern Azerbaijan province, Iran. Input variables, selected through sensitivity analysis, included GWLs, rainfall, average discharge, lake level, and temperature. The modeling process involved incremental experimentation with hidden neurons, ranging from

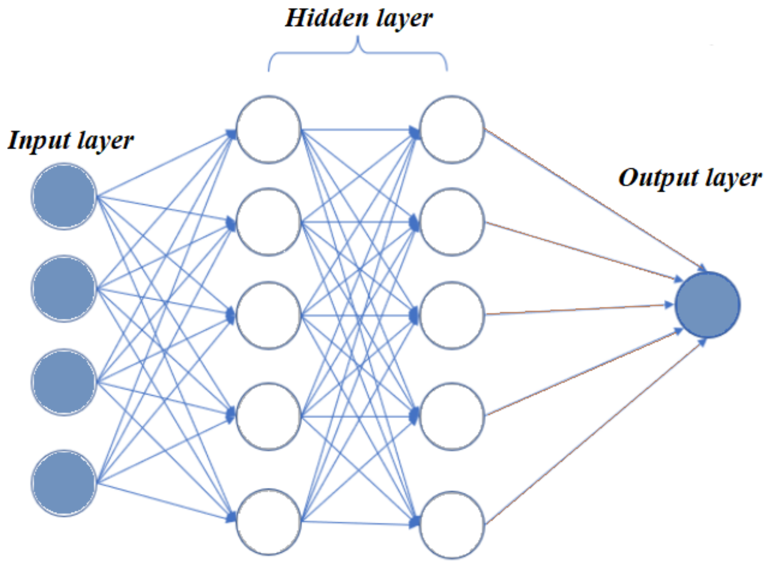


**Figure 6:** Standard ANN model Structure.

two to fifty, added one at a time. Batch training minimized mean square error using the Tangent Sigmoid for the hidden layer and a linear function for the output layer. Assessment using Root Mean Square Error (RMSE) and Coefficient Efficiency (CE) indicated that the Feedforward Neural Network trained with the LM algorithm stood out as the most proficient model for predicting groundwater levels in coastal aquifers. Sahoo et al. (2017), introduced an innovative automated hybrid artificial neural network (HANN) model, incorporating a unique approach to processing input covariates. This model serves as an alternative to intricate and computationally intensive physical models in the United States. This HANN model was designed to predict groundwater levels, and it utilized various input variables, including monthly precipitation, temperature, streamflow, irrigation demand, ENSO, and NAO. To ensure the identification of optimal input variables, the study employed singular spectrum analysis to decompose the time series data. Mutual information and a genetic algorithm were utilized to select the most influential principal components as input variables. Additionally, lag analysis was employed to identify the optimal time lags for these input variables. The ANNs developed in this research featured a single hidden layer with the number of neurons in this layer determined through a trial-and-error approach. The activation function used for the hidden layer was the logistic sigmoid, while the output layer employed a linear transfer function. Training of the models was accomplished using the LM algorithm. The model performance was assessed based on two key metrics, namely the correlation coefficient (R) and the RMSE. The results indicated that the HANN model consistently outperformed hybrid linear regression (HMLR) and hybrid nonlinear regression (HMNLR) models, showcasing its superior predictive capabilities. El Ibrahimi et al. (2017), introduced a novel approach for predicting groundwater levels in the Plain of Saïss, Morocco. This method hinged on the integration of discrete wavelets (DWT) with artificial neural networks featuring perceptron multilayers (ANN-PMC). The covariates for the model encompassed precipitation, temperature, and average groundwater levels. The architecture of the ANN-PMC employed in the study adhered to a straightforward three-layer design. Key parameters, including the number of neurons, were carefully selected through a systematic trial-and-error process. To evaluate model performance, the study employed essential metrics, namely the coefficient of determination ($R^2$), the RMSE, and the Nash Sutcliffe (Nash) coefficient. The findings consistently demonstrated that the DWT-ANN-PMC model significantly outperformed both the ANN-PMC model and the MLR model in terms of accuracy. Consequently, the authors recommended the integration of discrete wavelets (DWT) as a valuable component in future groundwater prediction studies. In Kalu et al. (2022) study, an ML algorithm based on a DBN was developed to simulate monthly groundwater level changes (CGWLs) in southern Africa. Input parameters included hydrological variables, water table level estimates, and global climate indices. Variable selection was optimized through correlation analysis. The optimal number of visible and hidden layers, as well as their nodes, were discovered by trial and error, taking into account the properties of the dataset. They employed the sigmoid activation function for the hidden layer. Model evaluation, using metrics like R, Nash-Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), and RMSE, indicated the DBN-based framework's effectiveness in simulating and forecasting water table levels. Kumar et al. (2020) used a Deep Learning (DL) model to forecast GWL in the Konan basin of Japan's Kochi Prefecture. The model incorporated key input variables, including temperature, recharge, precipitation, GWL, and river stage. The study employed wavelet coherence analysis to select the most influential lag between the independent variables and the target variable, GWL. The selection of appropriate input combinations was guided by the relative percentage error (RPE) method. The DL model consisted of three layers and utilized the Adam optimizer with MSE as the loss function. The activation function employed was ReLU, and the model underwent training over 360 epochs. An evaluation based on metrics like RMSE, R, NSE, and MAE revealed that the DL model consistently outperformed alternative models such as GPR and ELM, underscoring its effectiveness in groundwater level prediction. Dash et al. (2010) employed a hybrid neural network model, combining ANN with the Genetic Algorithm (GA) to predict GWL. This innovative model was compared to three different ANN models trained using various algorithms: Levenberg-Marquardt (LM) algorithm, back-propagation (BP), and Bayesian regularization (BR). Key hyperparameters, including the number of epochs (100), goal (0.001), and momentum coefficient (0.8), were selected by a trial-and-error approach. The optimal activation functions for the hidden and output layers varied: tansig-purelin for GDX, transig-transig for LM, and logsig-purelinear for BR. Performance evaluation employed metrics like Nash–Sutcliffe coefficient (E), correlation coefficient (R), index of agreement (IOA), RMSE, and MAE. They concluded that the BR-trained ANN was the superior model among all the models trained. Importantly, the hybrid ANN-GA model surpassed all three standalone ANN models, showcasing its superior predictive abilities. Choubin and Malekian (2017) performed a comparative analysis to assess two predictive models: ANN and Auto-Regressive Integrated Moving Average (ARIMA), and the Autoregressive Integrated Moving Average. The study aimed to simulate and predict GWLs in Iran's Shiraz basin. Input variables included precipitation, streamflow, temperature, evaporation, and GWL. The ANN model comprised an input layer (four neurons), a hidden layer (fourteen neurons), and an output layer (one neuron). The LM algorithm was employed in training the model. Activation functions were logistic-sigmoid for the hidden layer and purelinear for the output layer. Optimal input variables and data lengths were determined using the Gamma and M tests. Performance metrics like RMSE, MAE, and the correlation (R) were used. Surprisingly, ARIMA outperformed the ANN model based on the evaluation results. Wen et al. (2017) conducted a study comparing ANN coupled with Wavelet Analysis and the traditional ANN model for GWL forecasting. Input variables included GWLs, total precipitation, evaporation, and average temperature. The ANN model featured a three-layered architecture, with varying neuron numbers. The hidden layer of the WA-ANN model contained 3 to 6 neurons, whereas the input layer, across stations, contained 15 to 60 neurons. Both models had a single-neuron output layer, with sigmoid activation for hidden layers and linear for the output layer. Performance was evaluated using metrics including the R, MAE, RMSE, Nash–Sutcliffe efficiency coefficient (NS), and RMSE-to-standard deviation ratio (RSR). Results consistently favored the WA-ANN model over the traditional ANN model across all metrics. Nourani et al. (2015) conducted a study to develop predictive models for GWL simulation and prediction in the Aradabil plain of northwestern Iran. The study included three distinct scenarios, each with unique characteristics. The input variables for these models consisted of monthly data on rainfall, runoff, and GWL measurements from 15 piezometers distributed across the study area. To improve model accuracy, feature selection and the consideration of lagged values were integral components of the methodology, primarily guided by mutual information (MI). Furthermore, to optimize model performance, a sensitivity analysis was carried out. This analysis's goal was to identify the ideal setting for important model parameters, such as the number of neurons and epochs. This research endeavor aimed to offer valuable insights into the creation of dependable GWL forecasting models using ANNs, thereby enhancing the efficacy of groundwater management practices. Chen et al. (2020) studied GWL fluctuations in the Heihe River Basin using MODFLOW, MLP, RBF, and SVM. Historical groundwater and streamflow data calibrated and verified these models. For the Multilayer Perceptron (MLP), a neural network with a solitary hidden layer underwent training using the backpropagation method and was fine-tuned through gradient descent optimization. In the hidden layer, a hyperbolic tangent sigmoid function was applied, and in the output layer, a linear function was utilized. The optimal hidden neuron count was determined via trial and error, ranging from two to ten neurons, minimizing MSE. The LM algorithm adjusted weights and biases. Model performance was assessed using RMSE and $R^2$, with SVM and RBF outperforming MODFLOW by these measures. However, MODFLOW demonstrated better generalization due to incorporating physical parameters, highlighting the value of domain-specific knowledge in groundwater modeling. Jeong and Park (2019) employed Sophisticated ML models for simulating and predicting GWLs. They applied systematic data preprocessing techniques, which involved detrending to remove trend components, deseasonalization to eliminate seasonal variations, and normalization to standardize the data. The various ML models were used to simulate GWL time series data from monitoring wells in Jindo Uisin and Pohang Gibuk. A wide range of meteorological variables were employed as covariates. In the NARX model, a setup was utilized consisting of a singular input with 59 nodes, a single output layer, and a hidden layer comprising 16 nodes. Similarly, the LSTM and GRU networks were designed with 59 input nodes and two hidden states. The output from the ultimate cell was processed through a fully connected hidden layer, where two nodes were connected to an output node for interpretation. They employed the grid search approach and the trial and error approach to fine-tune all the models hyperparameters. Model performance was assessed using the RMSE metric, where both the NARX-DNN and LSTM models consistently demonstrated optimal predictive capabilities. Derbela and Nouiri (2020) applied ANNs with a sigmoid transfer function to forecast dynamic water table level fluctuations in Nebhana aquifers, located in Northeastern Tunisia. They conducted feature selection using correlation analysis and incorporated input variables such as evapotranspiration, monthly rainfall, and initial water table level. The optimal ANN structure was determined through the test and error approach. Evaluation metrics (RE, RMSE, $R^2$, NASH) indicated the remarkable efficiency of ANNs in accurately predicting groundwater levels, thus prompting their recommendation for future applications. Guzman et al. (2015) performed a comparative study involving two ML algorithms, ANN and the Support Vector Regression (SVR). The study aimed to simulate and forecast groundwater variations in the Mississippi River Valley Alluvial (MRVA) aquifer using precipitation and groundwater levels (GWL) as covariates. For the ANN algorithm, a Recurrent Neural Network (RNN) architecture was constructed employing a nonlinear autoregressive model with exogenous input (NARX) function in Matlab. This RNN had two hidden layers, 100 time delays, and utilized the Bayesian Regularization training algorithm. The SVR models, in contrast, used 392 data points and for the kernel function, the Radial Basis Function was employed. However, the study noted a challenge in evaluating the SVR model's architecture due to the complexity of multiple parameters, resulting in 30,000 distinct trials for a single type of kernel. The models capabilities were assessed using MSE, R, and computational time comparisons during training and testing. The RNN outperformed the SVR based on all the comparison criteria. Banadkooki et al. (2020) conducted a study to simulate and forecast GWL employing machine learning. They utilized precipitation and temperature data as covariates and assessed the influence of different time delays on prediction accuracy. Three models were assessed: RBF neural network with the Whale Algorithm (WA), MLP coupled with WA, and Genetic Programming (GP). Optimal input features were selected using cross-correlation and partial autocorrelation analyses. Evolutionary algorithms fine-tuned critical parameters like weights, biases, hidden neurons, and hidden layers. The activation function utilized was the Sigmoid transfer function. Model performance was assessed using metrics like NSE, MAE, and RMSE. The MLP-WA model outperformed the rest of the models. Lee et al. (2019) study predicted groundwater levels in South Korea's Yangpyeong riverside area using ANN models. Covariates employed included surface water level, GW abstraction, and GW heat pump. Optimal features were selected through correlation analysis. The hidden layer of the model incorporated a logistic-sigmoid activation function, while the output layer utilized a linear function. Training used the backpropagation algorithm. Across eight wells, optimal model parameters varied: hidden nodes (4 to 7), learning rate (0.001 to 0.009), and momentum coefficient (0.1 to 0.9). The study employed an extraction method to evaluate input variable contributions. Surface water level was highly influential, but the method didn't consider delay and lead times. Performance metrics included Mean Error (ME), RMSE, R, and NSE. The ANN models performed well in predicting groundwater levels based on these metrics. Yin et al. (2021) introduced an innovative groundwater ensemble model based on machine learning, incorporating Bayesian model averaging. It aimed to improve GW storage fluctuation predictions. The study employed three machine learning models, including ANN, SVM, and Response Surface Regression. The research utilized agricultural supply requirements (ASR), GW pumping (GP), and surface water delivery (SWD) data associated with land and water usage patterns as input variables for the model. The ANN had three layers: 8 neurons in the hidden layer, 8 neurons in the input layer, and a single neuron in the output layer. The hidden layer used the logistic-sigmoid function, and training ran for not more than 1000 epochs. The purelin function was employed for the output layer. The ANN was trained using the Levenberg-Marquardt method, with parameters fine-tuned. The kernel function used for the SVM model was the Gaussian kernel. They concluded that the ANN algorithm had low uncertainty, particularly at the sub-regional scale. Overall, the Bayesian model averaging technique delivered the most accurate and reliable predictions. Guzman et al. (2017) applied the NARX network to predict daily GWLs in the Mississippi River Valley Alluvial (MRVA) aquifer, located in the southeastern United States. The NARX network was trained using both LM and BR algorithms. Precipitation and GWL data were employed as covariates for the model. Sensitivity analysis identified historical GWL and precipitation as crucial variables. The optimal network featured two hidden nodes with sigmoid transfer functions and one output node with a linear function. Time delays of 50, 75, and 100 were tested based on autocorrelation function results. Evaluation metrics included Mean Squared Error (MSE), R-squared ($R^2$), and Normalized Coefficient (NC), where the NARX-BR model outperformed others, making it the preferred choice for accurate daily groundwater level predictions. Yadav et al. (2020) employed an ML technique involving singular spectrum analysis (SSA), MI, GA, ANN, and SVM. This methodology aimed to investigate the impact of various climatic and non-climatic factors on GW fluctuations in India. The input variables comprised GWL, rainfall, temperature, monthly population, and growth rate, and some climate indexes such as the Southern Oscillation Index (SOI). The ANN architecture featured three layers: seven neurons in the hidden layer and a single in the output layer. A hyperbolic tangent sigmoid transfer function was employed in the hidden layers. The remaining hyperparameters, such as the learning rate, were fine-tuned through empirical adjustments. The evaluation metrics, including R, RMSE, and NMSE, indicated that the hybrid models (SSA-MI-GA-ANN and SSA-MI-GA-SVM) outperformed the standalone models. Wunsch et al. (2018) employed the NARX model to simulate and predict groundwater level forecasts for multiple wells situated in southwest Germany. Precipitation and temperature were employed as the covariates for the model. To enhance the accuracy of the model, the determination of input and feedback delays was facilitated through a meticulous process. This involved the application of STL time series decomposition to the data and subsequent utilization of auto and cross-correlation functions on the residuals to identify and isolate highly influential time lags. Upon evaluation using key metrics including Relative Root Mean Square Error (RRMSE), R, and NSE, NARX exhibited remarkable promise in the domain of groundwater level modeling, thus establishing its efficacy in the context of this study. Collados-Lara et al. (2023) introduced a streamlined technique for short-term GWL prediction using various ANN models like NAR (Nonlinear AutoRegressive), NARX, and Elman Neural Networks. These ANNs modeled GWL variations with input variables: precipitation, minimum and maximum temperature. Correlation analysis identified influential variables. Hyperparameter optimization followed a systematic trial-and-error approach. Model performance was assessed using metrics like RMSE, R-squared ($R^2$), and MSE. Results highlighted NARX and Elman Neural Networks, especially when incorporating effective precipitation, as strong choices for short-term groundwater level forecasting. Also, Müller et al. (2021) analyzed four contemporary deep learning models (LSTM, MLP, RNN, CNN) for groundwater level prediction in Butte County, California. They compared three hyperparameter optimization approaches: surrogate model-based algorithms (RBFs and GPs) and random sampling. Ambient temperature, streamflow, and precipitation were employed as covariates for the model. Each model had input nodes matching the covariates. LSTM used ReLu activation and RMSprop optimizer. MLP employed ReLu activation for inner nodes and linear for output, optimized with ADAM. CNN had a fully connected hidden layer with 50 nodes. RNN used the same activation functions and optimizers as MLP. Results emphasized the importance of precise hyperparameter tuning, with MLP performing the best among the models. This underscores hyperparameter optimization's significance in accurate groundwater level predictions. Panahi et al. (2023) used ML to predict GWLs under changing climate conditions. They employed the ACCESS-CM2 model within the SSP 5–8.5 scenario for generating future climatic variables, extracted by the CMhyd model. Input variables included GWL, precipitation, max and min temperature, and evaporation. ML models like MLP, ANFIS, RBFNN, and SVM were employed for GWL simulation and forecast. Increasing hidden layer neurons in MLP and RBFNN, determined through trial and error, reduced predictive errors. The optimal configurations were 7 neurons for MLP and 33 neurons for RBFNN. The models were assessed $R^2$ and RMSE. RBFNN outperformed other models, making it suitable for predicting GWL fluctuations in a changing climate. Van Thieu et al. (2023) introduced the Augmented Artificial Ecosystem Optimization-based Multi-Layer Perceptron (AAEO-MLP) model for monthly GWL prediction at two Indian well sites. Input variables included mean temperature, tidal height precipitation, and historical GWL data. The model's architecture featured an input layer, a hidden layer, and an output layer using Exponential Linear Unit (ELU) activation. The MI measure selected the best input variables. The hidden layer's neuron count varied from inputs to 1 + twice the inputs, with one neuron in the output layer. Evaluation metrics encompassed MAE, RMSE, R, KGE, and A20. AAEO-MLP consistently outperformed other MLP models with metaheuristic algorithms like EAEO-MLP and CGO-MLP. Aderemi et al. (2023) performed a study focusing on GWL simulation and forecasting in the Karst belt region of South Africa, specifically in groundwater region 10. This research employed machine learning models, including Regression Models, Deep Auto-Regressive models, and the NARX model. Rainfall and temperature data were employed as covariates for the models. To identify the most effective covariates for the models, the study employed MI calculations. Interestingly, the MI analysis revealed that temperature exhibited a notably low MI concerning its relationship with GWLs. Evaluation of the model performance incorporated several metrics, including $R^2$, RMSE, MAPE, MASE, and MAE. The results indicated that both the NARX model and SVM consistently outperformed other models, showcasing their superior predictive capabilities in this groundwater-level forecasting study. Mohapatra et al. (2021) performed a detailed study assessing the predictive capabilities of three machine learning techniques: ANFIS, DNN, and SVM in various Agro-Ecological Zones (AEZs) across India. The study used input variables, including monthly mean temperature, monthly mean rainfall, and mean seasonal GWLs. For the DNN model, the Rectified Linear Unit (ReLU) was employed as the activation function. DNN hyperparameters for different AEZs were optimized using 'Bayesian optimization' on the validation dataset. They concluded that the DNN model consistently outperformed the other models. These findings highlight DNN's potential in groundwater level prediction, particularly when tailored to regional characteristics.

#### *4.1.3. Results*

Based on the reviewed papers we found that,

1. The primary optimization algorithm for training ANN models was the LM algorithm, often supplemented by Bayesian Regulation and the Backpropagation algorithm. The LM algorithm known for its efficiency, strikes a balance between two optimization approaches: Newton's method, known for its rapid convergence near minima but prone to divergence, and gradient descent, which ensures convergence when the step size is chosen wisely but converges at a slower pace (Tyagi et al., 2022). According to some researchers, the LM method is computationally efficient and has a lower probability of being trapped in the local minima than alternative training algorithms, which are frequently described as being more robust and effective (Daliakopoulos et al., 2005).
2. A typical ANN structure consists of three layers, incorporating the sigmoid activation function in the hidden layer and a linear activation function in the output layer. Some studies also employed ReLU and ELU. Notably, in most of the reviewed papers, the determination of the ANN structure, the number of hidden neurons, and hyper-parameter tuning were achieved using a trial-and-error approach. However, GP was used for hyperparameter optimization in specific cases. The reported learning rates mainly ranged between 0.001 and 0.009, with the highest recorded as 0.01
3. The selection of optimal input variables primarily relied on correlation analyses, including Partial Auto-correlation, Auto-correlation, and Cross-Correlation function. In some cases, MI was used to improve model performance through enhanced feature selection.
4. Among the hybrid models, the combinations consistently yield optimal performance involving ANN coupled with Wavelet Transformation.

### 4.2. ANFIS

#### *4.2.1. Overview*

ANFIS, initially introduced by (Jang, 1993), represents a versatile approach capable of precisely approximating continuous functions within a defined range. ANFIS seamlessly integrates two potent methodologies: the Adaptive Neural Network (AN) and the Fuzzy Inference System (FIS), harnessing the strengths of both approaches within a unified framework. Fuzzy logic, the cornerstone of FIS, operates on linguistic expressions to address uncertainty through qualitative reasoning rather than rigid numerical precision. This soft computing technique has found widespread applications in domains like hydrology and various engineering disciplines. The ANFIS architecture comprises a straightforward five-layered feed-forward network. The initial layer handles the conversion of input variables into a suitable format, while the subsequent layer employs specific operators to compute the initial part of fuzzy rules. Following this, the subsequent layer standardizes the rule strengths, and the subsequent layer calculates the final parameters for these rules. The output layer consolidates all incoming signals to generate the ultimate system output. Jang's pioneering work in 1993 introduced a learning procedure that makes use of a neural network learning algorithm to construct fuzzy if-then rules coupled with suitable membership functions (MF) based on specified input-output pairs. ANFIS utilizes backpropagation learning to determine the initial parameters linked to membership functions and uses least mean square estimation to ascertain the final parameters. This approach effectively resolves the fundamental challenges in fuzzy architecture design, namely, delineating MF parameters and generating a collection of fuzzy if-then rules. It leverages the discerning capabilities of ANNs to automatically generate and optimize fuzzy if-then rules. For more detailed insights into ANFIS, additional information can be found in Jang's seminal work in 1993, as well as subsequent studies by (Nayak et al., 2004). Figure 7 depicts the schematic structure of the ANFIS model consisting of 5 layers.

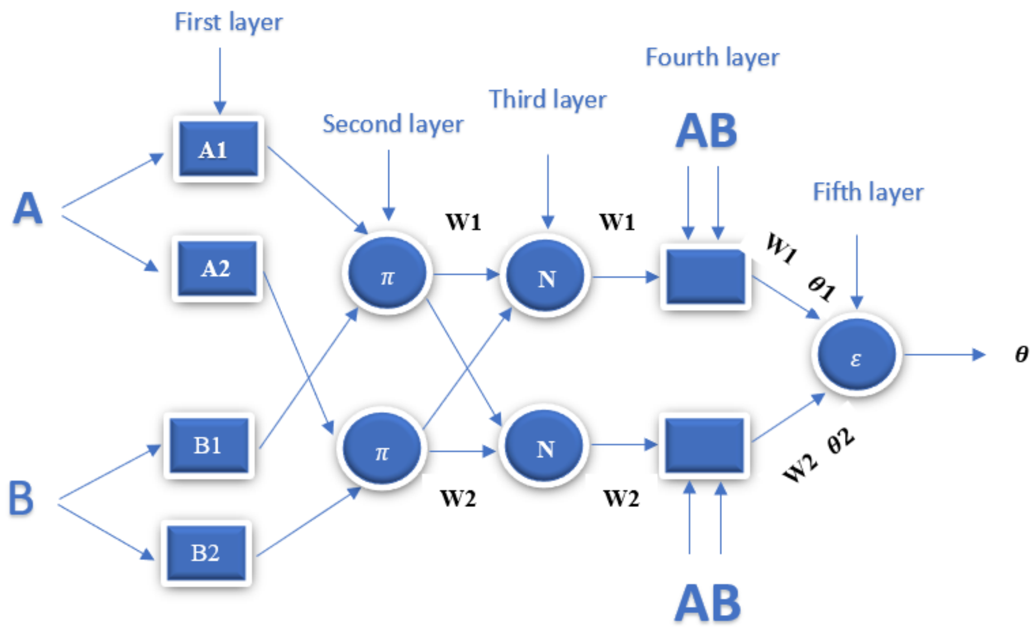


**Figure 7:** Standard ANFIS Model Structure.

#### *4.2.2. Bibliographic review*

When it comes to GWL modeling with ANFIS, in 2014, Emamgholizadeh et al. (2014) assessed the capabilities of two ML models namely, ANN and ANFIS, to predict GWLs in Bastam Plain, Iran, using a nine-year dataset of hydrological and hydrogeological parameters. A learning rate coefficient ($\alpha$) of 0.01 and momentum factor ($\alpha$) of 0.1 were used. The ANFIS model configured with trapezoidal input Membership Functions (MFs), a hybrid learning algorithm, and a linear output MF also yielded optimal results. Evaluation metrics, including RMSE, R-squared ($R^2$), and MAE, favored the ANFIS model, demonstrating superior predictive capabilities over the ANN algorithm. In the study conducted by Jalalkamali et al. (2011), an investigation into the predictive capabilities of NF and ANN models for GWL forecasting was undertaken. The input variables considered for this predictive modeling included rainfall, air temperature, and GWLs. To optimize the performance of the models, the hyper-parameters of the models were tuned using a systematic trial-and-error approach. For the ANFIS model, a consistent configuration of 3 rules was applied across all input combinations, with the number of epochs spanning from 50 to 80, and the membership function chosen as gaussmf. The performance evaluation, based on established metrics including RMSE, MAPE, and $R^2$, unmistakably demonstrated that the NF model consistently outperformed the ANN model in the task of water table level prediction. In Gong et al. (2016) study, multiple nonlinear time-series models, such as ANN, SVMs, and ANFIS, were examined for their effectiveness in simulating and forecasting groundwater levels. The input factors considered were GWL, precipitation, temperature, and lake levels. The relevant input factors were determined using the partial and autocorrelation coefficient. In the case of ANN, the Bayesian regularization (BR) training method produced the best results when using a model with 10 neurons in the hidden layer. The trial and error approach was used in tunning the models. The assessment of model performance, based on metrics such as NMSE, RMSE, NSE, R, and Akaike Information Criteria (AIC), indicated that ANFIS and SVM models consistently outperformed the ANN model in simulating and forecasting GWLs. In Seifi et al. (2020) study, six meta-heuristic methods (grasshopper optimization algorithm (GOA), cat swarm optimization (CSO), weed algorithm (WA), genetic algorithm (GA), krill algorithm (KA), and particle swarm optimization (PSO)) were combined with ANN, ANFIS, and SVM to predict monthly GWLs. The objective was to assess prediction uncertainty and spatial variability simultaneously. Principal component analysis reduced monthly time series data into intervals spanning up to 12 months, enabling the identification of the most influential covariates. The Taguchi model determined precise values for random parameters instead of using trial-and-error approaches. Performance metrics including RMSE, MAE, $R^2$, PBIAS, and NSE were used for evaluation. Results showed that ANFIS-GOA performed best, while SVM had less favorable results. In the study conducted by Maiti and Tiwari (2014), three soft computing techniques were compared: ANN with scaled conjugate gradient (SCG) optimization (ANN-SCG), BNN with SCG optimization (BNN-SCG) utilizing evidence approximation, and the ANFIS. They aimed to predict water table level fluctuations using covariates such as temperature and precipitation. Sensitivity analysis revealed maximum temperature and precipitation as more influential. Input variables were selected using partial auto-correlation functions (PACF) and auto-correlation functions (ACF). The ANN model was tunned with the trial and error approach, with a consistent sigmoid activation function. Model performance was evaluated using metrics including RMSE, error reduction, agreement index, and Pearson correlation coefficient. The study concluded that ANFIS performs better with noise-free data, while the BNN-SCG model excels in handling hydrological time series with red noise. Kayhomayoon et al. (2022) employed ANFIS to predict GWLs in the Urmia aquifer, Northwestern Iran, with covariates including precipitation, temperature, groundwater withdrawal, previous-month GWL, and river flow data. Metaheuristic optimization algorithms (Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization for Continuous Domains (ACOR), and Differential Evolution) were applied to enhance the ANFIS model's predictive capabilities. The optimal maximum iteration count was determined iteratively. The study found that the Sugeno-type function and linear output function worked best for the ANFIS model, which included ten fuzzy rules and a maximum of 1000 epochs. Hybrid optimization with Gaussian membership functions was employed. AFIS-ACOR outperformed the base model and the other hybrid models based on metrics like MSE, MAPE, RMSE, and $R^2$, demonstrating its effectiveness in improving GWL prediction capabilities. Shirmohammadi et al. (2013) conducted a study to predict groundwater levels in the Mashhad Plain, Iran, across various forecast periods. Input variables included average monthly discharge, monthly total precipitation, and average monthly evaporation data. Feature selection for the model used statistical techniques like cross-correlation, autocorrelation, and partial autocorrelation. The ANFIS model with five membership functions and 4000 iterations consistently outperformed other models, as evidenced by assessment criteria including the $R^2$, RMSE, and AIC.

#### 4.2.3. Results

Based on the reviewed papers we found that,

1. Gaussian Membership Functions (MF) were the most frequently employed, followed by Trapezoidal MF. Membership functions are a fundamental component of fuzzy logic systems, and they define how each input variable's value is associated with different fuzzy sets. These functions are essential to ANFIS's fuzzy inference procedure. In a study by Talpur et al. (2017), the influence of four common membership function shapes on the effectiveness of ANFIS in tackling diverse classification tasks was investigated. Their findings indicated that the Gaussian membership function, due to its superior accuracy and lower computational demands, emerged as the most promising choice. It is worth noting that several reviewed papers did not specify the MF utilized.
2. Hyperparameter tuning was primarily accomplished through a trial-and-error approach. However, in select cases, algorithms such as ACOR and Grasshopper Optimization Algorithm (GOA) were employed, producing favorable results.
3. Partial Autocorrelation and Autocorrelation analyses were the prevalent methods for selecting optimal features for model inputs.
4. Both standalone ANFIS models and hybrid ANFIS models consistently outperformed ANN models. This superior performance can likely be attributed to ANFIS models integrating both neural networks and fuzzy logic, making them more adept at handling non-stationary time series data.

### 4.3. SVM/Support Vector Regression (SVR)

SVM and SVR are machine learning techniques. SVM is mainly used for classification, while SVR deals with regression problems. In SVM, there's no predefined structure. It operates by identifying critical data points called "support vectors." These support vectors contribute to constructing the model. SVM aims to identify an optimal hyperplane in higher dimensions that effectively segregates data points into distinct classes, simultaneously maximizing the margin between these classes. SVM is resistant to outliers because of the margin, which represents the separation between the hyperplane and the closest data points from each class. To manage non-linear data, SVM utilizes kernel functions, transforming the original feature space into a higher-dimensional realm where the data achieves linear separability. Common kernels mostly employed include the radial basis function (RBF), linear, polynomial, and sigmoid. In contrast, SVR, a relatively recent development, is applied primarily for regression purposes. It aims to predict continuous output variables. SVR, similar to SVM, finds a hyperplane that fits the data while keeping a margin of tolerance around it. This margin of tolerance ensures that a maximum number of data points fall within it. Both SVM and SVR can utilize kernel functions to manage non-linear intricate patterns between covariates and the target variable. These techniques are well-suited for various applications, from predicting stock prices to estimating temperature or groundwater levels. For a comprehensive mathematical understanding of SVM, refer to (Vapnik, 1998). Figure 8 depicts the schematic figure of the SVM model.

#### 4.3.1. Bibliographic review

In a study conducted by Yoon et al. (2011), SVM and ANN models were developed to simulate and forecast the fluctuations in GWLs within a coastal aquifer in Korea. The input variables considered for these models included water table levels precipitation, and tide level. To identify the most influential features of the input variables, cross-correlation analysis was employed. During the training phase, specific weight update rules were applied: Backpropagation Algorithm (BPA) for ANN and Sequential Minimal Optimization (SMO) for SVM. In the testing stage, model parameters were carefully chosen to reduce errors within the test dataset, utilizing the test/fail approach. Performance evaluation was conducted using a suite of metrics, including RMSE, ME, MAPE, CORR, NS, and AIC. Considering these extensive metrics, the research findings consistently indicated that the SVM algorithm surpassed the ANN model in forecasting water table level fluctuations. Yoon et al. (2016) developed predictive models for GWLs in response to rainfall patterns in South Korea which were improved using a weighted error function approach. The input variables considered were rainfall and groundwater levels. Statistical techniques like partial autocorrelation (PACF), autocorrelation function (ACF), and cross-correlation (CC) were employed to identify suitable input variables. Model parameters for both ANN and SVM were fine-tuned for optimization. The hyper-parameters for the ANN and SVM models were tuned using the trial and error approach. The radial basis function was employed as the kernel function for the SVM model. The predictive capabilities of the models were evaluated using metrics like ME, MAPE, RMSE, and the R.

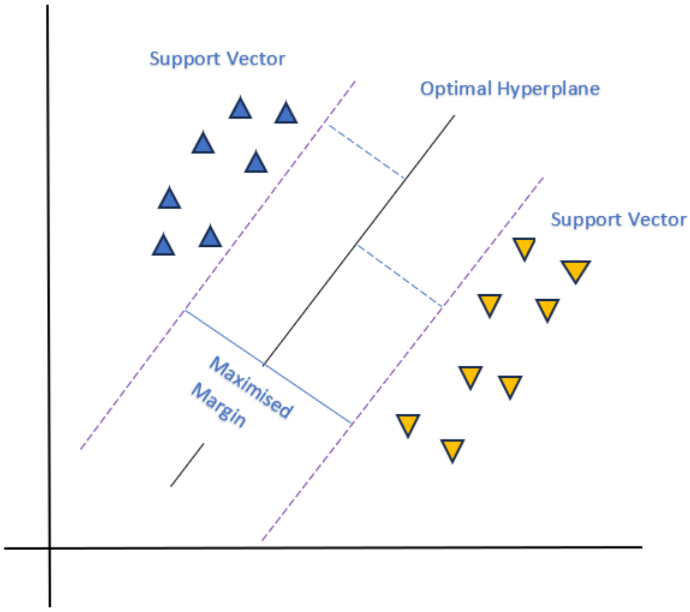


**Figure 8:** Schematic Structure of the SVM model.

SVM consistently outperformed ANN in terms of predictive performance. Behzad et al. (2010) extensively compared SVM and ANN for simulating and forecasting water table levels in a complex underground water system over various prediction horizons, including daily, weekly, biweekly, monthly, and bimonthly timeframes. Input variables included statistical factors such as mean daily pump rates, cumulative mean pumping rates, total precipitation, mean temperature, and initial groundwater level measurements. Hyper-parameter tuning was a critical aspect of model performance. The kernel function employed in the study was the Radial basis function. The regularization parameter was explored within a range of values from 0.5 to 41. The RBF parameter varied between 0.0114 to 0.5, and the error function parameter ranged from 0.001 to 0.0474. The number of support vectors also varied, spanning from 45 to 83. The models predictive capabilities were evaluated using key metrics, including RMSE, R-squared ($R^2$), and the coefficient of efficiency (E). The results consistently favored the SVM model over ANN in both the training and testing phases, establishing SVM as the more reliable choice for predicting GWLs across various timeframes. Suryanarayana et al. (2014) attempted to simulate and forecast monthly GWL fluctuations in Visakhapatnam, India, employing an integrated wavelet and SVR (WA-SVR) approach. The model's input variables included monthly data on groundwater depth, maximum temperature, mean temperature, and precipitation. The Kernel function employed was the Radial Basis Function (RBF). The optimization of model parameters was carried out through a test/error approach to ensure optimal feature selection. Model performance was assessed using various metrics, including Normalized Mean Square Error (NMSE), RMSE, MAPE, Nash-Sutcliffe Efficiency Coefficient (Ec), and $R^2$. The study's results demonstrated the superior performance of the proposed WA-SVR model compared to conventional methods such as SVR, ANN, and the traditional ARIMA model, as indicated by the evaluation metrics. Zhou et al. (2017) introduced, a data-driven prediction model, combining discrete wavelet transform (DWT) preprocessing with the SVM to simulate and forecast GWLs accurately. For comparison, standard ANN and conventional SVM algorithms were employed, alongside a variant called Wavelet Preprocessed ANNs (WANN). Lag values for GWL inputs were optimized using the Partial Autocorrelation Function. The kernel function employed was the Radial Basis Function (RBF) with hyperparameter tuning accomplished via a PSO-based optimization approach. Evaluation metrics included Relative Absolute Error (RAE), R, RMSE, and the NSE coefficient. The results highlighted the exceptional predictive capabilities of the Wavelet Preprocessed Support Vector Machine (WSVM) model in the study. Guzman et al. (2019) examined the predictive capabilities of two ML models namely: a Nonlinear Autoregressive with Exogenous Inputs (NARX) ANN and the SVR model with a Radial Basis Function (RBF) algorithm. The research centered on an irrigation well situated in the southeastern United States, examining input factors such as Groundwater Levels (GWL), Precipitation, and Evapotranspiration. For the SVR model, an RBF kernel function with specific parameter configurations ($\gamma$ = 0.01, C = 100, $\epsilon$ = 0.1) was identified as the optimal setup for both summer withdrawal and winter recharge seasons. Model performance, assessed using the MSE metric, consistently favored the SVR model, which demonstrated superior predictive capabilities in this analysis. Hussein et al. (2020) assessed the performance of five different machine learning algorithms in predicting GWLs. These algorithms included MLR, MLP, RF, Extreme Gradient Boosting (XGB), and SVR. For the prediction tasks, the XGB model was used, not only for predictions but also for selecting relevant features. Moreover, feature engineering was performed using the Gaussian Mixture Model. The dataset utilized in the study was obtained from GRACE (Gravity Recovery and Climate Experiment), a valuable resource in Earth sciences. To evaluate the models' performance, RMSE and MAE were employed as the primary assessment metrics. Consistently, the results demonstrated that SVR outperformed the other models in this thorough analysis. Yin et al. (2021) introduced a novel approach to groundwater ensemble modeling, incorporating machine learning techniques and Bayesian model averaging. This framework enhances predictions of GW storage changes, thereby strengthening the overall reliability of GW modeling. Three distinct machine learning models were developed: ANN, SVM, and Response Surface Regression. These models were fed with input variables, including monthly agricultural supply requirements (ASR), groundwater pumping (GP), and surface water delivery (SWD), associated with land and water use dynamics. The SVM model used the Gaussian kernel. The findings indicated that the SVM model exhibited relatively low uncertainty and strong prediction capabilities, especially at the regional scale. Yu et al. (2021) utilized, Grey Relational Analysis (GRA) and Factor Analysis (FA) for optimal feature selection in Minqin County, northwestern China. These methods were combined with Support Vector Machine (SVM) modeling and compared with standalone SVM, Backpropagation Neural Network (BPNN), and Radial Basis Function Neural Network (RBFNN). Input variables included various environmental and socio-economic factors. The kernel function utilized was the RBF. The evaluation, considering metrics such as RMSE, MAE, and R, demonstrated that GRA-FA-SVM exhibited superior performance, closely followed by GRA-SVM. Mukherjee and Ramachandran (2018) investigated the correlation between terrestrial water changes derived from GRACE data ($\triangle$TWS) and GWLs across various regions in India. Five observation wells from various geographic areas were selected for analysis. Three machine learning models were employed: LRM, SVR, and ANN. Input variables included $\triangle$TWS and meteorological parameters including wind, precipitation, temperature, and humidity. The study concluded that SVR outperformed ANN and LRM in modeling irregular time series GWL data. Mukherjee and Ramachandran (2018) research recommends the potential utility of $\triangle$TWS as a valuable tool for modeling GWL, particularly in scenarios with irregular time series data. Dehghani et al. (2022) assessed the impact of climate change's impact on groundwater levels in Iran's Khorramabad plain. Five Atmosphere-Ocean General Circulation Models (AOGCM) were used under the RCP8.5 scenario to predict meteorological parameters. These variables were utilized in hybrid machine learning frameworks, including Black Widow Spider-Support Vector Regression (BWO-SVR), WSVR, and AIG-SVR, to estimate GWLs. The models incorporated covariates including precipitation, temperature, GWLs, and water withdrawal data. Parameter tuning utilized the creative rifile and black widow approaches, considering various kernel functions. Evaluation metrics included $R^2$, RMSE, MAE, NSE, and PBIAS. Results showed all models performed well in simulating groundwater levels, with WSVR consistently offering the most accurate predictions. Dehghani et al. (2022) study underscores hybrid ML models' significance in assessing climate change's influence on GW, emphasizing WSVR's effectiveness for Khorramabad plain's groundwater level prediction and aiding groundwater management amid climate variability. Liu et al. (2021) conducted a study using SVM and SVM coupled with data assimilation (DA) to forecast short to medium-term GWL changes in the northeastern United States, spanning 1 to 3 months. Input variables included GRACE-informed groundwater anomalies, air temperature (t2m), precipitation, solar radiation, precipitation, infrared surface, and temperature. Correlation analysis determined influential variables. The RBF kernel function was employed, with trial-and-error optimizing $\sigma$, C, and $\epsilon$ SVM parameters. Evaluation metrics encompassed the R, NSE, MAE, and RMSE. Results showed both SVM and SVM-DA accurately predicted groundwater levels. SVM-DA, particularly with GRACE data, excelled as the most proficient model. Yadav et al. (2020) employed an ML modeling technique integrating mutual information (MI) theory, singular spectrum analysis (SSA), GA, ANN, and SVM. This approach aimed to investigate the impact of various climatic and non-climatic factors on GWL fluctuations within India. The model's input variables encompass GWL, rainfall, temperature, Northern Oscillation Index, Southern Oscillation Index (SOI), NINO3, monthly population data, and growth rate. SVM model parameters, including the regularization constant, insensitive loss function, and Radial Basis Function parameter ($\sigma$), were derived for each well location. Across all locations, the regularization constant ranged from 1.42 to 2.65, while insensitive loss function values spanned from 0.032 to 0.098. The Kernel Basis Function was employed for this study, and other hyperparameters were fine-tuned via a systematic trial-and-error approach. The assessment, based on metrics like R, RMSE, and NMSE, demonstrated that the hybrid models (SSA-MI-GA-ANN and SSA-MI-GA-SVM) outperformed the standalone models. Ebrahimi and Rajaee (2017), investigated the impact of wavelet analysis on the training of machine learning (ML) models, specifically ANN, MLR, and SVR. Their study focused on simulating one-month-ahead GWL predictions in the Qom plain, Iran, comparing the predictive capabilities of standalone models (ANN, MLR, SVR) with models enhanced by wavelet analysis, namely wavelet-ANN (WNN), wavelet-MLR (WLR), and wavelet-SVR (WSVR). The sole input variable for their models was GWL, and they employed auto-correlation analysis to optimize feature selection. The RBF served as the kernel function for SVR, with parameters fine-tuned through a test/error approach. Evaluation metrics, including the Efficiency coefficient (E) and RMSE, demonstrated that WNN, WLR, and WSVR consistently performed better than the standalone models. In a 2021 study by Kajewska-Szkudlarek et al. (2022), monthly Groundwater Level prediction for three wells in northern Greater Poland Province was explored. SVR and MLP techniques were employed, to identify the optimal predictors from hydrological and meteorological time series data. The Hellwig method was used for systematic predictor selection. Input variables included GWL, rainfall, and temperature data, with the RBF as the kernel. Parameters were fine-tuned; regularization was set to 10, insensitive loss function to 0.100, and RBF parameter ranged from 0.091 to 1, with support vectors varying from 48 to 117. Model performance metrics included $R^2$, MSE, and MAE. Kajewska-Szkudlarek et al. (2022) concluded that SVR outperformed MLP slightly.

#### 4.3.2. Results

SVMs/SVRs have emerged as robust machine learning methodologies with a proven track record in addressing diverse classification and prediction tasks. While the utilization of SVM in modeling GWL is not extensively explored, it's significant to highlight that SVMs have exhibited their efficacy in predicting diverse time series data in numerous real-world applications globally. In the SVM/SVR modeling, the correct selection of the kernel function and parameter values is very important. Based on the reviewed papers we found that,

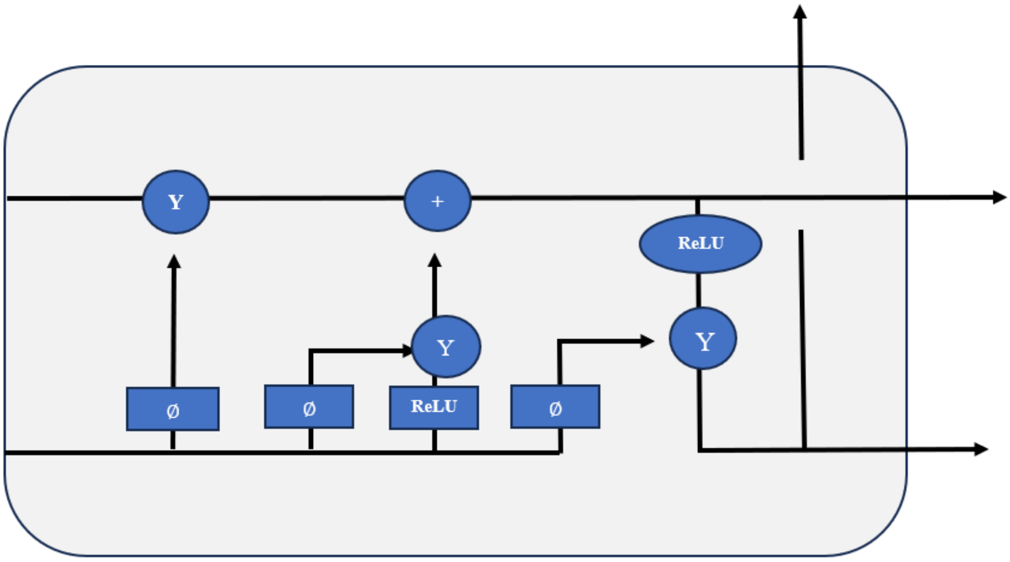


**Figure 9:** Standard LSTM model Structure.

1. The RBF that is the Radial Basis Function kernel was the most frequently employed, followed by the Polynomial and Linear kernels. The RBF kernel formulated by (Broomhead and Lowe, 1988) in 1988 is a mathematical function commonly used in machine learning, particularly in support vector machines (SVM) and other kernel-based algorithms. It is a type of kernel function that helps transform data into a higher-dimensional space, making it easier to classify or separate non-linear data. it's important to note that there's no one-size-fits-all kernel function. The choice of kernel relies on the particular problem, dataset, and its inherent characteristics. In some cases, other kernels like linear, polynomial, or sigmoid kernels may perform better.
2. Hyper-parameters were predominantly fine-tuned through a trial-and-error approach. However, in specific instances, alternative methods such as the Creative Rifle and Black Widow (Kajewska-Szkudlarek et al., 2022), the Taguchi Model (Seifi et al., 2020), and Grey Relational Analysis (GRA) and Factor Analysis (FA) (Yu et al., 2021) were utilized to optimize the tuning process.
3. In addition to correlation analysis, Principal Component Analysis (PCA) was commonly utilized to facilitate optimal feature selection.
4. SVMs, when tuned to optimal hyperparameters, consistently outperformed ANN and ANFIS models.

## 4.4. LSTM

### *4.4.1. Overview*

LSTM, a variant of recurrent neural networks (RNNs), was engineered for processing and forecasting sequential data patterns. It performs very well in tasks related to time series data, natural language processing, speech recognition, and similar domains. The design of LSTM addresses issues like the vanishing gradient problem often encountered in training traditional RNNs with lengthy data sequences (Hochreiter, 1998). The gradient vanishing issue arises when the gradients of the loss function diminish significantly. This phenomenon leads to minuscule weight updates during training, making it challenging for the network to capture long-range dependencies within the data effectively. The solution to this problem lies in the design of LSTMs (Hochreiter and Schmidhuber, 1997; Graves, 2012; Jozefowicz et al., 2015). Like RNNs, LSTMs are composed of chain-like modules. However, these repeating modules in LSTMs have more complex structures. Each module in LSTMs includes a memory block crafted to retain information over extended durations. This memory block comprises four components: a CEC (Constant Error Carousel) cell and three unique multiplicative units known as gates. The three fundamental gates within an LSTM include the input gate, the forget gate, and the output gate. These gates control the propagation of information within the memory block. This gate determines what novel information is relevant and should be retained in the memory block. It computes a new candidate value for the memory. The output gate decides which information should be revealed to the external layers of the LSTM. It evaluates both the present input and the internal state of the memory block to make this determination. These gates, working in tandem, allow LSTMs to efficiently capture long-range dependencies in sequences, making them a valuable tool for tasks like time series prediction, natural language processing, and various other sequential data analysis tasks. Figure 9 depicts the schematic figure of the LSTM model with the ReLU activation function.

### *4.4.2. Bibliographic review*

Kim et al. (2023) employed deep learning (DL) techniques to simulate and forecast GWLs in the volatile Gyorae area of Jeju Island. They utilized the LSTM model to simulate GWLs at the JH Gyorae-1 point. A dataset spanning 2012 to

2021, containing 12 daily hydro-meteorological variables, was collected. Cross-wavelet analysis and the Granger causality test were used to select five significant hydro-meteorological features: sun hours, minimum temperature, mean wind speed, evaporation, and daily precipitation. The LSTM model was configured with 10 layers and appropriate activation functions (hyperbolic tangent, sigmoid, and linear). A 10% dropout rate was set to prevent overfitting, and the Adam optimizer was used. Assessment metrics, including $R^2$, RMSE, and the Nash coefficient, consistently demonstrated the LSTM model's excellent performance in groundwater level forecasting. In a study by Haq et al. (2021), LSTM networks were employed for real-time tracking and prediction of Terrestrial Water Storage Change (TWSC) and Ground Water Storage Change (GWSC) in five Saudi Arabian basins. This analysis utilized GRACE datasets spanning from 2003 to 2025. Input variables included SatRain, GWSC, METRain, and TWSC. The study used correlation analysis to evaluate the influence of these variables on groundwater recharge. The LSTM model, comprising 4 nodes and trained for 2000 epochs with the ADAM optimizer at a learning rate of 0.1, displayed remarkable performance in both RMSE and computational efficiency. Comparative analysis against an autoregression-based model, utilizing comprehensive metrics including $R^2$, RMSE, MAPE, MAD, and NSE, revealed LSTM's superior performance, with the added benefit of faster computation times. Wu et al. (2021) introduced an innovative modeling strategy, the combined WT-multivariate LSTM (WT-MLSTM) method, for simulating and predicting groundwater levels (GWLs). This approach was tested in geographically diverse areas: the Liangshui River Basin in Beijing, China, and the Cibola National Wildlife Refuge along the lower Colorado River in the United States. The model's input variables consisted of river stage and groundwater table data, selected through data correlation analysis to optimize model performance. To fine-tune the model's hyperparameters, the study employed the Adam optimizer. Evaluation metrics, including $R^2$, RMSE, and NSE, were used to assess model performance. The results indicated that the combined WT-MLSTM model achieved superior prediction capabilities compared to standard LSTM, MLSTM, and WT-LSTM models. Furthermore, when compared to the SVM model, the proposed approach demonstrated distinct advantages. In a study by Zhang et al. (2018), the application and evaluation of the LSTM model were explored within five sub-areas of the Hetao Irrigation District in the arid region of northwestern China. The proposed model harnessed monthly data on evaporation, temperature, precipitation, water diversion, and time as inputs for predicting GWLs. To assess its efficacy, this LSTM model was compared with both the traditional FFNN and a double-layered LSTM model. After tuning via trial and error, the LSTM model's optimal hyperparameters were reported as follows: neurons = 40, learning rate = 0.001, dropout = 0.5, and iteration = 20000. Based on a comprehensive evaluation employing metrics such as $R^2$ and RMSE, the LSTM model exhibited superior performance in contrast to the FFNN and the double-layered LSTM model. Ao et al. (2021) assessed three different models in estimating Groundwater Levels (GWL) within the Hetao Irrigation District in China. These models included the kernel-based nonlinear extension of the Arps decline model (KNEA), the LSTM, and the GRU). The input variables used in the model comprised Lagged GWLs, t2m, precipitation, global solar radiation, and irrigation quantity. The model hyperparameters were optimized using a grid search method. Correlation analysis was executed to identify variables with significant influence. Based on the assessment's metrics, which included $R^2$, MSE, MAE, and NSE, the LSTM model emerged as the top performer. It was noted that the combination of temperature and GWL as input variables yielded the most accurate results. Vu et al. (2023), utilized deep learning to predict water dynamics in a Normandy karst massif in eastern France. The state-of-the-art Bidirectional LSTM (BiLSTM) model was employed. Input variables included river level, river flux, sea level, temperature, rainfall, GWLs, and Seinen River data. Feature relevance was determined through correlation analysis. The model's optimal configuration featured a single BiLSTM layer with a variable number of neurons, ranging from 5 to 50 based on input sequence complexity. The training process spanned 250 epochs and employed a consistent learning rate of 0.01, utilizing the Adam optimizer. Evaluation metrics included $R^2$, RMSE, NRMSE, and MAPE, all indicating that the BiLSTM model outperformed the standard LSTM in accurately forecasting water dynamics. In a recent study by Manna and Anitha (2023), groundwater level prediction in India was the focus. The study introduced a deep ensemble learning approach called the Double-Edge Bi-Directed Long Short-Term Memory (DEBi-LSTM) model. To enhance its performance, the model was approximated using the Randomized Low-Ranked Approximation algorithm (RLRA), and the Variance Inflation Factor (VIF) was used to feature selection and improve model accuracy. The study incorporated various data, including rainfall, groundwater recharge, and natural groundwater discharge. Model optimization involved fine-tuning several key parameters: a batch size of 32, 2 epochs, neuron configurations of 128 and 64, a dropout rate of 0.1, a learning rate of 0.01, and training with the Adam optimizer. Model performance was assessed using metrics such as Accuracy (AC), Precision (Pr), Recall (RC), and F1 score. The DEBi-LSTM model outperformed existing models like LSTM, bagging ensemble, and an ensemble model. Gaffoor et al. (2022) analyzed groundwater level variations in the Shire Valley Alluvial Aquifer using two ML techniques: gradient-boosted decision trees (GBDT) and LSTM-NN. Input variables included soil moisture, runoff, evapotranspiration, groundwater storage anomaly, precipitation, and surface temperature. Pearson's correlation analysis was used to explore relationships among these variables. For the LSTM model, hyperparameters were optimized individually for each of the four stations, including the number of epochs (100 to 1000), batch sizes (2 to 8), and the number of neurons (1 to 4). Model performance was assessed using RMSE, $R^2$, MAE, and NSE, with LSTM emerging as the superior model for simulating and forecasting GWL fluctuations. Patra et al. (2023) employed the LSTM model to simulate and forecast daily groundwater variations in the Choushui River Alluvial Fan, Central Taiwan, using GWL data. Two LSTM models were created: GLOBAL, for regional predictions, and LOCAL, for specific areas. The models employed an MSE loss function and ran for 200 epochs with early stopping to prevent overfitting (MSE improvement ceased after 10 epochs). Performance assessment metrics included RMSE, MAE, and the $R^2$. Results showed both global and local LSTMs achieved reasonable accuracy, and further improvements were made through transfer learning. Solgi et al. (2021), utilized LSTM-NN in groundwater level forecasting using historical GWL data as the sole input. This model was compared to a basic neural network (NN) for its effectiveness in predicting short-term and long-term GW

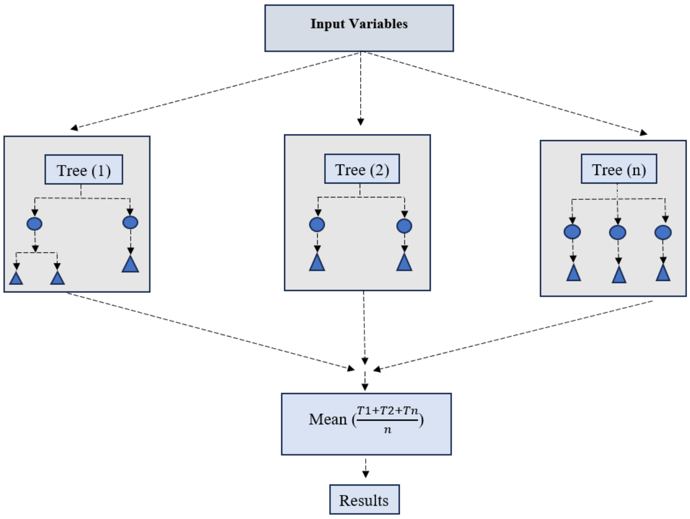


**Figure 10:** Standard RF model Structure.

levels within the Edwards aquifer in Texas. The LSTM-NN was trained using the Adam optimizer and featured an input layer, a single LSTM layer with 10 LSTM cells, and an output layer. The selection of optimal input variables followed a systematic trial-and-error approach. Assessments, incorporating metrics such as $R^2$, MAE, and MSE, consistently favored the LSTM-NN over the basic NN in all scenarios.

### *4.4.3. Results*

1. The Adam optimizer was predominantly utilized for training the LSTM model. The Adam optimizer is a relatively new optimizer developed by Kingma and Ba (2014). The Adam optimizer is known for its efficiency in terms of convergence speed. It combines the benefits of both the RMSprop optimizer and the Momentum optimizer. This allows it to converge faster and more reliably compared to some other optimization algorithms. The 100,000 plus citations in only 8 years show additionally the importance of the given paper. Adam dynamically adjusts the learning rates for each parameter during training. This adaptability is beneficial when dealing with complex models like LSTMs, where different parameters may require different learning rates to converge effectively. In terms of performance, LSTM consistently outperformed ANN models, possibly due to its inherent capability to overcome the limitations associated with local minima, which can hinder convergence in the training process.
2. The ReLU activation function was commonly utilized as the activation function for the LSTM model. The ReLU activation function was created by Nair and Hinton (2010) and it is well known for its ability to handle the gradient vanishing problem. Using the ReLU function as the activation in a neural network, as opposed to the sigmoid function, results in partial derivatives of the loss function having values of either 0 or 1. This property effectively mitigates the issue of gradient vanishing, making ReLU an effective choice for preventing gradient-related problems.
3. Hyperparameters were mostly adjusted through trial and error. However, in some cases, like in the study by (Ao et al., 2021), the grid search method was used. The grid search approach is a systematic method used in machine learning to find the optimal hyperparameters for a model. it involves defining a grid of possible values for each hyperparameter and then evaluating the model's performance for every possible combination of these values.
4. The selection of optimal input variables primarily relied on correlation analyses. However, in some select cases, methods such as Cross-wavelet analysis and the Granger causality (Kim et al., 2023), and Variance Inflation Factor (VIF) (Manna and Anitha, 2023) were employed to improve model performance through enhanced feature selection
5. In terms of performance, LSTM consistently outperformed ANN models, possibly due to its inherent capability to overcome the limitations associated with local minima, which can hinder convergence in the training process.

## 4.5. Random Forest (RF)

RF is a machine learning method grounded in decision trees, versatile for classification and regression tasks (Breiman, 2001). Decision trees (DT) are versatile tools in supervised learning, capable of handling both classification and regression tasks. RF, specifically, stands out due to its ensemble of multiple independent decision trees. This independence ensures that each tree is unique, as it's trained using slightly different samples of the training data, resulting in minor performance variations and reduced overall model variance. The final prediction of the RF model combines inputs from all decision trees in the ensemble. The performance of the RF model is intricately tied to essential parameters: "ntree" (representing the number of decision trees), "mtry" (indicating the number of variables examined at each decision tree node), and "max depth" (denoting the maximum allowed node divisions in decision trees) (Biau and Scornet, 2016; Brédy et al., 2020; Rahman et al., 2020). Figure 10 depicts the schematic figure of the RF model.

### *4.5.1. Bibliographic review*

In the scope of water table simulation and modeling with RF, Gonzalez and Arsanjani (2021) investigated water level changes in Denmark under various climate change scenarios. Three ML algorithms – ANN, SVM, and RF were applied using the R programming environment. The dataset included diverse independent variables: soil parameters, topography, and climate variables such as maximum temperature, precipitation, minimum temperature, and average temperature. PCA and correlation tests were employed to refine the dataset by selecting relevant variables and eliminating highly correlated or less informative ones. Model predictive capabilities was assessed using standard metrics, including $R^2$, RMSE, and MAE. Results consistently favored the RF model as the best performer, emphasizing its suitability for the study's objectives. In a study by Zhou et al. (2022), an investigation was undertaken to assess the capability of satellite data from the GRACE, the Global Land Evaporation Amsterdam Model (GLEAM) data, and the Global Land Data Assimilation System (GLDAS), in combination with meteorological variables, to predict GWL utilizing three distinct ML models: ELM, SVR, and RF. The meteorological variables considered for the analysis included temperature, precipitation, and actual evapotranspiration. Hyperparameter tuning for the RF model across all three wells involved adjustments to Ntree (ranging from 100 to 500) and Mtry (ranging from 1 to 3). Evaluations, utilizing metrics such as R, NSE, and RMSE, consistently indicated RF as the superior performer, followed by SVR and ELM in that order. In a study by Liu et al. (2022), ML and DL techniques were employed to simulate GWLs within the lower Tarim River basin. They used SVM, General Regression Neural Network (GRNN), DT, RF, CNN, LSTM, and GRU. The input data for these models comprised temperature, relative humidity, and additional relevant variables. Notably, precipitation was omitted from consideration, as it was deemed inconsequential in contributing to GW supply within the arid and semi-arid regions of interest. To gain insights into the impact of covariates on model performance, the SHAP (SHapley Additive exPlanations) method was applied. An evaluation of the models' performance based on the ($R^2$, PBIAS, MARE, RF), reviewed that the RF model consistently performed better than the other models, establishing its superiority in this groundwater level simulation task. Lendzioch et al. (2021), evaluated the predictive capabilities of ultrahigh-resolution Unmanned Aerial Vehicle (UAV) maps for peat bog GWL and soil moisture. The study used the RF model, employing a leave-location-out (LLO) cross-validation (CV) approach to assess model performance accurately. To ensure robust and accurate predictions, a forward feature selection (FFS) technique was incorporated, allowing for the inclusion of only the most pertinent predictor variables for both spatial and temporal model predictions. Moreover, an initial correlation analysis was undertaken to identify and eliminate highly correlated and redundant variables from consideration. The mtry parameter for the RF model was set at 2. The model utilized 34 predictor variables as inputs. Based on the RMSE and $R^2$, they reported that the RF model demonstrated commendable performance in predicting peat bog GWL and SM. Pham et al. (2022) performed a contrastive study to assess the predictive capabilities of seven distinct ML models for simulating and forecasting GWLs. These models included Random Tree (RT), RF, Decision Stump, M5P, SVM, Locally Weighted Linear Regression (LWLR), and Reduced Error Pruning Tree (REP Tree). The input variables for these models comprised lagged GWLs, mean temperature, rainfall, and relative humidity. The study utilized Bootstrap Aggregating (bagging) as a technique to refine the models, with specific parameters such as batch size (100), bag size percent (80), classifier (REPTree), max depth (0), number of execution slots (1), number of iterations (100), and random seed (1) being fine-tuned for optimal results. To assess model performance, the study employed several metrics, including Root Relative Squared Error (RRSE), RMSE, Relative Absolute Error (RAE), Pearson Correlation Coefficient (CC), MAE, and Taylor Diagram. They concluded that the Bagging RF and Bagging RT models consistently demonstrated superior performance compared to the other models, establishing their suitability for GWL prediction tasks. Mosavi et al. (2021) conducted a comprehensive investigation employing a diverse array of models, including the Boosted Generalized Additive Model (GamBoost), Adaptive Boosting Classification Trees (AdaBoost), Bagged Classification and Regression Trees (Bagged CART), and Random Forest (RF), to simulate and forecast groundwater levels (GWLs) within the Dezekord-Kamfiruz watershed in Iran. The study encompassed an extensive selection of geological and meteorological variables, emphasizing a holistic approach to model development. In selecting the optimal variables, the Recursive Feature Elimination (RFE) method was employed, accompanied by an assessment of multicollinearity through the application of the Variance Inflation Factor (VIF). The Topographic Position Index emerged as the most influential variable among the considered factors. Utilizing performance metrics such as Accuracy, Kappa, Precision, and Recall, the authors deduced that the Bagging models, specifically Random Forest and Bagged CART, exhibited superior performance compared to the Boosting models (AdaBoost and GamBoost). Notably, Random Forest demonstrated the most exemplary performance overall.

### *4.5.2. Results*

1. In the extensive body of research we've examined, it's clear that both standalone RF models and their hybrid counterparts consistently outperform traditional models like ANN and SVM in various fields. RF's strength primarily lies in its exceptional predictive accuracy, which makes it a valuable tool across many applications. However, a common concern emerges from the majority of the reviewed papers. This concern centers on the computational speed of RF models, which tends to be slower compared to the alternative models they're compared against. While RF's predictive capability is robust, its relatively slower computational speed is an important factor to consider.
2. In conjunction with correlation analysis, the SHAP (SHapley Additive exPlanations) and the Recursive Feature Elimination (RFE) (Mosavi et al., 2021) methods were occasionally employed to select optimal input variables for the models. A noteworthy observation is that many papers did not explicitly specify the hyperparameter values for 'ntree' and 'mtry.'

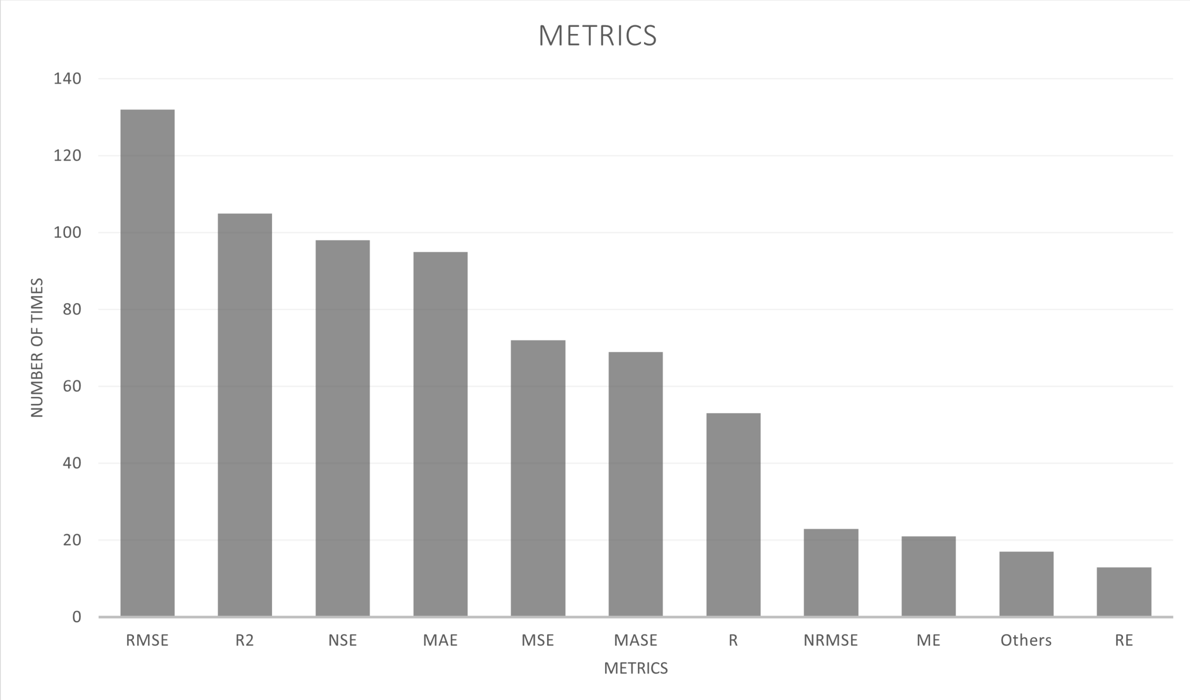


**Figure 11:** Various metrics used in validation reviewed ML models' performance.

## 5. General Overview and Discussion

In this section, we will highlight key findings from the analysis of the 170 reviewed papers. These findings encompass various aspects, including the treatment of time steps, selection of input variables, validation metrics, etc.

### 5.1. Validation metrics

Machine learning models are not immune to inherent limitations that can impact their performance. For instance, ANN models, a prevalent choice in this domain, are susceptible to overfitting. Overfitting occurs when a model excessively captures noise in the data, often stemming from redundant or irrelevant input variables. This limitation impedes the model's capacity to generalize efficiently when confronted with new, unseen data during testing. Given these challenges, a rigorous assessment of model performance is imperative. Throughout our review of existing literature, we observed a wide range of evaluation metrics utilized to assess the effectiveness of the employed models. The choice of these performance metrics is crucial, as they measure how accurately a model's predictions align with the actual values. Among the metrics commonly adopted by researchers, we noted the prevalence of RMSE, NRMSE, MAE, MSE, R, mean error (ME), RE, and $R^2$. While these metrics have all found their place in GWL modeling studies, RMSE and $R^2$ emerged as particularly prominent choices in the majority of cases. Figure 11 illustrates various performance evaluation metrics utilized by different experts in GWL prediction.

### 5.2. Covariates Used

ML models offer a unique advantage by learning patterns in data, whether simple or complex, to predict specific outcomes. In the context of this systematic review, we examine the use of different types of data for groundwater modeling, including climate variables, hydrogeological parameters, and aquifer characteristics, albeit the latter being non-mandatory compared to conventional models. The choice of these covariates is critical, significantly affecting model performance. Groundwater levels are closely tied to climate conditions, and the ever-growing concerns of climate change, marked by events like droughts, floods, and shifting precipitation patterns, emphasize the urgency of groundwater management. Figure 12 depicts that historical GWL data is the most employed covariate for ML models predicting groundwater levels. Out of 170 papers, 163 incorporate groundwater level data as an input, with 63 using it as the sole input without additional factors. Precipitation data is also frequently used, appearing in 108 instances. Other hydrological data, such as temperature, river discharge, evapotranspiration, and surface water levels, have been employed as inputs. Some papers have explored additional variables like irrigation patterns, population figures, seasonal factors, and more, though to a lesser extent. These variables may present challenges during the input selection process.

### 5.3. Programming Languages Utilised

In the review, we realized that most of the research papers used MATLAB, PYTHON, and R to build the various ML algorithms used. Researchers predominantly utilizing these programs for developing machine learning algorithms in their studies can be attributed to the fact that these programming languages offer extensive libraries and frameworks specifically tailored for machine learning, simplifying algorithm development and implementation. Python, in particular, boasts a vast

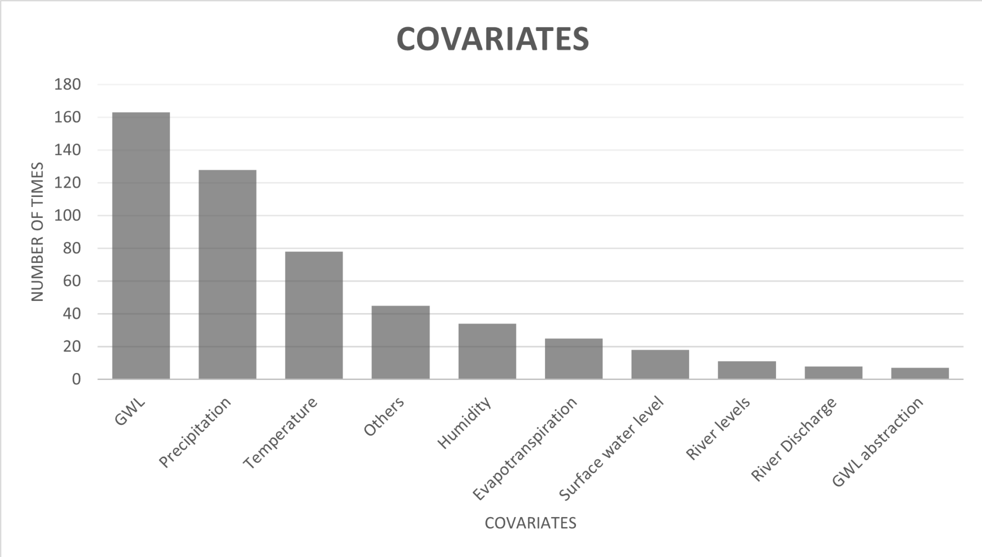


**Figure 12:** Various covariates employed in reviewed articles.

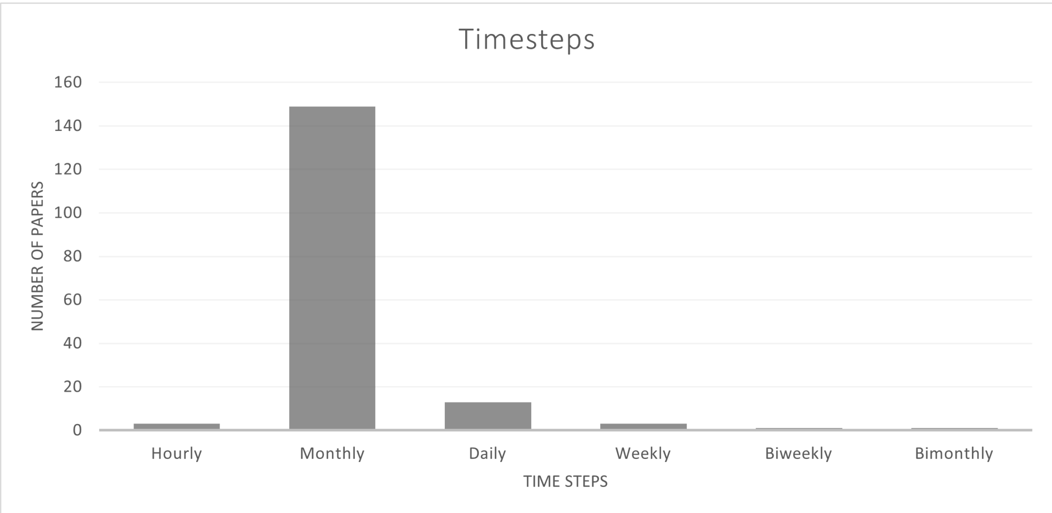


**Figure 13:** Different time steps used in GWL modeling

machine-learning ecosystem, including popular libraries like Scikit-Learn and TensorFlow, making it highly versatile and ideal for a wide variety of ML tasks. R is favored for its exceptional statistical capabilities and visualization tools, providing researchers with robust data analysis and model interpretation capabilities alongside machine learning functionalities. These languages are open-source, facilitating collaboration and accessibility for researchers globally, while also significantly reducing research costs. Their active and supportive communities continuously contribute to the development and improvement of machine learning tools and resources, ensuring researchers have access to the latest advancements in the field. Information regarding these software programs is available online, and we do not delve into their specifics here. Nevertheless, it's noteworthy that MATLAB is commonly favored in the development of AI models, although a number of papers have not explicitly mentioned the software used.

## 5.4. Time Steps Used

Figure 13 presents an overview of the time intervals predominantly employed in the analyzed papers. A significant majority of the AI models under review, encompassing 151 out of 170 papers, adopted monthly time intervals for GWL modeling. This preference for monthly intervals was followed by daily intervals, which were featured in 13 papers. The frequent use of monthly intervals can be explained by the ready accessibility of monthly GWL data in contrast to data at other temporal resolutions. Additionally, this choice aligns with the consideration that many of these papers incorporated precipitation as a covariate. Precipitation's impact on groundwater typically exhibits a time lag, necessitating a longer temporal scale, as it traverses through the vadose zone to reach the water table. In many regions around the world, GWL typically exhibits minimal variations on an hourly, daily, or even weekly basis. However, specific geographic areas, such as coastal aquifers (Yoon et al., 2011; Taormina et al., 2012), or locations in proximity to large reservoirs like lakes or dams, experience notable fluctuations in GWLs due to tidal or lake-related influences (Rajaee et al., 2019).

## 6. Conclusion

Machine Learning(ML) algorithms have proven highly effective across various domains, including hydrological and groundwater modeling. This comprehensive analysis involves a systematic review of 170 research papers sourced from diverse online databases, all focusing on the application of ML models in groundwater modeling. The investigation spans from 2010 to September 2023, providing insight into contemporary methodologies employed with these models. After a thorough examination of this body of literature, it is evident that ML models excel at simulating and predicting GWLs across diverse geographical locations. What makes ML particularly intriguing is its ability to identify subtle patterns within groundwater-related data variables and the groundwater data itself. Leveraging this knowledge, ML models make precise predictions. It's important to note that this predictive capability relies on the availability of well-structured data. An important finding from our review is the critical role of variable selection in optimizing model performance. Several papers emphasized that the judicious selection of covariates arguably supersedes the selection of the model itself. In addition to input variables, ML models involve various hyper-parameters, and accurately tuning them is essential for peak model performance. We found that, in most cases, these parameters are adjusted through a trial-and-error process. However, some instances employ optimization algorithms to streamline the tuning process. This study serves as a valuable resource for researchers, offering guidance on established techniques for constructing ML models that yield superior results. Furthermore, it encourages the exploration of diverse approaches in feature selection and hyper-parameter tuning. Such diversification promises to unlock the full potential of ML models, expanding our ability to leverage their capabilities. Furthermore, in light of our extensive review of hybrid models, specifically, those integrating wavelet analysis with other techniques for extracting input time series, it became evident that these approaches offer a valuable means of enhancing our comprehension and capability to simulate GWL. Notably, commonly used mother wavelets for analyzing groundwater levels, specifically Daubechies-2 (db2) wavelet (the most popular wavelet) (Mallat, 1989), and Daubechies-4 (db4), showed remarkable effectiveness in groundwater-level modeling. Additionally, we recommend further exploration of the use of modeled meteorological variables from different IPCC-reported climate change scenarios, such as the various Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways(RCP) scenarios. This research promises to provide a more comprehensive understanding of how changing climates impact our groundwater resources, contributing to our knowledge of this critical issue. Moreover, to achieve optimal feature selection, some of the less conventional methods that we can recommend to be considered based on the reviewed literature include; the wavelet coherence analysis, the recursive feature elimination (RFE), the Shannon entropy, the pairwise correlation coefficient, and the Spearman correlation coefficient. These approaches can provide valuable insights into selecting the most suitable features for the models.

## Declaration of competing interest

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

## Acknowledgement

Support for implementation of project activities was made possible by the Research Grant (109705-001/002) by the Responsible Artificial Intelligence Network for Climate Action in Africa (RAINCA) consortium made up of WASCAL, RUFORUM and AKADEMIYA 2063 provided by IDRC.

## References

Aderemi, B. A., Olwal, T. O., Ndambuki, J. M., and Rwanga, S. S. (2023). Groundwater levels forecasting using machine learning models: A case study of the groundwater region 10 at karst belt, south africa. *Systems and Soft Computing*, 5:200049.

Afan, H. A., Ibrahem Ahmed Osman, A., Essam, Y., Ahmed, A. N., Huang, Y. F., Kisi, O., Sherif, M., Sefelnasr, A., Chau, K.-w., and El-Shafie, A. (2021). Modeling the fluctuations of groundwater level by employing ensemble deep learning techniques. *Engineering Applications of Computational Fluid Mechanics*, 15(1):1420–1439.

Afrifa, S., Zhang, T., Appiahene, P., and Varadarajan, V. (2022). Mathematical and machine learning models for groundwater level changes: a systematic review and bibliographic analysis. *Future Internet*, 14(9):259.

Ahmadi, A., Olyaei, M., Heydari, Z., Emami, M., Zeynolabedin, A., Ghomlaghi, A., Daccache, A., Fogg, G. E., and Sadegh, M. (2022). Groundwater level modeling with machine learning: a systematic review and meta-analysis. *Water*, 14(6):949.

Ao, C., Zeng, W., Wu, L., Qian, L., Srivastava, A. K., and Gaiser, T. (2021). Time-delayed machine learning models for estimating groundwater depth in the hetao irrigation district, china. *Agricultural Water Management*, 255:107032.

Arabameri, A., Roy, J., Saha, S., Blaschke, T., Ghorbanzadeh, O., and Tien Bui, D. (2019). Application of probabilistic and machine learning models for groundwater potentiality mapping in damghan sedimentary plain, iran. *Remote Sensing*, 11(24):3015.

Banadkooki, F. B., Ehteram, M., Ahmed, A. N., Teo, F. Y., Fai, C. M., Afan, H. A., Sapitang, M., and El-Shafie, A. (2020). Enhancement of groundwater-level prediction using an integrated machine learning model optimized by whale algorithm. *Natural resources research*, 29:3233–3252.

Behzad, M., Asghari, K., and Coppola Jr, E. A. (2010). Comparative study of svms and anns in aquifer water level prediction. *Journal of Computing in Civil Engineering*, 24(5):408–413.

Biau, G. and Scornet, E. (2016). A random forest guided tour. *Test*, 25:197–227.

Brédy, J., Gallichand, J., Celicourt, P., and Gumiere, S. J. (2020). Water table depth forecasting in cranberry fields using two decision-tree-modeling approaches. *Agricultural Water Management*, 233:106090.

Breiman, L. (2001). Random forests. *Machine learning*, 45:5–32.

Broomhead, D. S. and Lowe, D. (1988). Radial basis functions, multi-variable functional interpolation and adaptive networks. *Royal signals and radar establishment Malvern (United Kingdom)*, 25(3):1–8.

Brunner, P. and Simmons, C. T. (2012). Hydrogeosphere: a fully integrated, physically based hydrological model. *Ground water*, 50(2):170–176.

Butler Jr, J., Stotler, R., Whittemore, D., and Reboulet, E. (2013). Interpretation of water level changes in the high plains aquifer in western kansas. *Groundwater*, 51(2):180–190.

Chakraborty, S., Maity, P. K., and Das, S. (2020). Investigation, simulation, identification and prediction of groundwater levels in coastal areas of purba midnapur, india, using modflow. *Environment, Development and Sustainability*, 22:3805–3837.

Chen, C., He, W., Zhou, H., Xue, Y., and Zhu, M. (2020). A comparative study among machine learning and numerical models for simulating groundwater dynamics in the heihe river basin, northwestern china. *Scientific reports*, 10(1):3904.

Chidepudi, S. K. R., Massei, N., Jardani, A., Henriot, A., Allier, D., and Baulon, L. (2023). A wavelet-assisted deep learning approach for simulating groundwater levels affected by low-frequency variability. *Science of The Total Environment*, 865:161035.

Choubin, B. and Malekian, A. (2017). Combined gamma and m-test-based ann and arima models for groundwater fluctuation forecasting in semiarid regions. *Environmental earth sciences*, 76:1–10.

Collados-Lara, A. J., Pulido-Velazquez, D., Ruiz, L., Pegalajar, M., Pardo-Igúzquiza, E., and Baena-Ruiz, L. (2023). A parsimonious methodological framework for short-term forecasting of groundwater levels. *Science of the Total Environment*, 881:163328.

Cortes, C. and Vapnik, V. (1995). Support-vector networks. *Machine learning*, 20:273–297.

Daliakopoulos, I. N., Coulibaly, P., and Tsanis, I. K. (2005). Groundwater level forecasting using artificial neural networks. *Journal of hydrology*, 309(1-4):229–240.

Dash, N. B., Panda, S. N., Remesan, R., and Sahoo, N. (2010). Hybrid neural modeling for groundwater level prediction. *Neural Computing and Applications*, 19:1251–1263.

Dehghani, R., Poudeh, H. T., and Izadi, Z. (2022). The effect of climate change on groundwater level and its prediction using modern meta-heuristic model. *Groundwater for Sustainable Development*, 16:100702.

Deka, P. C. et al. (2014). Support vector machine applications in the field of hydrology: a review. *Applied soft computing*, 19:372–386.

Derbela, M. and Nouiri, I. (2020). Intelligent approach to predict future groundwater level based on artificial neural networks (ann). *Euro-Mediterranean Journal for Environmental Integration*, 5:1–11.

Ebrahimi, H. and Rajaee, T. (2017). Simulation of groundwater level variations using wavelet combined with neural network, linear regression and support vector machine. *Global and Planetary Change*, 148:181–191.

El Ibrahimi, A., Baali, A., Couscous, A., Hamdani, N., et al. (2017). Comparative study of the three models (ann-pmc),(dwt-ann-pmc) and (mlr) for prediction of the groundwater level of the surface water table in the saïss plain (north of morocco). *International Journal of Intelligent Engineering & Systems*, 10(5).

Emamgholizadeh, S., Moslemi, K., and Karami, G. (2014). Prediction the groundwater level of bastam plain (iran) by artificial neural network (ann) and adaptive neuro-fuzzy inference system (anfis). *Water resources management*, 28:5433–5446.

Famiglietti, J. S. (2014). The global groundwater crisis. *Nature Climate Change*, 4(11):945–948.

Gaffoor, Z., Pietersen, K., Jovanovic, N., Bagula, A., Kanyerere, T., Ajayi, O., and Wanangwa, G. (2022). A comparison of ensemble and deep learning algorithms to model groundwater levels in a data-scarce aquifer of southern africa. *Hydrology*, 9(7):125.

Garg, A. X., Hackam, D., and Tonelli, M. (2008). Systematic review and meta-analysis: when one study is just not enough. *Clinical journal of the American Society of Nephrology*, 3(1):253–260.

Gharehbaghi, A., Ghasemlounia, R., Ahmadi, F., and Albaji, M. (2022). Groundwater level prediction with meteorologically sensitive gated recurrent unit (gru) neural networks. *Journal of Hydrology*, 612:128262.

Gong, Y., Zhang, Y., Lan, S., and Wang, H. (2016). A comparative study of artificial neural networks, support vector machines and adaptive neuro fuzzy inference system for forecasting groundwater levels near lake okeechobee, florida. *Water resources management*, 30:375–391.

Gonzalez, R. Q. and Arsanjani, J. J. (2021). Prediction of groundwater level variations in a changing climate: A danish case study. *ISPRS International Journal of Geo-Information*, 10(11):792.

Govindaraju, R. S. et al. (2000). Artificial neural networks in hydrology. i: Preliminary concepts. *Journal of Hydrologic Engineering*, 5(2):115–123.

Graves, A. (2012). Sequence transduction with recurrent neural networks. *arXiv preprint arXiv:1211.3711*.

Gupta, A. and Kumar, A. (2022). Two-step daily reservoir inflow prediction using arima-machine learning and ensemble models. *Journal of Hydro-environment Research*, 45:39–52.

Guzman, S. M., Paz, J. O., and Tagert, M. L. M. (2017). The use of narx neural networks to forecast daily groundwater levels. *Water resources management*, 31:1591–1603.

Guzman, S. M., Paz, J. O., Tagert, M. L. M., and Mercer, A. (2015). Artificial neural networks and support vector machines: Contrast study for groundwater level prediction. In *2015 ASABE annual international meeting*, page 1. American Society of Agricultural and Biological Engineers.

Guzman, S. M., Paz, J. O., Tagert, M. L. M., and Mercer, A. E. (2019). Evaluation of seasonally classified inputs for the prediction of daily groundwater levels: Narx networks vs support vector machines. *Environmental Modeling & Assessment*, 24:223–234.

Haq, M. A., Jilani, A. K., and Prabu, P. (2021). Deep learning based modeling of groundwater storage change. *CMC-Computers, Materials & Continua*, 70:4599–4617.

Haykin, S. (1999). Neural networks a comprehensive foundation (sec2 ond edition).

Hochreiter, S. (1998). The vanishing gradient problem during learning recurrent neural nets and problem solutions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 6(02):107–116.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8):1735–1780.

Hussein, E. A., Thron, C., Ghaziasgar, M., Bagula, A., and Vaccari, M. (2020). Groundwater prediction using machine-learning tools. *Algorithms*, 13(11):300.

Jalalkamali, A., Sedghi, H., and Manshouri, M. (2011). Monthly groundwater level prediction using ann and neuro-fuzzy models: a case study on kerman plain, iran. *Journal of hydroinformatics*, 13(4):867–876.

Jang, J.-S. (1993). Anfis: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, 23(3):665–685.

Jeong, J. and Park, E. (2019). Comparative applications of data-driven models representing water table fluctuations. *Journal of Hydrology*, 572:261–273.

Jozefowicz, R., Zaremba, W., and Sutskever, I. (2015). An empirical exploration of recurrent network architectures. In *International conference on machine learning*, pages 2342–2350. PMLR.

Kajewska-Szkudlarek, J., Kubicz, J., and Kajewski, I. (2022). Correlation approach in predictor selection for groundwater level forecasting in areas threatened by water deficits. *Journal of Hydroinformatics*, 24(1):143–159.

Kalu, I., Ndehedehe, C. E., Okwuashi, O., Eyoh, A. E., and Ferreira, V. G. (2022). A new modelling framework to assess changes in groundwater level. *Journal of Hydrology: Regional Studies*, 43:101185.

Kayhomayoon, Z., Babaeian, F., Ghordoyee Milan, S., Arya Azar, N., and Berndtsson, R. (2022). A combination of metaheuristic optimization algorithms and machine learning methods improves the prediction of groundwater level. *Water*, 14(5):751.

Kenda, K., Čerin, M., Bogataj, M., Senožetnik, M., Klemen, K., Pergar, P., Laspidou, C., and Mladenić, D. (2018). Groundwater modeling with machine learning techniques: Ljubljana polje aquifer. In *Proceedings*, volume 2, page 697. MDPI.

Kim, D., Jang, C., Choi, J., and Kwak, J. (2023). A case study: Groundwater level forecasting of the gyorae area in actual practice on jeju island using deep-learning technique. *Water*, 15(5):972.

Kingma, D. P. and Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Koohestani, N., Halaghi, M. M., Dehghani, A., et al. (2013). Numerical simulation of groundwater level using modflow software (a case study: Narmab watershed, golestan province). *International Journal of Advanced Biological and Biomedical Research*, 1(8):858–873.

Kuhn, M., Johnson, K., Kuhn, M., and Johnson, K. (2013). Data pre-processing. *Applied predictive modeling*, pages 27–59.

Kumar, D., Roshni, T., Singh, A., Jha, M. K., and Samui, P. (2020). Predicting groundwater depth fluctuations using deep learning, extreme learning machine and gaussian process: a comparative study. *Earth Science Informatics*, 13:1237–1250.

Kurniawan, B., Tapriziah, E., Aryantie, M., Rahmani, R., and Purnomo, A. (2021). Application of groundwater modeling to predict the effectiveness of various peat dome restoration methods in pulang pisau district, central kalimantan province. In *IOP Conference Series: Earth and Environmental Science*, volume 909, page 012004. IOP Publishing.

Lee, S., Lee, K.-K., and Yoon, H. (2019). Using artificial neural network models for groundwater level forecasting and assessment of the relative impacts of influencing factors. *Hydrogeology Journal*, 27(2).

Lendzioch, T., Langhammer, J., Vlček, L., and Minařík, R. (2021). Mapping the groundwater level and soil moisture of a montane peat bog using uav monitoring and machine learning. *Remote Sensing*, 13(5):907.

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., and Moher, D. (2009). The prisma statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. *BMJ*, 339.

Liu, D., Mishra, A. K., Yu, Z., Lü, H., and Li, Y. (2021). Support vector machine and data assimilation framework for groundwater level forecasting using grace satellite data. *Journal of Hydrology*, 603:126929.

Liu, Q., Gui, D., Zhang, L., Niu, J., Dai, H., Wei, G., and Hu, B. X. (2022). Simulation of regional groundwater levels in arid regions using interpretable machine learning models. *Science of The Total Environment*, 831:154902.

Maier, H. R., Jain, A., Dandy, G. C., and Sudheer, K. P. (2010). Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions. *Environmental modelling & software*, 25(8):891–909.

Maiti, S. and Tiwari, R. (2014). A comparative study of artificial neural networks, bayesian neural networks and adaptive neuro-fuzzy inference system in groundwater level prediction. *Environmental earth sciences*, 71:3147–3160.

Mallat, S. G. (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE transactions on pattern analysis and machine intelligence*, 11(7):674–693.

Manna, T. and Anitha, A. (2023). Deep ensemble-based approach using randomized low-rank approximation for sustainable groundwater level prediction. *Applied Sciences*, 13(5):3210.

Markovics, D. and Mayer, M. J. (2022). Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction. *Renewable and Sustainable Energy Reviews*, 161:112364.

Mayer, M. J. and Gróf, G. (2021). Extensive comparison of physical models for photovoltaic power forecasting. *Applied Energy*, 283:116239.

Mendeley (2022). Mendeley. `https://www.mendeley.com`. Accessed: July 17, 2023.

Milan, S. G., Kayhomayoon, Z., Azar, N. A., Berndtsson, R., Ramezani, M. R., and Moghaddam, H. K. (2023). Using machine learning to determine acceptable levels of groundwater consumption in iran. *Sustainable Production and Consumption*, 35:388–400.

Mohanty, S., Jha, M. K., Kumar, A., and Sudheer, K. (2010). Artificial neural network modeling for groundwater level forecasting in a river island of eastern india. *Water resources management*, 24:1845–1865.

Mohapatra, J. B., Jha, P., Jha, M. K., and Biswal, S. (2021). Efficacy of machine learning techniques in predicting groundwater fluctuations in agro-ecological zones of india. *Science of the Total Environment*, 785:147319.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., and Group*, P. (2009). Preferred reporting items for systematic reviews and meta-analyses: the prisma statement. *Annals of internal medicine*, 151(4):264–269.

Moravej, M., Amani, P., and Hosseini-Moghari, S.-M. (2020). Groundwater level simulation and forecasting using interior search algorithm-least square support vector regression (isa-lssvr). *Groundwater for Sustainable Development*, 11:100447.

Mosavi, A., Sajedi Hosseini, F., Choubin, B., Goodarzi, M., Dineva, A. A., and Rafiei Sardooi, E. (2021). Ensemble boosting and bagging based machine learning models for groundwater potential prediction. *Water Resources Management*, 35:23–37.

Motagh, M., Shamshiri, R., Haghighi, M. H., Wetzel, H.-U., Akbari, B., Nahavandchi, H., Roessner, S., and Arabi, S. (2017). Quantifying groundwater exploitation induced subsidence in the rafsanjan plain, southeastern iran, using insar time-series and in situ measurements. *Engineering geology*, 218:134–151.

Mukherjee, A. and Ramachandran, P. (2018). Prediction of gwl with the help of grace tws for unevenly spaced time series data in india: Analysis of comparative performances of svr, ann and lrm. *Journal of hydrology*, 558:647–658.

Müller, J., Park, J., Sahu, R., Varadharajan, C., Arora, B., Faybishenko, B., and Agarwal, D. (2021). Surrogate optimization of deep neural networks for groundwater predictions. *Journal of Global Optimization*, 81:203–231.

Naganna, S. R., Beyaztas, B. H., Bokde, N., and Armanuos, A. M. (2020). On the evaluation of the gradient tree boosting model for groundwater level forecasting. *Knowledge-Based Engineering and Sciences*, 1(01):48–57.

Nair, V. and Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)*, pages 807–814.

Nayak, P. C., Rao, Y. S., and Sudheer, K. (2006). Groundwater level forecasting in a shallow aquifer using artificial neural network approach. *Water resources management*, 20:77–90.

Nayak, P. C., Sudheer, K., Rangan, D., and Ramasastri, K. (2004). A neuro-fuzzy computing technique for modeling hydrological time series. *Journal of Hydrology*, 291(1-2):52–66.

Nordin, N. F. C., Mohd, N. S., Koting, S., Ismail, Z., Sherif, M., and El-Shafie, A. (2021). Groundwater quality forecasting modelling using artificial intelligence: A review. *Groundwater for Sustainable Development*, 14:100643.

Nourani, V., Alami, M. T., and Vousoughi, F. D. (2015). Wavelet-entropy data pre-processing approach for ann-based groundwater level modeling. *Journal of Hydrology*, 524:255–269.

Nourani, V., Ejlali, R. G., and Alami, M. T. (2011). Spatiotemporal groundwater level forecasting in coastal aquifers by hybrid artificial neural network-geostatistics model: a case study. *Environmental Engineering Science*, 28(3):217–228.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., et al. (2021). The prisma 2020 statement: an updated guideline for reporting systematic reviews. *International journal of surgery*, 88:105906.

Panahi, G., Hassanzadeh Eskafi, M., Faridhosseini, A., Khodashenas, S. R., and Rohani, A. (2023). Prediction of groundwater level fluctuations under climate change based on machine learning algorithms in the mashhad aquifer, iran. *Journal of Water and Climate Change*, 14(3):1039–1059.

Patra, S. R., Chu, H.-J., et al. (2023). Regional groundwater sequential forecasting using global and local lstm models. *Journal of Hydrology: Regional Studies*, 47:101442.

Pham, Q. B., Kumar, M., Di Nunno, F., Elbeltagi, A., Granata, F., Islam, A. R. M. T., Talukdar, S., Nguyen, X. C., Ahmed, A. N., and Anh, D. T. (2022). Groundwater level prediction using machine learning algorithms in a drought-prone area. *Neural Computing and Applications*, 34(13):10751–10773.

Piesse, M. (2020). Global water supply and demand trends point towards rising water insecurity.

Pullin, A. S., Frampton, G., Livoreil, B., and Petrokofsky, G. (2018). Collaboration for environmental evidence. *Guidelines and standards for evidence synthesis in environmental management. version*, 5.

Rahman, A. S., Hosono, T., Quilty, J. M., Das, J., and Basak, A. (2020). Multiscale groundwater level forecasting: Coupling new machine learning approaches with wavelet transforms. *Advances in Water Resources*, 141:103595.

Rajaee, T., Ebrahimi, H., and Nourani, V. (2019). A review of the artificial intelligence methods in groundwater level modeling. *Journal of hydrology*, 572:336–351.

Rao, P., Wang, Y., Liu, Y., Wang, X., Hou, Y., Pan, S., Wang, F., and Zhu, D. (2022). A comparison of multiple methods for mapping groundwater levels in the mu us sandy land, china. *Journal of Hydrology: Regional Studies*, 43:101189.

Sahoo, S. and Jha, M. K. (2013). Groundwater-level prediction using multiple linear regression and artificial neural network techniques: a comparative assessment. *Hydrogeology Journal*, 21(8):1865.

Sahoo, S., Russo, T., Elliott, J., and Foster, I. (2017). Machine learning algorithms for modeling groundwater level changes in agricultural regions of the us. *Water Resources Research*, 53(5):3878–3895.

Seifi, A., Ehteram, M., Singh, V. P., and Mosavi, A. (2020). Modeling and uncertainty analysis of groundwater level using six evolutionary optimization algorithms hybridized with anfis, svm, and ann. *Sustainability*, 12(10):4023.

Sharafati, A., Asadollah, S. B. H. S., and Neshat, A. (2020). A new artificial intelligence strategy for predicting the groundwater level over the rafsanjan aquifer in iran. *Journal of Hydrology*, 591:125468.

Shi, B., Wan, C., Hu, W., Xu, C., Liu, D., Li, M., Li, R., Feng, C., and Xi, B. (2023). Analysis and prediction of the changes in groundwater resources under heavy precipitation and ecological water replenishment. *Journal of Water and Climate Change*.

Shirmohammadi, B., Vafakhah, M., Moosavi, V., and Moghaddamnia, A. (2013). Application of several data-driven techniques for predicting groundwater level. *Water Resources Management*, 27:419–432.

Solgi, R., Loaiciga, H. A., and Kram, M. (2021). Long short-term memory neural network (lstm-nn) for aquifer level time series forecasting using in-situ piezometric observations. *Journal of Hydrology*, 601:126800.

Solomatine, D. P. (2006). Data-driven modeling and computational intelligence methods in hydrology. *Encyclopedia of hydrological sciences*.

Suryanarayana, C., Sudheer, C., Mahammood, V., and Panigrahi, B. K. (2014). An integrated wavelet-support vector machine for groundwater level prediction in visakhapatnam, india. *Neurocomputing*, 145:324–335.

Talpur, N., Salleh, M. N. M., and Hussain, K. (2017). An investigation of membership functions on performance of anfis for solving classification problems. In *IOP conference series: materials science and engineering*, volume 226, page 012103. IOP Publishing.

Tao, H., Hameed, M. M., Marhoon, H. A., Zounemat-Kermani, M., Heddam, S., Kim, S., Sulaiman, S. O., Tan, M. L., Sa'adi, Z., Mehr, A. D., et al. (2022). Groundwater level prediction using machine learning models: A comprehensive review. *Neurocomputing*, 489:271–308.

Taormina, R., Chau, K.-w., and Sethi, R. (2012). Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the venice lagoon. *Engineering Applications of Artificial Intelligence*, 25(8):1670–1676.

Tyagi, K., Rane, C., and Manry, M. (2022). Supervised learning. In *Artificial Intelligence and Machine Learning for EDGE Computing*, pages 3–22. Elsevier.

Van Thieu, N., Barma, S. D., Van Lam, T., Kisi, O., and Mahesha, A. (2023). Groundwater level modeling using augmented artificial ecosystem optimization. *Journal of Hydrology*, 617:129034.

Van Walsum, P. and Veldhuizen, A. (2011). Integration of models using shared state variables: Implementation in the regional hydrologic modelling system simgro. *Journal of Hydrology*, 409(1-2):363–370.

Vapnik, V. (1998). The support vector method of function estimation. In *Nonlinear modeling: Advanced black-box techniques*, pages 55–85. Springer.

Vu, M. T., Jardani, A., Massei, N., Deloffre, J., Fournier, M., and Laignel, B. (2023). Long-run forecasting surface and groundwater dynamics from intermittent observation data: An evaluation for 50 years. *Science of The Total Environment*, 880:163338.

Wen, X., Feng, Q., Deo, R. C., Wu, M., and Si, J. (2017). Wavelet analysis–artificial neural network conjunction models for multi-scale monthly groundwater level predicting in an arid inland river basin, northwestern china. *Hydrology Research*, 48(6):1710–1729.

Wu, C., Zhang, X., Wang, W., Lu, C., Zhang, Y., Qin, W., Tick, G. R., Liu, B., and Shu, L. (2021). Groundwater level modeling framework by combining the wavelet transform with a long short-term memory data-driven model. *Science of The Total Environment*, 783:146948.

Wu, W., Dandy, G. C., and Maier, H. R. (2014). Protocol for developing ann models and its application to the assessment of the quality of the ann model development process in drinking water quality modelling. *Environmental Modelling & Software*, 54:108–127.

Wunsch, A., Liesch, T., and Broda, S. (2018). Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (narx). *Journal of Hydrology*, 567:743–758.

Yadav, B., Gupta, P. K., Patidar, N., and Himanshu, S. K. (2020). Ensemble modelling framework for groundwater level prediction in urban areas of india. *Science of the Total Environment*, 712:135539.

Yang, C.-C., Chang, L.-C., Chen, C.-S., and Yeh, M.-S. (2009). Multi-objective planning for conjunctive use of surface and subsurface water using genetic algorithm and dynamics programming. *Water resources management*, 23:417–437.

Yin, J., Medellín-Azuara, J., Escriva-Bou, A., and Liu, Z. (2021). Bayesian machine learning ensemble approach to quantify model uncertainty in predicting groundwater storage change. *Science of The Total Environment*, 769:144715.

Yoon, H., Hyun, Y., Ha, K., Lee, K.-K., and Kim, G.-B. (2016). A method to improve the stability and accuracy of ann-and svm-based time series models for long-term groundwater level predictions. *Computers & geosciences*, 90:144–155.

Yoon, H., Jun, S.-C., Hyun, Y., Bae, G.-O., and Lee, K.-K. (2011). A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. *Journal of hydrology*, 396(1-2):128–138.

Yu, S., Qiu, L., Xu, X., and Yang, Y.-S. (2021). Machine learning-based algorithm for predicting the groundwater level in minqin oasis region of china. In *2021 7th International Conference on Hydraulic and Civil Engineering & Smart Water Conservancy and Intelligent Disaster Reduction Forum (ICHCE & SWIDR)*, pages 89–95. IEEE.

Zhang, J., Zhu, Y., Zhang, X., Ye, M., and Yang, J. (2018). Developing a long short-term memory (lstm) based model for predicting water table depth in agricultural areas. *Journal of hydrology*, 561:918–929.

Zhou, T., Wang, F., and Yang, Z. (2017). Comparative analysis of ann and svm models combined with wavelet preprocess for groundwater depth prediction. *Water*, 9(10):781.

Zhou, T., Wen, X., Feng, Q., Yu, H., and Xi, H. (2022). Bayesian model averaging ensemble approach for multi-time-ahead groundwater level prediction combining the grace, gleam, and gldas data in arid areas. *Remote Sensing*, 15(1):188.