Neurocomputing 489 (2022) 271–308

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Groundwater level prediction using machine learning models: A comprehensive review

Hai Tao [a,b,c], Mohammed Majeed Hameed [d], Haydar Abdulameer Marhoon [e,f], Mohammad Zounemat-Kermani [g], Salim Heddam [h], Sungwon Kim [i], Sadeq Oleiwi Sulaiman [j], Mou Leong Tan [k], Zulfaqar Sa'adi [l], Ali Danandeh Mehr [m], Mohammed Falah Allawi [j], S.I. Abba [n,o], Jasni Mohamad Zain [c,p], Mayadah W. Falah [q], Mehdi Jamei [r], Neeraj Dhanraj Bokde [s], Maryam Bayatvarkeshi [t], Mustafa Al-Mukhtar [u], Suraj Kumar Bhagat [v], Tiyasha Tiyasha [v], Khaled Mohamed Khedher [w,x], Nadhir Al-Ansari [y], Shamsuddin Shahid [z], Zaher Mundher Yaseen [aa,ab,*]

[a] School of Electronics and Information Engineering, Ankang University, China
[b] School of Computer Sciences, Baoji University of Arts and Sciences, Shaanxi, China
[c] Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
[d] Department of Civil Engineering, Al-Maarif University College, Ramadi, Iraq
[e] Information and Communication Technology Research Group, Scientific Research Center, Al-Ayen University, Thi-Qar, Iraq
[f] College of Computer Sciences and Information Technology, University of Kerbala, Karbala, Iraq
[g] Department of Water Engineering, Shahid Bahonar University of Kerman, Kerman, Iran
[h] Faculty of Science, Agronomy Department, Hydraulics Division University, 20 Août 1955, Route EL HADAIK, 26 Skikda, BP, Algeria
[i] Department of Railroad Construction and Safety Engineering, Dongyang University, Yeongju 36040, South Korea
[j] Dams and Water Resources Engineering Department, College of Engineering, University of Anbar, Ramadi, Iraq
[k] GeoInformatic Unit, Geography Section, School of Humanities, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia
[l] Centre for Environmental Sustainability and Water Security (IPASA), School of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310 UTM Sekudai, Johor, Malaysia
[m] Civil Engineering Department, Antalya Bilim University, Antalya, Turkey
[n] Interdisciplinary Research Center for Membrane and Water Security, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[o] Faculty of Engineering, Department of Civil Engineering, Baze University, Abuja, Nigeria
[p] Faculty of Computer and Mathematical Sciences, University Technology MARA, Malaysia
[q] Building and Construction Engineering Technology Department, AL-Mustaqbal University College, Hillah 51001, Iraq
[r] Faculty of Engineering, Shohadaye Hoveizeh Campus of Technology, Shahid Chamran University of Ahvaz, Dashte Azadegan, Iran
[s] Department of Civil and Architectural Engineering, Aarhus University, Denmark
[t] Department of Geography and Environmental Management, the faculty of Environment, the university of Waterloo, Canada
[u] Civil Engineering Department. University of Technology, Baghdad, Iraq
[v] Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Viet Nam
[w] Department of Civil Engineering, College of Engineering, King Khalid University, Abha 61421, Saudi Arabia
[x] Department of Civil Engineering, High Institute of Technological Studies, Mrezgua University Campus, Nabeul 8000, Tunisia
[y] Civil, Environmental and Natural Resources Engineering, Lulea University of Technology, 97187 Lulea, Sweden
[z] School of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia (UTM), 81310 Johor Bahru, Malaysia
[aa] Adjunct Research Fellow, USQ's Advanced Data Analytics Research Group, School of Mathematics Physics and Computing, University of Southern Queensland, QLD 4350, Australia
[ab] New era and Development in Civil Engineering Research Group, Scientific Research Center, Al-Ayen University, Thi-Qar 64001, Iraq

A R T I C L E I N F O

Article history:
Received 12 July 2021
Revised 7 January 2022
Accepted 10 March 2022
Available online 14 March 2022

Keywords:
State-of-the-art
Machine learning

A B S T R A C T

Developing accurate soft computing methods for groundwater level (GWL) forecasting is essential for enhancing the planning and management of water resources. Over the past two decades, significant progress has been made in GWL prediction using machine learning (ML) models. Several review articles have been published, reporting the advances in this field up to 2018. However, the existing review articles do not cover several aspects of GWL simulations using ML, which are significant for scientists and practitioners working in hydrology and water resource management. The current review article aims to provide a clear understanding of the state-of-the-art ML models implemented for GWL modeling and the milestones achieved in this domain. The review includes all of the types of ML models employed for GWL

* Corresponding author at: Adjunct Research Fellow, USQ's Advanced Data Analytics Research Group, School of Mathematics Physics and Computing, University of Southern Queensland, QLD 4350, Australia.

E-mail address: yaseen@alayen.edu.iq (Z.M. Yaseen).

https://doi.org/10.1016/j.neucom.2022.03.014

Groundwater level
Input parameters
Prediction performance
Catchment sustainability

modeling from 2008 to 2020 (138 articles) and summarizes the details of the reviewed papers, including the types of models, data span, time scale, input and output parameters, performance criteria used, and the best models identified. Furthermore, recommendations for possible future research directions to improve the accuracy of GWL prediction models and enhance the related knowledge are outlined.

1. Introduction

1.1. Research background

Groundwater resources, as one of the most valuable and important sources of water in the world, play a direct and crucial role in various aspects of human lives, such as agriculture, industrial development, and potable water supply [1,2]. In addition, the indirect effects of groundwater resources on the environment and communities are undeniable. The groundwater level (GWL) is a direct and simple measure of groundwater availability and accessibility. Having a proper understanding of the past, current, and future situations of GWL can provide policy-makers and practitioners in water sectors with better insight and perception to develop strategies for the planning and management of water resources, to ensure sustainable socioeconomic development [2]. However, GWL consists of an integrated response to several climatic, topographic, and hydrogeological factors and their interactions, which makes the simulation of GWL a challenging task [3,4].

Numerous studies using different simulation approaches have been conducted for the quantitative and qualitative prediction of GWL. These methods cover a wide range of physically based conceptual models, experimental models [5–7], and numerical models. Modeling groundwater using numerical models consists of several approaches, such as finite difference [8], finite volume [9], finite element [10], and element-free [11] methods. Even though these classical models are robust and reliable, the precision and accuracy of numerical models are confined by several factors, such as their high dependency on large volumes of data related to aquifer properties, the geology of the porous media, and basement topography [12]. Moreover, properly demarcating domain boundaries, defining an efficient grid size for solving the associated differential equations, and calibrating/validating the executed model have made numerical modeling a complex and sophisticated task.

In last two decades, artificial intelligence (AI) models have been widely used to overcome the drawbacks of conventional numerical models for GWL simulation. Fig. 1 presents the goal map, depicting the two major pieces of information, one being the most studied geographical locations and other those which have not yet been studied. Furthermore, Fig. 1 highlights the four major countries which have done extensive GWL modeling-related studies, whereas the black color zone reveals the areas where the application of AI has not yet gained in popularity. Around 70% of areas have not yet used GWL, as many do not need GW-related studies, due to a sufficient amount of surface water or less habitants, such as in polar areas, Russia, and so on. Moreover, some underdeveloped countries, such as Africa, and some parts of Asia and North America, may not have explored AI techniques yet. As per Fig. 2, there has been a significant increase in studies in this field in the last few years; however, more studies should be done, based on different geographical locations, to test the efficiency of the proposed models. The usability and reliability of AI models in dealing with complex and high-dimensional engineering problems have been proven in the last few decades [13–15]. AI consists of multidimensional systems combining various mathematical and statistical components and arithmetic and heuristic algorithms. AI has been extensively employed in different fields of science, engineering design, energy, robotics, and economics [16–18]. It has also been intensively used for solving various civil and environmental engineering problems [19,15]. Some examples include soft computing techniques [20], Machine Learning (ML) methods [21–23], probabilistic analysis [24], and Fuzzy-based systems [25]. In recent years, more attention has been paid to the successful use of AI in different hydrological fields, including water resources [26], surface and groundwater hydrology [27], sediment contamination [28], and hydraulics [29].

1.2. Research significance

Proper measurement, nowcasting, and forecasting of GWL in aquifers are highly important for the sensible management of groundwater resources [30]. Monitoring GWL can provide hydrologists and hydrogeologists valuable information to understand the short- and long-term variations in groundwater availability. The ability of AI models to simulate and predict GWL without requiring deep and comprehensive knowledge of the underlying topographical and hydro-geophysical parameters makes them appealing methods compared to physically based and numerical methods

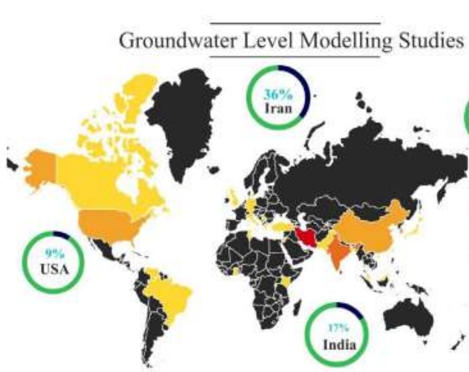

Fig. 1. Map representation of sampling location of GWL data all over the globe with specified area with no related research on GWL modeling using AI models.

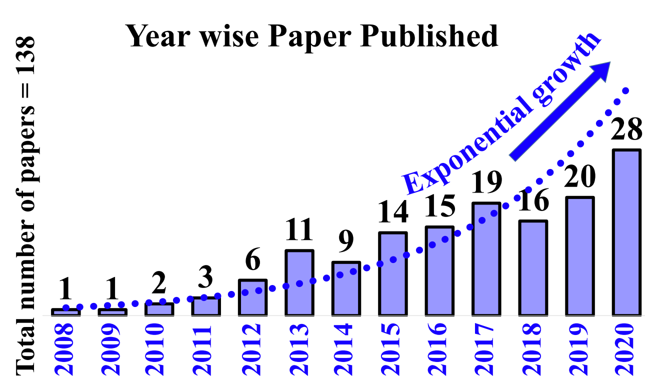

Fig. 2. Arithmetical conceptualization of growth observed in GWL research using AI based model during 2008–2020.

[31]. A large volume of studies have already investigated and reported the applicability of AI in modeling GWL over the last two decades [32]. Most of the early works included simple and standard AI methods, such as perceptron Artificial Neural Networks (ANNs) [33]. However, in the last decade, the application of a variety of ML models for GWL simulation has been witnessed; examples include different types of ANNs [34], fuzzy-based models [35], Support Vector Machines (SVMs) [36], tree-based models [37], Genetic Programming (GP) [38], and Gene Expression Programming (GEP) models [39].

Most recently, along with the application of novel AI models, including Deep Learning (DL) [40], Extreme Learning Machine (ELM) [41], and Long Short-Term Memory (LSTM) [42], novel strategies, such as integrated and hybrid AI models [43], ensemble learning [44], and AI-GIS (Artificial Intelligence-Geographic Information System)-based models [45], have been implemented for modeling GWL. Rajaee et al. [46], for instance, studied 67 journal papers and provided a bibliographic review of the applications of AI in GWL simulation and forecasting. Considering the outcomes of different classic AI methods, such as ANNs, Adaptive Neuro-fuzzy Inference System (ANFIS), SVM, GP, and hybrid AI methods, the study concluded that AI methods can be successfully used to model and forecast GWL in aquifers located in regions with different geology and climate. Some studies have attempted to combine the advantages of AI and numerical methods to develop hybrid models. For example, Nourani and Mousavi [47] introduced a hybrid AI-meshless model for modeling GWL. They used AI methods, such as ANN and ANFIS, for temporal modeling of GWL, while the meshless method was used for solving the governing differential equations to estimate the GWL in places with no observations [48]. Chen et al. [49] carried out a comparative study using a finite difference numerical model versus three ML models, including ANNs and SVM, for simulating GWL. Comparing the general performance of the two distinct approaches revealed that the ML models acted better than the numerical model. Nevertheless, they also mentioned the superiority of the finite difference method, due to its generalization ability in including the physical mechanism of the aquifer.

1.3. Research objectives

As complete descriptions and detailed analyses on the application of ML models for GWL prediction are provided in the following sections, giving more information on this matter herein-that is, as the literature review-would be repetitive and unnecessary. It is quite understandable that many hydrologists and hydrogeologists have recognized the potential capability of ML models, in particular, for their use in GWL simulation. Even though there have been a few comprehensive review studies published on the subject of GWL modeling using ML models, such as the recent one conducted by Rajaee et al. [46], this review article tries to fill in the literature gap regarding the emergence and application of novel AI models in groundwater simulation. Furthermore, the focus of the present article is the recent developments, progresses, restrictions, and shortcomings of advanced AI methods in dealing with GWL. Thus, this article is aimed at researchers, groundwater engineers, environmentalists, and hydrogeologists who find the prospects of AI in the groundwater domain attractive.

2. Artificial intelligence models for GWL simulation

2.1. Application of artificial neural network models

An ANN is a computer system designed to mimic the manner in which information is processed and analyzed by the human brain. It is a major sort of AI applications, which is capable of handling complex issues which are difficult, according to statistical and human standards [19]. Furthermore, ANNs have efficient abilities to approximate functions that are commonly unknown or to predict future values based on potentially noisy time-series data [50–52]. The structure of an ANN is comprised of several simple elements working in parallel. The determination of the function of an ANN mainly depends on the connections between elements, as in natural processing [53]. In general, an ANN is comprised of three layers, including the input layer (which is used to input the variables) and the output layer (which is used to compute the desired target) [54]. The hidden layer is an important component of an ANN, due to its location between the input layer and output layer, where the neurons receive a set of weighted inputs and, hence, generate an output by applying a certain activation function [15]. The information transfers from one layer to another through neurons (processing elements). An activation function is always used, regardless of using an ANN with a single or several hidden layers. Feed-forward neural networks (FFNNs), which are often called multilayer perceptrons (MLPs) are one of the most famous and powerful types of ANN and have been widely used for solving hydrological issues [55–58]. An FFNN has three layers, as shown in Fig. 3. In a classical FFNN, the initial weight and bias values are assigned randomly and, then, the algorithm starts to correct the values, in order to minimize the loss function. Gradient descent back-propagation and Levenberg–Marquardt back-propagation algorithms have increasingly been employed in training FFNNs, in order to optimize the magnitudes of the weights and biases [59–62]. In a traditional FFNN, three parameters need to be considered, in order to accomplish more accurate predictions: (1) The number of hidden nodes and transfer functions; (2) the initial weight and bias values; and (3) choosing a sufficient number of epochs [63].

A large volume of literature is available on the application of ANN models to forecast GWL in different regions. Nair and Sindhu [65] conducted a study for estimating the GWL in the Mamom river basin in Trivandrum region, India. They used an ANN model based on hydrological parameters to estimate the GWL in three wells during monsoon and non-monsoon seasons. The predictive models were constructed using only four meteorological factors as predictors: Rainfall (Raf), potential Evapotranspiration (EVP), Tempera-

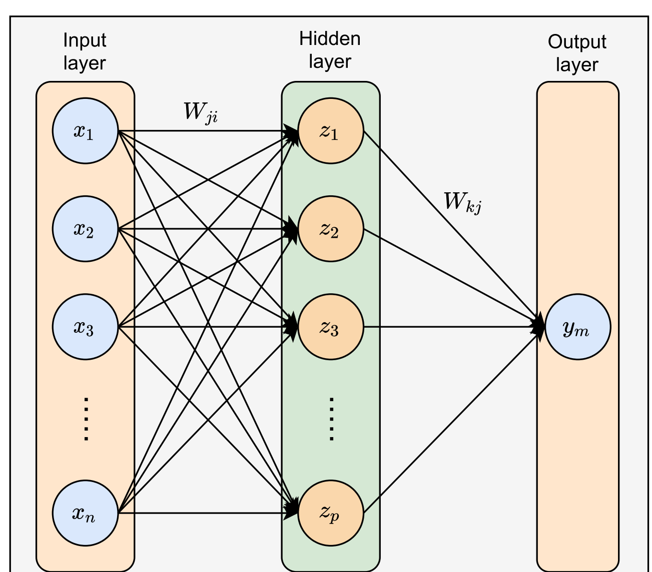

Fig. 3. The structure of the classical ANN model [64].

ture (T), and Humidity (H%). Moreover, the Levenberg–Marquardt (LM) algorithm was applied to train several ANN model sturctures, in order to optimally choose the weight and bais values. Another study in India used an ANN approach to estimate the monthly GWL at four sites located in south-east Punjab for the period of 2006 to 2013 [66], where Raf and preceding GWL were used as inputs. The results showed that the use of an ANN using the LM back-propagation algorithm provides more accurate predictions, compared to other algorithms.

In the African continent, Nouiri and Malek [67] developed an ANN model to estimate monthly GWL in four aquifers of the Nebhana watershed, located in Tunisia. Only three input parameters (Raf, antecedent GWL, and EVP) were used to develop the forecasting models. The ANN model gave higher prediction accuracy and was also able to capture the dynamic fluctuations in piezometric levels. The study revealed that the monthly GWL depended mainly on monthly precipitation, EVP, and antecedent values of GWL.

Iqbal et al. [68] developed an ANN model for forecasting daily GWL from three meteorological variables in a study area located between the Ravi and Sutlej Rivers in Pakistan. The input parameters were Raf, T_{max}, T_{min}, solar radiation, relative H%, wind speed (WS), area elevation, and polygon area. In order to select the most accurate GWL prediction model, the authors applied different types of ANN architectures with different transfer functions, hidden layers, and different percentages of data in the training, validation, and testing phases. LM back-propagation was used as a learning algorithm. The study revealed that the proposed model was able to estimate GWL more accurately, in terms of different statistical criteria. Furthermore, the results revealed that the tangent sigmoid transfer function was most efficient and the data division with 80% for training, 10% for validation, and 10% for testing was more effective and optimistic, compared to other data divisions.

Guzman et al. [69] employed two predictive models based on two approaches-support vector regression (SVR) and Recurrent Neural Network (RNN)-for the estimation of GWL for a well located in Sunflower county, Mississippi, USA. Daily GWL was the only variable used for developing both models. The authors concluded that both models produced preferable predictions, but the RNN gave higher accuracy.

Hong [70] presented a study to estimate hourly GWL using a feed-forward back-propagation neural network (FFBPNN) to achieve two main aims: (1) prediction of next hour GWL and (2) forecasting the fluctuations and changes in GWL between the current and one-lag-ahead GWL. The outcomes of the study illustrated that the proposed model managed to simulate the fluctuations in GWL between a lag much more accurately than one-lag-ahead prediction of GWL.

Kouziokas et al. [71] used an FFANN model to estimate the daily GWL from meteorological variables in the district of Montgomery country in Pennsylvania, USA. Different ANN model structures were investigated, with different transfer functions and learning algorithms, such as Resilient Back-propagation, Scaled Conjugate Gradient, LM, and BFGS Quasi-Newton. The simulated GWL values were found to be higher than those of comparable models found in the literature.

An FFANN was employed by [72] to forecast hourly GWL at eight wells in South Korea. The study considered the surface water level and groundwater abstraction parameters as input. The estimated GWL values were very accurate, in accordance with the actual magnitudes of GWL and, therefore, the proposed model was considered to be efficient in capturing the non-linear relationship between the targets and predictors.

In Longyan city, Fujian Province of southeast China, a study has been conducted [73] to forecast the monthly GWL using two robust approaches: GM(1, 1) and radial basis function neural network (RBFNN). Quantitative assessments revealed that both models can provide accurate GWL estimates; however, the RBFNN model was more competent in forecasting GWL, compared to the GM(1, 1) model. The comparable model, GM(1, 1), demonstrated an inability to generate highly accurate estimations, especially in short-term forecasting, compared to the adopted model (RBFNN). The study concluded that, despite the efficiency of the RBFNN model, it might still need to be improved to overcome the overfitting issue.

The process of understanding and predicting the fluctuations of GWL is usually very complex, as several parameters play significant roles in determining the storage capacity of water in a certain aquifer. Shamsuddin et al. [74] carried out an attempt to forecast daily GWL using the MLP technique in a tropical region, Jenderam Hilir in Selangor state of Malaysia. To achieve better estimation performance, different ANN structures were chosen, based on different input parameters including meteorological and hydrological factors. It is important to mention that the LM algorithm was utilized to train the predictive models. The outcomes of the study exhibited the robustness of Multiple linear regression (MLR) in forecasting the GWL, based on several statistical criteria. Additionally, the study presented a good relationship between the hydrological parameters and GWL.

The extreme learning machine, an advanced version of an ANN, was invented in 2006 and has gained good popularity, in recent years, in solving water resource issues and groundwater estimation tasks. The main structure of the classical ELM model is about the same as a single-layer FFANN model. However, the input weights and biases in the ELM algorithm are always assigned randomly and the output weights are calculated using the singular value decomposition (SVD) method. ELM models have many advanced aspects, which make them superior to traditional ANN models in solving complex engineering problems. ELM models are easier to train and have the characteristics of faster convergence, better generalization, and a lower chance of becoming stuck in a local minimum, compared to other types of ANN models. Moreover, the ELM algorithm can be trained quickly with minimal data [75]; hence, it has shown promising successes in several sectors of engineering, especially hydrological areas.

Alizamir et al. [41] published a paper on modeling GWL using hydrological and climatic data. The study developed an ELM model and three other ML models (i.e., RBFNN, MLR, and autoregressive-moving-average; ARMA) to predict monthly GWL in the Shamil-Ashekara Plain, Iran. The study found that the ELM model obtained much higher estimation accuracy than the other models. Moreover, the proposed model showed better performance in predicting multi-month GWL than the other employed models.

A study has been carried out [76] for the prediction of GWL in Canada using two different approaches: ELM and SVR models. Meteorological and hydrological data were used as inputs to develop both forecasting models. The obtained results showed the superiority of ELM over SVR in forecasting monthly GWL. A list of articles on the prediction of GWL using the ANN models are tabulated in Table 1.

2.2. Fuzzy logic and neuro-fuzzy models applications

Neuro-Fuzzy models belong to the category of hybrid models, which combine two paradigms-ANNs and fuzzy logic (FL)-to utilize the relative advantages of each algorithm. FL is mainly used to transform linguistic labels into mathematical expressions using if-then rule formulations [77]. The combination of ANN and FL has helped to form the famous ANFIS model [78]. The ANFIS model uses an ensemble of if-then rules and membership functions (MFs) to map a set of input variables (x_i) to an output variable (y). It consists of five layers; namely, a fuzzification layer, a multiplication

Table 1
The established research on the GWL prediction using the applications of ANN models.

Research	Applied AI Models	Case study	Data Span	Input parameters	Output parameters	Performance metrics
[65]	MLP	India	2002–2016	Raf, P, T, H	GWL	R^2
[66]	MLP	India	2006–2013	Raf, GWL	Monthly GWL	R^2, RMSE
[67]	ANN	Tunisia	2000–2018	Raf, GW, P	Monthly GWL	RE, RMSE R^2, NASH
[68]	MLP	Pakistan	2003–2014	Raf, SR,T_{max}, T_{min}, polygon area,		
area elevation, RH	Daily GWL	MAE,MSE,R				
[69]	RNN, SVR	USA	1987–1994	GWL	Daily GWL	MSE
[70]	FFBPNN	Taiwan	2008	GWL	Hourly GWL, GWF	R^2, RMSE
[71]	FFBPNN	USA	2014	RH, T, Raf	Daily GWL	RMSE
[72]	FFBPNN	South Korea	2014	SWL, GWA-WCC, GWA- GWHP	Hourly GWL	ME, RMSE, R, NASH
[73]	RBFN, GM(1,1)	China	2003–2011	GWL	Monthly GWL	R^2,RMSE, MAE
[74]	MLP	Malyasia	2015–2016	GWL, Raf, RS, WL, SFR, T	Daily GWL	R, R^2, MSE RMSE
[41]	ELM, RBFN, MLP, ARMA	Iran	Not mentioned	GWL, Raf, eV	Monthly GWL	MSE, MAE, NASH, R^2
[76]	ELM	Canada	2006–2014	GWL, Raf, T, EVP,	Monthly GWL	R^2, RMSE, NASH

layer (i.e., firing strength layer), a normalization layer, a defuzzification layer and, finally, the output layer (i.e., summation) [79]. Like any other machine learning model, ANFIS possesses a set of parameters to be optimized during the learning process [19]. The structure of an ANFIS model is very close to that of an ANN, except that it contains two kinds of parameters-linear and non-linear-making its training very difficult, especially for large numbers of input variables. The linear parameters (i.e., consequent parameters) are those of the fuzzy rules, while the non-linear parameters are those of the MFs. During the training process, the two kinds of parameters are optimized simultaneously. An example of the ANFIS model architecture is presented in Fig. 4. Fuzzy logic and Neuro-Fuzzy are among the most common models used in the area of hydrological sciences [80]. However, the majority of the reported studies have used the famous ANFIS model; for example, for precipitation forecasting [81], soil moisture simulation [82], modeling of reference EVP [83], sediment load modeling [14], and for modeling total dissolved solids [84].

The number of studies focused on modeling GWL using neuro-fuzzy models has constantly increased over the last two decades (as shown in Table 2); however, the ANFIS model remains the most-used model, with or without the inclusion of meteorological variables as predictors. On the other hand, our literature review revealed that only a few studies have investigated the application of ANFIS in predicting GWL using only antecedent GWL data.

Moravej et al. [85] applied ANFIS and GP models to predict monthly GWL from evaporation (EP) and precipitation (P). In addition, they exploited the abilities of metaheuristics optimization algorithms, interior search algorithm (ISA), and genetic algorithm (GA) to improve the performance of the least-squares support vector machine (LSSVM). A relative performance analysis of ANFIS, GP, GA-LSSVM, and ISA-LSSVM models showed that the highest accuracy was achieved using the ISA-LSSVM algorithm. The study also reported that the inclusion of P and EP did not contribute to the improvement of model performance. Bak and Bae [86] used the ANFIS model to predict GWL using P and T_{mean} and reported acceptable results, with RMSE and MAPE of 0.1381 and 37.869%, respectively. The feasibility of fuzzy logic (FL) for GWL prediction has been demonstrated in a recent study [35]. They proposed FL models, including Sugeno (SFL), Mamdani (MFL), and Larsen (LFL). In addition, multiple models were proposed, according to three principal forms: Simple averaging, weighted averaging, and committee machine techniques. The results showed the superiority of the simple committee fuzzy logic (SCFL) model, with an R^2 value ranging from 0.690 to 0.940 and RMSE ranging from 0.252 to 0.103. see Table 3.

An alternative model was developed, by Jahanara and Khodashenas [87], by combining three paradigms: Neuro-fuzzy (NF), group method of data handling (GMDH) and metaheuristics optimization algorithms; that is, particle swarm optimization (PSO)

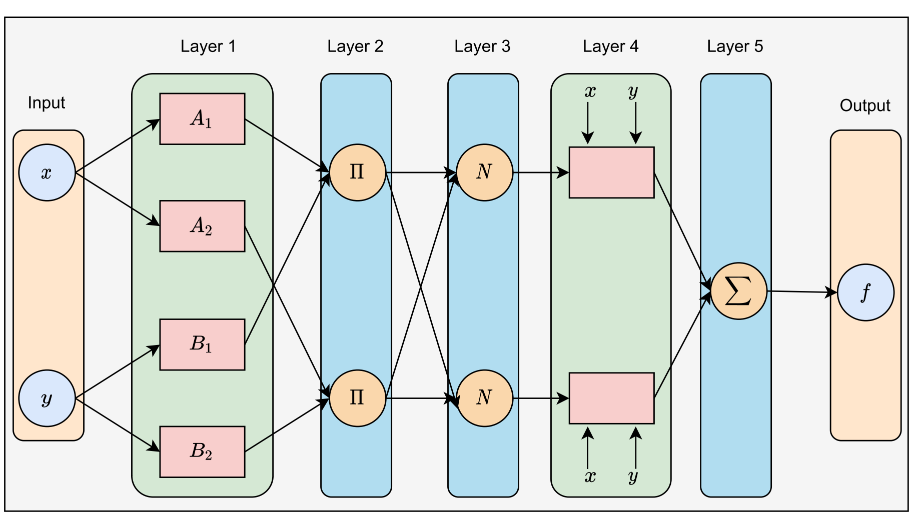

Fig. 4. The structure of ANFIS model.

Table 2
List of reviewed papers related to modeling groundwater level using ANFIS models.

Research	Applied AI models	Case study Location	Data span	Time scale	Input parameters	Output parameter	Performance metrics	Commentary (Best model)
Moravej et al. [85]	ANFIS, GA-LSSVR, ISA-LSSVR	Iran	2002–2008	Monthly	P, EP	GWL	R^2, NSE, RMSE	ISA-LSSVR*
Nourani and Mousavi [47]	ANFIS, FFNN, WANFIS WFFNN	Iran	2001–2011	Monthly	P, Q	GWL	R^2, RMSE	ANFIS-RBF*
Zhang et al. [88]	ANFIS, RBFNN, GSM	China	2000–2009	Monthly	GWL	GWL	R, NSE, MARE, RMSE	ANFIS*
Wen et al. [105]	ANFIS, WANFIS, FFNN	China	2007–2009	Weekly	GWL	GWL	R, MARE, RMSE	WANFIS*
Khaki et al. [91]	ANFIS, FFNN, CFN	Malaysia	2007–2013	Monthly	GWL, P, EP, H %, T_{max}, T_{min}	GWL	R, MSE	ANFIS*
Bak and Bae [86]	ANFIS	Korea	2015–2017	-	P, T_{mean}	GWL	MAPE, RMSE	Unknown
Nadiri et al. [35]	SFL, MFL, LFL, CFL-SA, CFL-WA, SCFL	Iran	2007–2016	Monthly	GWL, Q, P, T_{mean}	GWL	R^2, RMSE	SCFL
Shiri et al. [100]	ANFIS, FFNN, GEP, SVM, ARMA	Korea	2001–2008	Daily	ET, P	GWL	R, NSE, RMSE, CO	GEP*
Sridharam et al. [106]	ANFIS, WANFIS	India	1990–2017	Daily	ET, P, T_{mean}, IL, GWL	GWL	R^2, MAE, RMSE	WANFIS*
Kisi and Shiri [99]	ANFIS, WANFIS	USA	2001–2008	Daily	GWL	GWL	R^2, RMSE	WANFIS*
Sreekanth et al. [102]	ANFIS, FFNN	India	2000–2006	Monthly	P, EP, H%, T_{max}, T_{min}	GWL	R^2, RMSE, EV	FFNN*
Emamgholizadeh et al. [95]	ANFIS, FFNN	Iran	2002–2011	Monthly	GWL	GWL	R^2, MAE, RMSE	ANFIS*
Fallah-Mehdipour et al.[104]	ANFIS, GP	Iran	Not reported	Monthly	GWL, P, EP	GWL	R^2, NSE, RMSE	GP*
Gong et al.[89]	ANFIS, FFNN, SVM	USA	1998–2009	Monthly	GWL, P, LL, T_{mean}	GWL	R, NSE, RMSE, NMSE, AIC	ANFIS*
Shirmohammadi et al.[103]	ANFIS, ARMA, ARIMA, SARIMA, Fuzzy-ARX, Fuzzy-ARMAX, ARX, ARMAX,	Iran	1992–2007	Monthly	GWL, P	GWL	R^2, RMSE, AIC	ANFIS*
Jahanara and Khodashenas [87]	NF-GMDH-PSO, RBFNN-NF-GMDH-PSO	USA	2001–2008	Daily	GWL	GWL	R, RMSE,	NF-GMDH - PSO
Jeihouni et al. [107]	ANFIS, WANFIS, W-LSSVM, LSSVM, NARX, W-NARX	Iran	2002–2016	Monthly	P, T_{mean}	GWL	R^2, RMSE	W-NARX*
Djurovic et al.[92]	ANFIS, FFNN	Serbia	1990–2010	Daily	P, EP, T_{max}, T_{min}	GWL	R, NSE, RMSE	ANFIS*
Kholghi and Hosseini [101]	ANFIS, OKR	Iran	Unknown	Unknown	LNG, LAT	GWL	NSE, MAE, MSE	ANFIS*
Samantaray et al. [106]	CANFIS, RNN	India	1988–2017	Monthly	P, H%, T_{mean}, IL	GWL	R^2, MSE, RMSE	CANFIS
Maiti and Tiwari [94]	ANFIS, FFNN, BNN	India	1972–2001	Monthly	P, T_{max}, T_{min}, T_{mean}	GWL	R, IA, RE, RMSE	ANFIS*
Zare and Koch [98]	ANFIS-FCM, WANFIS-FCM	Iran	1991–2013	Monthly	P, GWL	GWL	R^2, RMSE	WANFIS -FCM
Moosavi et al.[97]	ANFIS, WANFIS, FFNN, WFFNN	Iran	1992–2007	Monthly	GWL, P, EP, Q	GWL	R^2, NSE, RMSE	WANFIS*
Moosavi et al. [96]	ANFIS, WANFIS, FFNN, WFFNN	Iran	1992–2007	Monthly	GWL, P, T_{max}, T_{min}, T_{mean}	GWL	RMSE, IA	WANFIS*
Raghavendra and Deka [90]	ANFIS, GPR	India	2000–2013	Monthly	GWL	GWL	R, NSE, RMSE	GPR*

and gravitational search algorithm (GSA). Consequently, two hybrid models were obtained; namely, NF-GMDH-PSO and NF-GMDH-GSA. The accuracies of the two hybrid models were evaluated against RBFNN and it was found that the NF-GMDH-PSO performed significantly better than the NF-GMDH-GSA and RBFNN, showing higher R^2 and RMSE values (0.969 and 0.618, respectively). Zhang et al. [88] analysed the differences in GWL prediction by three AI models: ANFIS, RBFNN, and the grey self-memory model (GSM). They found that all models could be successfully applied to model the GWL. They also reported that the ANFIS model was generally more accurate than the GSM and RBFNN models, as it obtained the highest performance metrics (i.e., R^2, NSE, MARE, and RMSE). Gong et al. [89] modeled GWL using previous GWL, P, lake level (LL), and T_{mean} as predictors. The authors compared the results obtained using ANFIS, FFNN, and SVM with a monthly time step, and reported that the ANFIS model was more accurate.

Raghavendra and Deka [90] proposed the multi-step-ahead forecasting of monthly GWL in the river basin near Sullia Taluk, India, using ANFIS and Gaussian process regression (GPR) approaches. Four input variables, including the GWL measured in the previous four months, were used to forecast GWL up to six months in advance. The results showed that GPR had significantly higher accuracy in prediction than the ANFIS model. In addition, it was demonstrated that the performances of the two models (i.e., ANFIS and GPR) decreased from one to three months ahead. Similarly, Khaki et al. [91] quantified monthly GWL measured at Langat Basin, in the southeastern part of Selangor state, Malaysia. A large number of regressors were used; namely, previous GWL, P, EP, H %, T_{max}, T_{min}. Three models were used: ANFIS, FFNN, and the cascade

Table 3
List of reviewed papers related to modeling groundwater level using kernel function embedded models.

Research	Applied Models	Case Study Location	Data Span	Time Scale	Input Parameters	Output Parameter	Performance metrics	Used Kernal Function
Fang et al. [124]	SOM-SVM, MOGA-SVM	Taiwan	1998–2007	Monthly	GWL, P, TA_{mean}, WS, SD, RH	GWL	RMSE, bias, MAE, NS	Polynomial
Gong et al. [89]	ANN, SVM, ANFIS	Florida, USA	1998–2009	Monthly	GWL, P, TA_{mean}, TA_{max}, TA_{min}, LL	GWL	R, NMSE, RMSE, NS, AIC	–
Guzman et al. [125]	NARX-ANN, RBF-SVR	Mississippi, USA	1985–1994	Daily	GWL, P, ET	GWL	MSE	Polynomial Radial Basis Function Sigmoid
Nie et al. [126]	RBF-NN RBF-SVM	Jilin, China	2003–2014	Monthly	P, TA_{mean}, E	GWL	CC, RMSE, MAE, NS	Radial Basis Function
Sahoo et al. [127]	RBF-SVR, RF, GB	Indo-Gangetic, India	2002–2011	Monthly	P, SM	GWL	MAE, RMSE, bias, CV(RMSE)	Radial Basis Function
Sattari et al. [129]	SVR, M5Tree	Ardebil, Iran	1997–2013	Monthly	GWL, PV, WD	GWL	CC, RMSE	Polynomial
Tang et al. [130]	LS-SVM, SVM, ANN, RF, kNN	United Kingdom	2016	Hourly	GWL*	GWL	MAE, MAPE, MSE, RMSE	Radial Basis Function
Yoon et al. [131]	ANN, SVM	South Korea	2003–2008	Daily	GWL, P	GWL	CC, MAPE, ME, RMSE	Radial Basis Function

forward network (CFN). Their performances were evaluated using R and MSE. The results showed that the ANFIS model had a significantly higher accuracy (R^2 = 0.94, MSE = 0.005) than that of the FFNN and CFN. Moreover, Djurovic et al. [92] applied ANFIS and FFNN models to predict daily GWL in the riparian lands of the Danube basin in Serbia. Four input variables were selected, including, P, EP, T_{max}, and T_{min}, for GWL prediction. The obtained results revealed that both models could be applied successfully with a high level of accuracy. Samantaray et al. [93] demonstrated that co-adaptive neuro-fuzzy inference systems (CANFISs) are more accurate than RNNs in predicting monthly GWL using P, H %, T_{mean}, and infiltration loss (IL) measured in the region of Odisha, India, with R^2, RMSE, and MSE equal to 0.953, 0.0393, and 0.00378, respectively. Maiti and Tiwari [94] and Emamgholizadeh et al. [95] have conducted extensive studies and compared the performance of ANFIS and FFNN models in different regions of the worlds in simulating GWL. They reported ANFIS as more suitable for GWL prediction, compared to the FFNN model, with either only antecedent GWL or meteorological variables with antecedent GWL as inputs.

Data transformations, such as wavelet transforms, provide methods for data decomposition allowing us to obtain highly improved data signals and, thus, leading to a significant improvement of model accuracy. Such a data pre-processing approach has been employed, by Moosavi et al. [96,97], to simulate monthly GWL using ANFIS, WANFIS, FFNN, and WFFNN in Iran from P, $T_{max}, T_{min}, T_{mean}$, EP, and the GWL measured at the previous lag. They found that wavelet data transformation is an effective method for capturing the non-linearity in the time-series by removing noise from data. However, they highlighted that the wavelet transform may become more suitable and further contribute to the performance of ANFIS, compared to FFNN. In order to ensure a robust prediction strategy of GWL, Zare and Koch [98] have recently proposed a prior wavelet transform with several decomposition levels to provide inputs to the ANFIS with fuzzy c-mean clustering model (ANFIS-FCM). Although this strategy of decomposition, accompanied with a good choice of the number of clusters, worked very well, the authors highlighted the importance of adequate selection of the mother wavelets, which plays a fundamental role in obtaining excellent accuracy. They showed that the best performance (with R^2 and RMSE values of 0.983 and 0.18, respectively) was obtained during the testing phase using the sym4 mother wavelet. In light of this, many researchers have simplified the daily GWL using the discrete wavelet transform (DWT) and introduced the decomposed signal as an input variable to the ANFIS and FFNN models. For example, Kisi and Shiri [99] have demonstrated that the DWT helps in improving the performance of the ANFIS model, allowing R^2 values close to 0.99 during the testing phase.

Despite the increased use of machine learning, several authors have tried to apply several kinds of models with the overall objective of acquiring high-level prediction accuracy and exploiting the advantages of the available information from input variables. For instance, Shiri et al. [100] used P and ET for predicting daily GWL using ANFIS, FFNN, SVM, and GEP models. Although the first three models have been documented in the literature, the GEP was considered as one of the novelties of the investigation. They reported that the GEP model was more accurate in terms of prediction. Some investigations must be discussed here due to their unconventional and novel approaches. Kholghi and Hosseini [101] published an article related to modeling GWL using an unconventional approach: Ordinary Kriging (OK). In fact, [101] pioneered the use of OK for modeling GWL using only the Latitude and Longitude as predictors. The performance of OK was compared with ANFIS in predicting GWL in the Qazvin plain, located in the west of Tehran, Iran. The results showed that the ANFIS model had higher accuracy than the OK model. Another group of researchers-Sreekanth et al. [102], Shirmohammadi et al. [103], and Fallah-Mehdipour et al. [104], have explored the significance of GWL prediction using GP, the seasonal autoregressive integrated moving average (SARIMA) model, and hybrid fuzzy-SARIMA. For instance, Fallah-Mehdipour et al. [104] highlighted the superiority of GP, compared to ANFIS, in predicting monthly GWL in Iran.

The aim of the study was to develop a new modeling strategy using GP based on two readily available meteorological variables: P and EP. Interestingly, another study conducted by Shirmohammadi et al. [103] in the same year proposed different models for GWL prediction from precipitation and antecedent GWL data. They tested a suite of models (i.e., ANFIS, ARMA, ARIMA, SARIMA, Fuzzy-ARX, Fuzzy-ARMAX, ARX, and ARMAX) and reported the superiority of the ANFIS model.

2.3. Kernel models applications

Due to their simplicity and generality, kernel functions play progressively outstanding roles in machine learning and its application. This was inaugurated with the launching of support vector machines and extended with the improvement of other kernel function-embedded models [108,109]. As a kernel function can be described on any input space, diverse kernel functions have been successfully applied to describe the non-linear relationships defining complicated data architectures. The support vector machine is a well-established Kernel model, which has been implemented widely in several fields, such as regression, bioinformatics, pattern recognition, and environmental engineering [110]. It is a novel kind of categorizer, stimulated by two approaches: First, converting data into a high-dimensional area can reconstruct complicated problems into simple ones. Second, it is inspired by the theory of training and uses only relevant inputs [111–113]. The resolution of a traditional ANN may fall into a regional optimized solution, while an overall optimized solution is guaranteed by the SVM model [114]. Kernel function embedded models have been utilized for the solution of hydrological processes, such as Raf-runoff [115,116], EP [117,118], EVP [119,120], water stage [121,122], and so on. A detailed list of reviewed papers related to modeling groundwater level using kernel function embedded models is given in Table 3. The non-linear SVM Vapnik's ϵ-insensitivity loss function is presented in Fig. 5.

Numerous researchers have recently developed SVM models to estimate, predict, and forecast GWL fluctuations. Fang et al. [124] employed a two-stage approach for the development of self-organizing maps (SOM) and multi-objective genetic algorithm (MOGA)-based SVM (i.e., SOM-SVM and MOGA-SVM) models to forecast spatial–temporal GWL in the Choushui River Alluvial Fan, Taiwan. A polynomial kernel function was implemented in the construction of the SVM model. In the first stage, the SOM-SVM model applied a clustering method to segregate the geographical and hydrological components into spatial groundwater zones. In the second stage, the MOGA-SVM model decided the optimal input combinations. The results showed that the MOGA-SVM model was appropriate for forecasting the fluctuation of GWL with short and long lead-times, while the MOGA-SVM model was more efficient and accurate.

The accurate prediction of GWL fluctutations is a very complicated and non-linear phenomenon in the natural environment, as it depends on many diverse components such as P, EP, T, and so on. Gong et al. [89] developed three machine learning models (i.e., ANN, SVM, and ANFIS) to predict the fluctuation of monthly GWL in Florida, USA. The kernel function was used to form the SVM model architecture. They reported that the models were effective and accurate for predicting the fluctuation of GWL with three month lead-times (i.e., one, two, and three months). The predictive results using P, T, previous GWL, and lake level accomplished better performance than those using P, T, and previous groundwater level only. This demonstrates that the interaction between groundwater and surface water is required for predicting GWL fluctuation. Besides, the ANFIS and SVM models accomplished better predictions than the ANN model.

Guzman et al. [125] developed the non-linear autoregressive with exogenous inputs-based ANN (NARX-ANN) and RBF-based support vector regression (RBF-SVR) models, in order to evaluate GWL in irrigation wells in Mississippi, USA. Three kernel functions (i.e., polynomial, radial basis function, and sigmoid) were employed to determine the optimal SVR model with the lowest training error. Among them, the RBF kernel function furnished the best accuracy. They classified the total historical time-series into withdrawn (i.e., summer) and recharge (i.e., winter) seasons. The RBF-SVR model accomplished better prediction than the NARX-ANN model for individual (summer or winter) seasons. Therefore, the prediction of GWL by individual season was more accurate than that using the total time-series. Furthermore, the results indicated that the winter season presented as a linear problem, which decreased the computational requirements of the RBF-SVR model.

Nie et al. [126] employed the RBF-NN and RBF-SVM models to predict the fluctuation of monthly GWL in Jilin, China. The RBF kernel function was implemented to set the SVM model structure. The uncertainties generated from the measured errors of input and output variables were computed based on 95 % confidence intervals. Their research reported that the RBF-SVM model achieved more accurate and less uncertain results to predict the fluctuation of monthly GWL, compared to the RBF-NN model.

The Gravity Recovery and Climate Experiment (GRACE), an artificial satellite, can follow the variation of groundwater level. Gridded rainfall (GR) and soil moisture (SM) data can also support the development of hydrological models. Unique research using GRACE, GR, and SM data to predict the variation of GWL in the Indo-Gangetic basin, India, has been accomplished by Sahoo et al. [127]. The RBF-SVR, random forest (RF), and gradient boosting (GB) models computed the ground assignment of satellite data. The RBF kernel function was used to construct the SVR model architecture. The addressed research explained that nine pixels of the GRACE satellite data were applied to identify the relationship between well-measured and satellite-acquired data. The nine pixels were categorized based on the presence or absence of hydrological features. The pixels identifying perennial streams provided

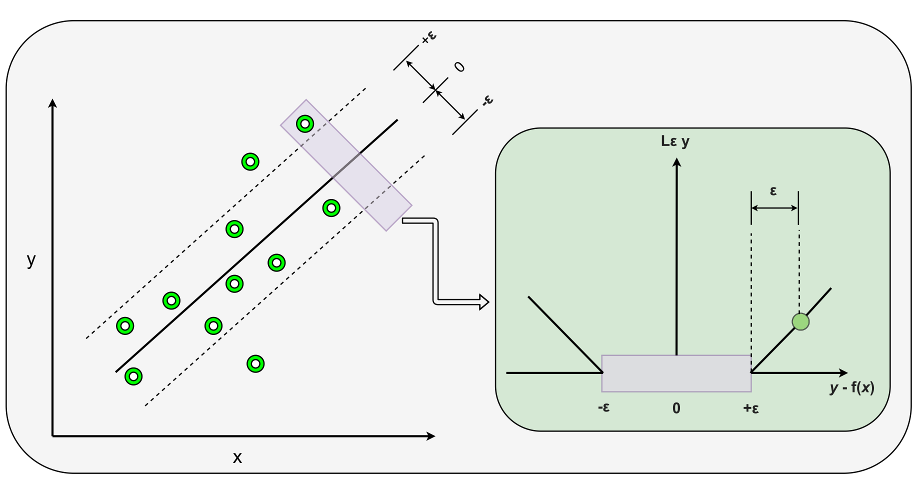

Fig. 5. Non-linear SVR vapnik's ϵ-insensitivity loss function [123].

reasonable prediction, while the pixels displaying wells near the streams supplied poor prediction for the variation of groundwater level. Additionally, the RBF-SVR model supported better prediction than the RF and GB models. Another investigation was conducted on GWL using the feasibility of GB model within the Karnataka state, India and the research approved the proposed model significant on the prediction accuracy [128].

Sattari et al. [129] resolved the SVR and M5 Model Tree (M5Tree) models, in order to predict the variation of monthly GWL in the Ardebil plain, Iran. The polynomial kernel function was built in the networks of the SVR model. The variables of the input combination involved the previous groundwater level, P volume, and well discharge, while GWL was considered as the output variable. Both models (i.e., SVR and M5Tree) predicted the variation of monthly GWL accurately. However, the addressed research explained that the prediction processes applying the M5Tree model were simpler and easier than those when employing the SVR model.

A novel two-phase scheme to predict the variation of hourly GWL utilizing temporal-spatial analysis and the LSSVM model in the United Kingdom has eben proposed by Tang et al. [130]. In the first phase, the temporal analysis utilizing the autocorrelation function (ACF) and partial autocorrelation function (PACF) is carried out to analyze the temporal behaviors of GWL. The LS-SVM model is also constructed to predict the variation of hourly GWL, based on the results of the temporal analysis. The RBF kernel function was embedded in the architectures of the LS-SVM and SVM models. The results of the LS-SVM model were compared with four machine learning models: SVM, ANN, RF, and k-nearest neighbors (kNN). In the second phase, the spatial analysis, employing the cross-correlation technique, was carried out to compute the cross-correlation of mean sea level between the attractive and neighbor-measured locations. The results revealed that the LS-SVM model was superior to the other machine learning models for predicting the variation of hourly GWL.

Yoon et al. [131] investigated ANN and SVM models to predict the variation of daily GWL in South Korea using the weighted error function (WEF) approach. The ANN model was trained by the backpropagation (BP) algorithm, while the SVM model was calibrated by the sequential minimal optimization (SMO) algorithm. The prediction scheme consisted of a direct and recursive strategy. The RBF kernel function was utilized in the SVM model design. The WEF approach clearly enhanced the predictive accuracy of two models (i.e., ANN and SVM). A comparison of the models demonstrated that the SVM model with the recursive strategy was better than the ANN model with the recursive strategy to predict the variation of hourly GWL.

Our review of previous articles concerning kernel function embedded models (e.g., SVM, SVR, and LS-SVM) for predicting the fluctuation of GWL revealed the following: First, the RFB kernel function has frequently been employed to construct the model architectures, as it has few adjusting parameters, compared with other kernel functions (e.g., polynomial and sigmoid) and can well-capture non-linear behavior to accomplish the accurate prediction of GWL fluctuations. Second, the kernel function embedded models can predict the fluctuation of GWL effectively, based on hourly, daily, and monthly lead-times. Finally, considering the kernel function embedded models, using few input data can provide more effective prediction than other models for predicting the fluctuation of GWL.

2.4. Deep learning models applications

Deep learning, a subset of machine learning which specializes in generating outputs from unstructured input data through unsupervised learning approaches, has become popular in groundwater level simulation [132]. One of the major advantages of deep learning is the capability of analyzing complex and high-dimensional data in a relatively short period with minimal manpower, compared to conventional data collection [133]. Deep learning models are comprised of an input layer, hidden layers, and an output layer, where a neural network is used to map features into the output layer [134]. CNN and LSTM are the most widely applied deep learning algorithms in hydrology studies [134]. As this review focuses solely on the application of deep learning to groundwater quantity, studies on groundwater contamination were excluded. In general, the application of deep learning in groundwater, as reported in the literature, can be divided into three major groups: (1) Comparison of the performance of different deep learning algorithms; (2) filling missing data values; and (3) improvement of the simulation framework.

A total of 10 articles on deep learning and groundwater level were identified, as listed in Table 4. Identification of the best deep learning algorithm is one of the most popular research topics in this field. Kumar et al. [135] compared deep learning, ELM, and GPR in predicting groundwater level in the Konan basin, Japan, with P, river stage, T, recharge, and groundwater level in the input data layer. Similar studies have been conducted by Supreetha et al. [136] in the Udipi district in Karnataka state of India, who found that the Long Short-term Memory-Lion Algorithm (LSTM-LA) outperformed the LSTM and Feedforward Neural Network (FNN) in groundwater level prediction. The proposed predictive model is demonstrated in Fig. 6, as an example for the readers. Park and Chung [137] and Shin et al. [138] both reported the reliable performance of the LSTM model in groundwater level simulations in Southeast Korea. Interestingly, Shin et al. [138] found that the duration of the training period did not have a significant impact on the simulation performance, where the NSE value only differed by 0.02 between the 6-year and 19-year study periods. The modeling scheme proposed by Shin et al. [138] is reported in Fig. 7.

Missing GWL records is a common issue, particularly in developing and underdeveloped countries. Human factors, equipment failure, and fluctuations of water level are among the factors that contribute to such missing records [139]. Therefore, reconstructing missing GWL values can help us to better understand aquifer systems. Vu et al. [140] evaluated the capability of an LSTM for filling in the 50-year GWL data at 31 piezometers to predict future GWL fluctuations in northwestern Normandy, Italy. They concluded that the use of deep learning is viable to reconstruct GWL fluctuations, with correlation coefficient and RMSE values of 0.64–0.99 and 0.07–1.08 m, respectively. The integration of deep learning and hydrological models for fusing GRACE satellite data with NOAH-a land surface model developed by NASA-has been conducted by Sun et al. (2019) [141] to improve groundwater storage prediction in India. The deep convolution neural network (CNN) model was applied to learn the Spatio-temporal mismatch in groundwater patterns between GRACE and NOAH. Their findings indicated that CNN improved the GRACE-NOAH match and successfully filled in the data gaps between GRACE missions.

Several studies have proposed strategies to improve deep learning-based GWL simulation frameworks; for instance, Bowes et al. [42] explored the effects of algorithm selection, training data type, and integration of forecast data on GWL predictive model accuracy in Norfolk, Virginia, USA. The proposed model consisted of data pre-processing, a learning process, and result post-processing, as reported in Fig. 8. The results showed that the LSTM had better performance, as compared to the Recurrent Neural Network (RNN), in this region. The architectures of the RNN and LSTM models are displayed in Fig. 9. The authors also found that the model trained with a data set of only storm events outperformed the models trained with continuous and forecast data using a thousand bootstrapped data set (see Fig. 10).

Table 4
The surveyed literature on the implementation of deep learning models for GWL modeling.

	Applied AI models	Case study	Data span	Input parameters	Output parameter	Performance metrics	Features
[135]	DL, ELM, GPR	Konan, Basin, Japan	Not reported	P, River Stage, T, Groundwater depth	Groundwater level	RMSE, R and NSE	DL is more reliable and robust than ELM and GPR
[136]	LSTM, FFNN, LSTM-LA	Udupi district, Karnataka state, India	2000–2018	Raf, Groundwater level	Groundwater level	RMSE, MAE	LSTM-LA outperformed LSTM and FFNN
[137]	LSTM	Hankyung-myeon, Jeju Island, South Korea	2001–2013	Raf, Groundwater level	Groundwater level	R^2	Accuracy R^2 - 0.98
[138]	LSTM	Pyoseon watershed, Jeju Island, South Korea	2001–2019	Raf, Groundwater withdrawal data,groundwater level	Groundwater level	NSE, RMSE	Short and long training periods both gave similar model performance.
[42]	LSTM, Recurrent Neural Network (RNN)	Norfolk, Virginia USA	2010–2018	Raf, groundwater level, sea level	Groundwater level	RMSE	- LSTM outperformed RNN
[142]	Two-layer LSTM	Hetao Irrigation District, Northwestern China	2000–2013	Water diversion, EP, P, T, time	Groundwater level	R^2	- Model trained with only storm events performed better than continuous data LSTM much better than FFNN
[140]	LSTM	Upper Normandy, Italy	1970–2005	Groundwater level	Groundwater level	RMSE, R	-Good performance in filling missing values
[143]	LSTM	Gangjin-Seongjeon and Pohang-Gibu, South Korea	2005–2016	Groundwater level	Groundwater level	MSE	-Unreliable input could lead to poor prediction -development of a cost function for robust training.
[144]	LSTM, gated recurrent unit (GRU)	Jindo Uisin and Pohang Gibuk, Jeju Island, South Korea	2005–2014	Groundwater level	Groundwater level	RMSE, R	Pre-processing data before applying DL to estimate groundwater level
[141]	CNN	India	2002–2016	Total Groundwater Storage (TGWS)	Total Groundwater Storage	NSE	CNN was trained to learn the TGWS spatial mismatch between GRACE and NOAH

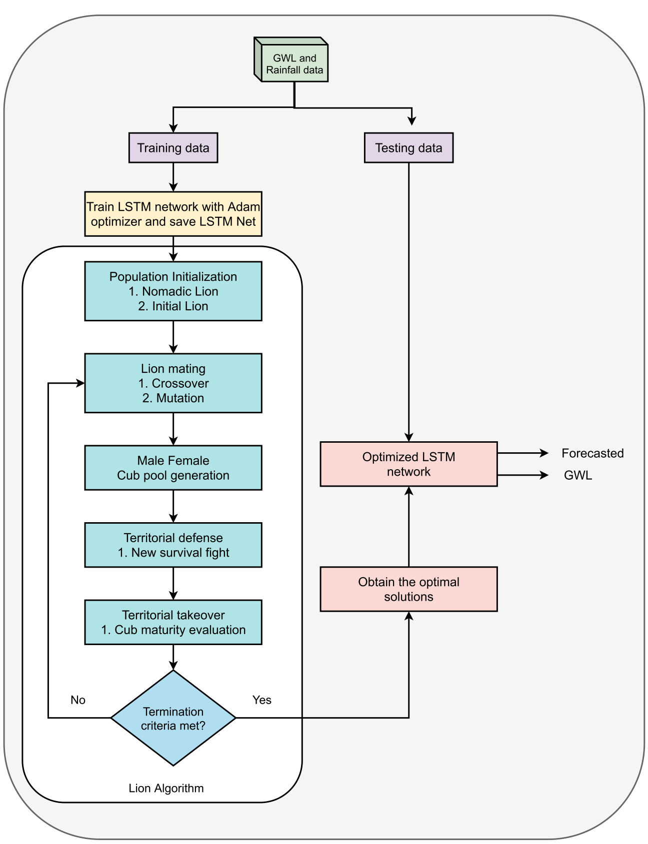

Fig. 6. The proposed predictive model based on the hybridization of the LSTM-LA for modeling GWL [136].

Zhang et al. [142] developed a two-layer LSTM model to predict groundwater level in the Hetao Irrigation District of Northwestern China. Their findings showed that the proposed model could achieve considerably higher R^2 values (0.79–0.95), when compared to the FNN (0.0–0.50). Another two improvement studies have been conducted in South Korea, where Jeong et al. [143] developed a cost function for robust data training purposes and Jeong and Park [144] proposed a massive pre-processing data scheme before the training step. Both studies showed that the removal of data noises before implementing the deep learning simulations could improve the model accuracy.

2.5. Hybrid ML models applications

Despite significant advancement in recent years, in terms of handling non-stationary, dynamic, and non-linear time-series data using ML models-particularly applied in hydro-environmental and water resource management-there are still some weakness associated to such approaches. A variety of problems in hydrological simulation reserach related to a single AI-/machine learning-based modeling has been addressed, regardless of their promising performances demonstrated in various studies [145–154]. According to [155–159], hybrid models have proved not only their merit and superiority to the use of a single model, but can also address a variety of different problems associated with the use of single techniques.

The concept of Hybrid methods implies the combination of one or more AI-based models, computing machine learning models, and/or classical regression models for improving the performance accuracy or to obtain optimal outcomes. Hybrid methods could be utilized in the prediction or optimization stages, based on their specific purposes. Hence, it can be justified that hybrid methods comprise several combined single techniques and/or optimization

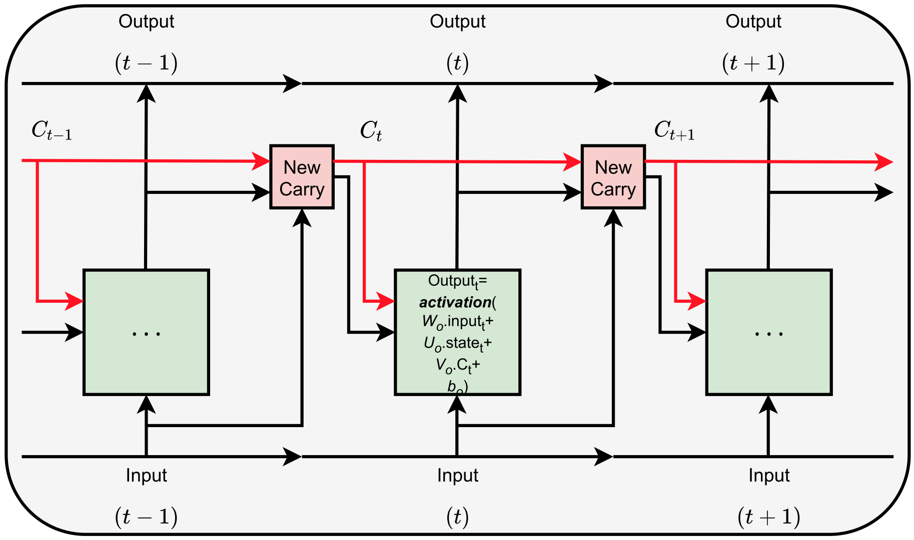

Fig. 7. The proposed LSTM predictive model for GWL modeling by Shin et al. [138].

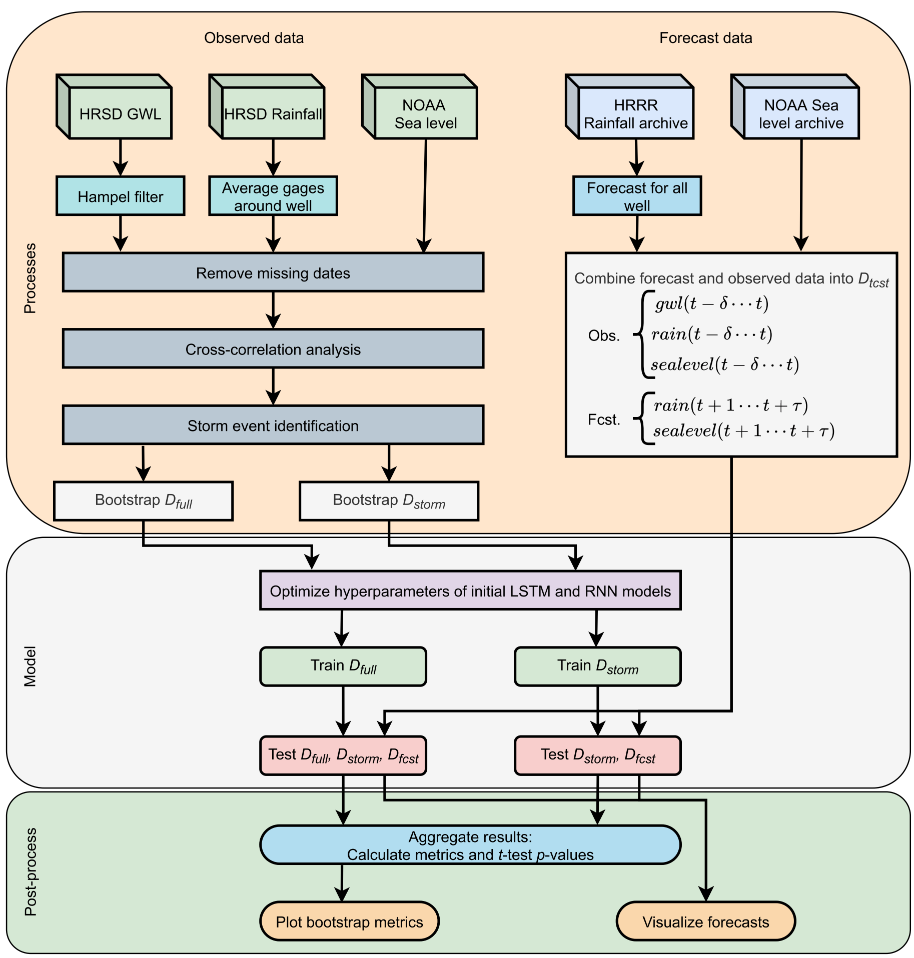

Fig. 8. The proposed modeling procedure consisting the data preprocessing, predictive model process and post-processing [42].

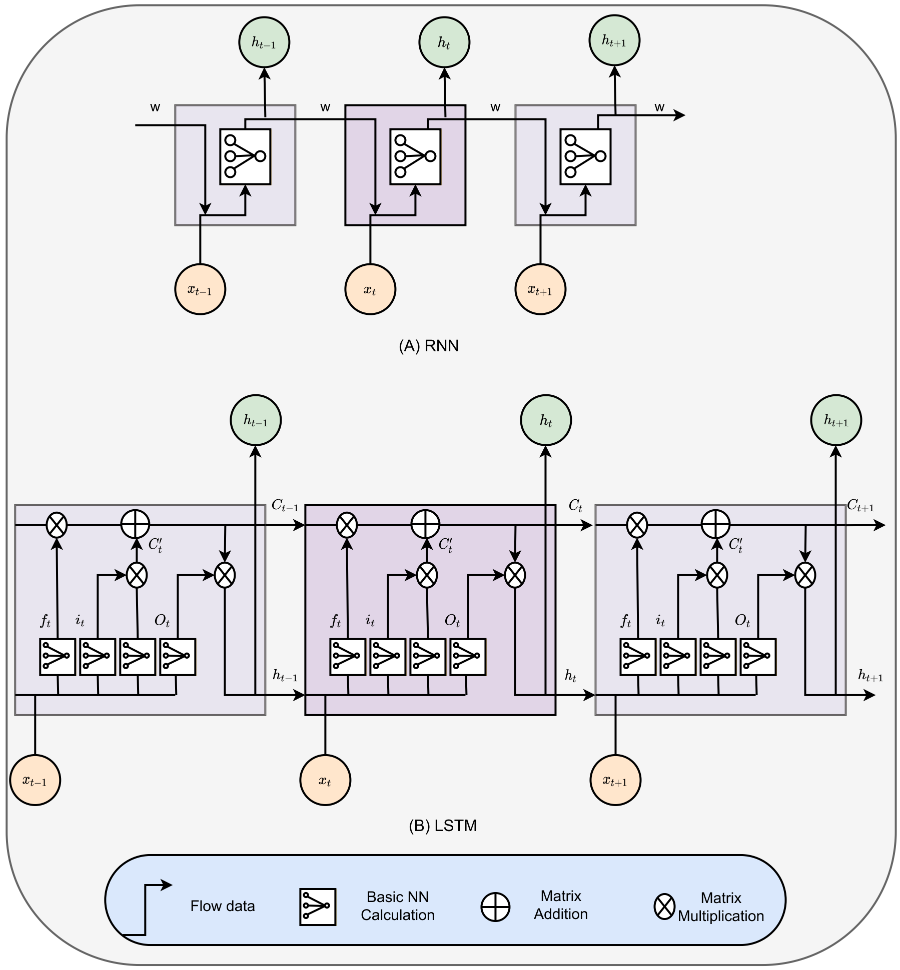

Fig. 9. The models' architectures of the RNN and LSTM developed by Bowes et al. [42].

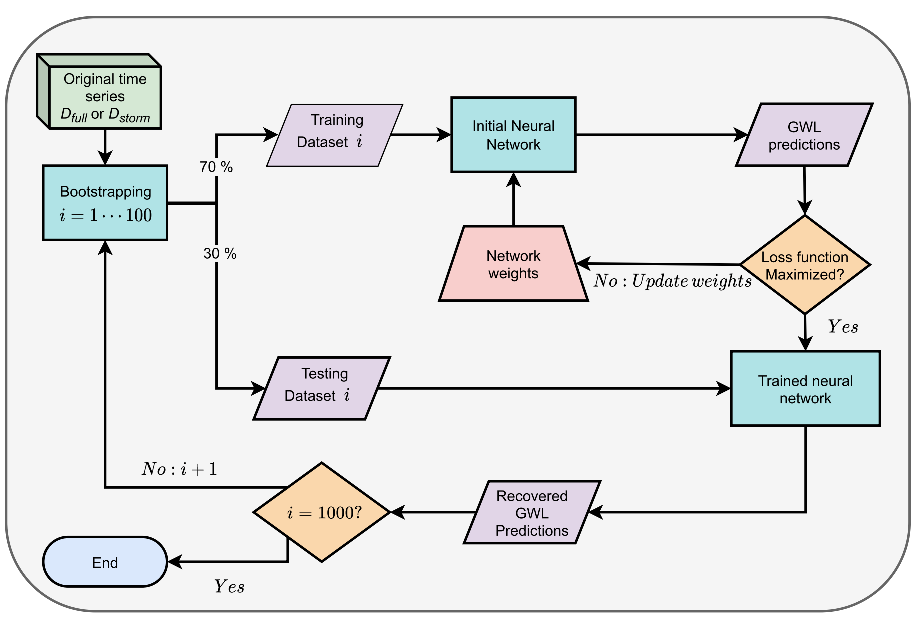

Fig. 10. The proposed Model training and evaluation with bootstrapped datasets by Bowes et al. [42].

algorithms, which have been proved to be more reliable and capable of outperforming single models, with regards to modeling accuracy [160].

Among the different categories of hybrid methods reported by the various researchers in the field of water resource management and hydro-environmental engineering, ANNs have generally shown outstanding improvement in GWL prediction [161,162]. Nourani et al. [47] integrated a wavelet hybrid neural network (WT-FFNN) for GWL simulation using SOM clustering techniques at different piezometer positions in the Ardabil plain. The results were compared with the traditional FFNN and ARIMA models, where the output reported that the hybrid WT-FFNN increased the average performance by up to 15.3% over FFNN. Mathur [163] proposed single and hybrid SVM with POS (SVM-PSO), in order to investigate the feasibility of GWL modeling at Andhra Pradesh, India. The comparison was made using ANFIS and ARIMA models, which indicated that SVM-PSO is far more reliable and has higher accuracy than other single models. Chang et al. [164] developed a new hybrid soft-computing approach using SOM-NARX techniques. The study used monthly regional data recorded from 203 stations during 2000–2013 in Zhuoshui River basin, Taiwan. The results, based on statistical indicators, demonstrated the suitability and reliability of the hybrid SOM-NARX method in modeling GWL. The outcomes also depicted that the proposed techniques could provide an environmental solution toward water resource management. Huang et al. [165] determined the daily GWL using standalone and hybrid models (PSO-SVM and PSO-BPNN) in the Three Gorges Reservoir Area in China. Chaos theory was applied to obtain the best input combination for the non-linear models. The results indicated that non-linear PSO-SVM had better prediction skill than the simple linear PSO-SVM and chaos-BPNN. Zare and Koch [98] employed AI and regression models for the simulation of GWL using different input combinations; after that, a new hybrid wavelet technique, WA-ANFIS, was proposed. Observational data were obtained from a case study in the Miandarband plain, Iran. The overall results confirmed the accuracy of the hybrid model. Rakhshandehroo et al. [166] estimated GWL through a new hybrid model using wavelet neural networks (WNNs) calibrated with an improved harmony search (IHS) algorithm. The efficiency of the model was compared with classical differential evolution (DE), PSO, RBFNN, MLP, and harmony search (HS) models. The outcomes established for GWL modeling indicated the dominance of the proposed hybrid model over other single models. Balavalikar et al. [167] used monthly GWL variation data from 2000–2013 in Brahmavar, Kundapur, and Hebri in Udupi district, India, in order to predict the GWL using the combinations of ANN and hybrid POS-ANN. For this purpose, the models were calibrated using different input combinations. The performance results demonstrated the capability of PSO-ANN over ANN in modeling GWL. POS and GA are popularly known hybrid learning techniques, due to their effectiveness in determining the RBFNN optimization parameters. The insensitive nature of GA in optimizing the initial guess parameters is the main merit of employing GA over other hybrid approaches [168,169]. The advantage of the Whale algorithm (WA) has been attributed to its high convergence, suitability with other optimization algorithms, and its capability to handle a huge amount of decision variables [170,171]. Further literature regarding the merits and supremacy of other hybrid optimization algorithms are enclosed in this review. However, investigating the aforementioned studies coupling popular AI-based hybrid models (e.g., ANN), it is worth mentioning that hybrid techniques have achieved considerable attention over the last few decades; for instance, Dash et al. [172] made an attempt to develop a hybrid NN with GA (ANN-GA) using several learning algorithms for GWL modeling in the Mahanadi river basin, India. The prediction outcomes using different performance criteria revealed that the hybrid ANN-GA produced the best GWL simulation. Jalalkamali and Jalalkamali [173] studied the potential of a hybrid ANN-GA model for the prediction of GWL. The classical FFNN and RNN were compared, in order to demonstrate the performance accuracy of the models when using several input variables. The obtained results indicated that ANN-GA can serve as a reliable model for GWL simulation. Adamowski and Chan [174] coupled a hybrid WA-ANN for GWL prediction using different hydro-climatology variables. Recorded monthly GWL data were obtained from the Chateauguay watershed in Quebec, Canada during 2002–2009. The GWL simulation results, based on evaluation and comparison, indicated that the hybrid WA-ANN performed better than ANN and ARIMA models. Yadav and Mathur [76] applied the new hybrid Quantum behaved Particle Swarm Optimization function (SVM-QPSO), in order to estimate the GWL in Rentachintala region, Andhra Pradesh, India. The results showed that SVM-QPSO performed better, with regards to performance evaluation, than the ANN model. Moosavi et al. [96] presented several soft-computing models, including ANN and ANFIS, which were coupled with optimization algorithms to develop hybrid models (i.e., WA-ANN and WA-ANFIS) to estimate monthly GWL. The forecasting skill of the models indicated that the hybrid ANFIS (WA-ANFIS) outperformed the other models, in term of performance criteria. Tapoglou et al. [175] introduced hybrid ANN-Kriging techniques for spatial–temporal modeling of GWL at different places in Bavaria, Germany. The results showed that hybrid model can fully achieve the expected GWL prediction outcomes.

More recently, Yaseen et al. [26] developed an evolutionary hybrid algorithm based on the comparison of the bat algorithm (BA) and PSO algorithm, called the hybrid bat-swarm algorithm (HB-SA), for dam and reservoir optimization. The obtained outcomes showed the suitability and generalizability of the proposed HB-SA method. Malekzadeh et al. [176] presented a study using a hybridized wavelet of Self-Adaptive Extreme Learning Machine (SAELM) and Wavelet-SAELM (WA-SAELM) in Kabodarahang region, Iran. The results of the proposed methods were compared to standalone hybrid AI-based models (i.e., WA-ANN and WA-SVM). The predictive results proved that hybrid WA-SAELM produced the best outcomes and, hence, served as the most reliabile approach. Supreetha et al. [177] investigated hybrid ANNs, including hybrid ABC and PSO algorithms, for the forecasting of GWL using the observational GWL at Manipal from Udupi, Karnataka, India. The models were evaluated using RMSE, MAE, and R, and the results indicated the superiority of the hybrid ABD-PSO techniques. Roshni et al. [178] developed a traditional FFNN with a hybrid WANN model for the prediction of complex GWL in an alluvial aquifer. The results integrated the Gamma and M-tests (GT) approach for the same purposes, while a different evaluation matrix was used to assess the model's performance. The examined calibrated results justified the robustness of GTWANN for the estimation of GWL. Kombo et al. [147] presented a long-term multi-step GWL estimation using a hybrid K-Nearest Neighbors-Random Forest (KNN-RF) technique in eastern Rwanda using climate variables (T, P, max. solar radiation, and GWL). The modeling results, based on NSE, RMSE, MAE, and R^2, confirmed that the hybrid model provided a reliable approach. Moravej et al. [85] developed a novel hybrid model based on ISA and GA for the simulation of GWL, using Raf, EP, and GWL data obtained from an unconfirmed aquifer in the northwest of the Karaj plain, Iran. Comparison of ANFIS and GP models in GWL prediction justified the superiority of the novel hybrid ISA-LSSVR methods. Roshni el al. [161] presented a comparison of novel hybrid Emotional ANN coupled with a genetic algorithm (EANN-GA), generalized regression neural network (GRNN), and FFNN for the estimation of GWL at three different sites in a coastal aquifer. The performance evaluation of the models was carried out using several indicators. The prediction results indicated that EANN-GA outperformed EANN, GRNN, and FFNN for the simulation of spatial–temporal GWL. Banadkooki et al. [179] explored a hybrid RBF with whale algorithm (WA) model (RBF-WA), GP, and MLP-WA for modeling GWL under different scenarios based on temporal P data. The performance of the predictive models showed that MLP-WA emerged as the best hybrid model for the prediction of GWL in Yazd province, Iran. Natarajan and Sudheer (2020) [154] explored the capability of different data-driven models (ANN, SVM, ELM, and GP) for modeling GWL at six different locations in Vizianagaram, Andhra Pradesh, India. The results confirmed the superiority of the ELM model over other single models; on the other hand, the hybrid SVM-QPSO was found to be the best predictive model on some occasions. Seifi et al. [180] explored the performance of different optimization algorithms-GA, grasshopper optimization algorithm (GOA), cat swarm optimization (CSO), PSO, weed algorithm (WA), GA, and krill algorithm (KA)-integrated with AI-based models (ANN, ANFIS, SVM). Observed monthly data for 144 months recorded in the Ardebil plain (Iran) were used. The modeling results were evaluated based on a number of evaluation criteria, which proved the superiority of ANFIS-GOA over standalone models. The reported research in the literature on hybrid ML models for GWL modeling are collected in Table 5.

2.6. Decision tree and data mining and Evolutionary computing models applications

Evolutionary computing is a subfield of AI, in which biological evolution (based on Darwin's principle) is used to solve stochastic problems. Despite the variety of existing EC techniques, such as GA, evolutionary algorithm, particle swarm optimization, ant colony algorithm, GP, and so on, they use the same automated problem-solving procedure, starting with an initial set of candidate solutions and iteratively improving solutions through mutation, cross-over, and natural selection. Current reviews of the application of AI methods in hydrology (see, e.g., [46,196]) have shown that GP is one of the most popular EC techniques for GWL simulation. Various types of GP algorithms have been used for GWL prediction, including classic GP (e.g., [104]), GEP [197], and multigene GP (MGGP) [198]. All of these GP variants have been well-described in [199]. To avoid duplication, we briefly describe the main concept of classic GP herein, in order to secure the integrity of the current review paper.

Like other EC techniques, GP uses an automatic problem-solving technique to attain the best solution among randomly generated potential solutions called genes. In the classic GP method [200], each gene is represented by a tree structure having a root node, inner nodes, and terminal nodes (called leaves); see Fig. 11.

Fig. 11 illustrates a genome, including a root node (multiplication), inner nodes of subtraction, and terminal nodes of X_1, X_2, and a random number (5.25). Each terminal node in a GP tree can adopt an independent variable or any random floating point number.

To solve any time-series or regression problem using GP, the algorithm begins with the formation of an initial population of genes. Then, the evolutionary operators of natural selection-cross-over and mutation-are used to modify the existing genes [201]. The modified genes, or offspring, that show the highest fitness survive to the next generation of the population (potential solutions). This is the evolutionary process, which must be iterated until an individual meets the desired accuracy. Fig. 12 demonstrates the cross-over operator between two parents creating two offspring. Each offspring has the same materials as their parents, but a different combination of them. Indeed, the parents exchange some of their branches (the red and blue parts in Fig. 12)) to produce offspring. Various studies have shown that the offspring may solve a problem better than their parents [202–204].

Mutation is an operator in which a parent's node or branch is replaced with a randomly created node/branch using the materials existing in functional or terminal sets. As illustrated in Fig. 13, the sub-tree $1 + x_2$ in the parent gave its place to the branch $tan(x_1)$ in the offspring.

In order for the best individual to survive in each iteration, it directly moves to the new population without any change. This is a natural selection process, which allows the modeler to keep improvement continuing in each generation. All of the above-mentioned operations are carried out in any GP variant; however, the process may not necessarily be done using a tree shape. Like other AI techniques, a set of training data is used to train the GP and the evolved solution must be generalized for unseen testing data sets. To minimize computational costs, a set of suitable functions, input variables, evolutionary operation rates, and a maximum depth of the GP trees must also be considered in the modeling process (Mehr and Noyrani 2018 [196]; Tur 2020 [204]). To avoid over-fitting, a lower number of functions and short trees are recommended [201,205].

Comparison of GEP with ANFIS for short-term GWL prediction in Illinois State has been conducted by Shiri and Kisi [197], perhaps one of the earliest applications of EC-based regression models using GEP. The authors used daily P and antecedent GWL data as the predictors of GWL in two wells: Bondville and Perry. The results showed that GEP and ANFIS can be applied to predict GWL. An explicit expression of GEP was highlighted as the advantage of GEP over ANFIS. In a similar study, Fallah-Mehdipour et al. [104] compared the classic GP algorithm with ANFIS, in order to predict and simulate GWLs in three observation wells in the Karaj plain, Iran. The study focused on the monthly variation of GWLs and suggested the use of P and EP from a surface water body to fill possible gaps in the GWL data sets. The results showed the effective and promising role of GP in solving the problem, as it was superior to ANFIS by up to 11 percent in the testing period. Kasiviswanatha et al. [38] implemented the classic GP method to model and forecast GWL variations and emphasized the quantification of uncertainties due to input selection. To this end, observations from three wells (K. Paramathy, Keeranur, and Kuthiraiyar) in India were used. The authors demonstrated that the quantification of uncertainty may help to improve the confidence of GP-based GWL models. The authors discovered that the EP is not an effective input. By contrast, river stage data near the wells was introduced as the input, which may improve the model accuracy. More recently, Sadat-Noori et al. (2020) [206] showed that GP can provide more accurate GWL predictions for wells close to meteorological stations when P data are used as input. A list of the articles on the developed evolutionary computing predictive models for GWL modeling is given in Table 6.

Data mining techniques are relatively new methods for discovering patterns and finding anomalies and connections relating to complex processes in large data sets, which can be exploited to forecast future trends [207]. As hydrological criteria follow a complicated process, particularly in the long-term scale, finding novel models with high accuracy seems to be essential and indispensable [208]. Therefore, these techniques are uniquely able to leverage the large amounts of real-time, multivariate data now being collected for hydrological systems. Karthik and Vijayarekha [209] believe that data mining techniques can be employed for quicker classification of water portability. A broad range of algorithms is used, in these methods, for classification and prediction. The application of each model has been evaluated in several investigations in the hydrology field. Further details of some models with the highest level of application are discussed in the following:

Table 5
The list of the reported research over the literature on the hybrid ML mdoels for GWL modeling

No.	Author (year)	Location of study	Hybrid AI models	Input Combination	Frequency	Data Span	Performance metrics
1	Kholghi and Hosseini, (2009) [101]	Qazvin plain, Iran	ANFIS-Kriging	GWL	Monthly	Not mention	R^2, MAE, MSE, RSS, CE
2	Dash et al. (2010) [172]	Mahanadi river basin, India	ANN-GA	GWL	Monthly	1993–2002	R, E, MAE, IOA, RMSE
3	Nourani et al. (2011) [181]	Shabestar plain, Iran	ANN-GS	LL, GWL, R	Monthly	1995–2007	R^2, RMSE
4	Jalalkamali and Jalalkamali, (2011) [173]	Kerman plain (Kerman, Iran)	GA-ANN, FFNN, RNN	Piezometers, T, R	Monthly	1988–2009	R^2, RMSE, MAPE
5	Adamowski and Chan, (2011) [174]	Quebec, Canada	WA-ANN, ANN, ARIMA	P, E, GWL	Monthly	Nov2002-Oct2009	R^2, RMSE, E
6	Kisi and Shiri, (2012) [99]	USA	WA-ANFIS	GWL	Daily	Jan 2001-Dec2008	R, RMSE, CO, NSE
7	Sudhee et al. (2012)	Andhra Pradesh, India	SVM-QPSO, ANN	GWL	Monthly	Nov 1984-Dec 2001	EFF, R, RMSE
8	Moosavi et al. (2012) [182]	Mashhad plain, Iran	WA-ANN, WA-ANFIS	GWL, P, E, average Q	Monthly average	1992 to 2007	R^2, RMSE
9	Shiri et al. (2013) [100]	South Korea	GP (ANN, SVM, ANFIS)	GWL, R, ET	Daily average	Not mention	AARE, MSE, MAE
10	Fallah-Mehdipour et al. (2013) [104]	Karaj plain, Iran	GP, ANFIS	GWL, P, E	Monthly	84-month	R^2, RMSE, E
11	Maheswaran and Khosa, (2013) [183]	Northern Saanich Peninsula, Canada	WA-ANN, ANN	GWL	Monthly average	May 1975-Apr 2002	NSE, RMSE, MAE, MRE
12	Moosavi et al. (2013) [97]	Mashhad plain, Iran	WA-ANN, WA-ANFIS	GWL, P, E, average Q	Monthly average	1992 to 2007	R^2, RMSE, E
13	Emamgholizadeh et al. (2014) [184]	Bastam plain, Iran	ANFIS, ANN	R recharge, IRF, PR	Monthly	2002–2011	C, MAE
14	Suryanarayana et al. (2014) [185]	Visakhapatnam, India	ANN, SVR, WA-SVR	GWL, P, T_{max}, T_{mean}	Monthly	12 Month	R^2, RMSE, EC, NMSE, MAPE
15	Tapoglou et al. (2014) [186]	Bavaria, Germany	ANN-ANFIS- GS	GWL, SWL, T, R	Daily	2008–2012	RMSE, RMSEE, MAE, Bias
16	He et al. (2014) [187]	Ganzhou region, China	WA-ANN, ANN	GWL	Monthly	1994–2004	RMSE
17	Mathur, (2015) [163]	Andhra Pradesh, India	SVM-PSO, ANFIS, ARIMA	GWL, R, H,T	Monthly	1985 to 2004	RMSE, EFF, CORR
18	Jha and Sahoo, (2015) [188]	Konan basin, Kochi, India	ANN-GA	GWL, R, T,	Monthly	1999 to 2004	R^2, RMSE, IOA, NSE, Bias, CV
19	Yang et al. (2015) [189]	Fujian, China	WA-ANN, ANN	GWL	Monthly average	1985–2004	RMSE, R, EFF
20	Khalil et al. (2014) [190]	Quebec, Canada	WA-ANN, ANN	P, T	Daily	1991–2012	R^2, RMSE, E, MAPE, MAE
21	Nourani et al. (2015) [191]	Ardabil plain, Iran	WA-ANN, ANN	GWL, R, runo?	Monthly	1998–2012	R^2, RMSE
22	Chang et al. (2016) [164]	Zhuoshui River basin, Taiwan	ANN (SOM-NARX)	GWL, Q, R	Monthly average	1985–2004	RMSE, CORR, EFF
23	Han et al. (2016) [192]	Northwest China	ANN-SOM	GWL, Q, climatic	Monthly	1998 to 2010	NSE, R, RMSE
24	Hosseini et al. (2016) [193]	Shabestar plain, Iran	ANN-Ant colony	GWL, R, E, Q, T	Monthly	1996–2006	R, RMSE, RAE
25	Nourani and Mousavi, (2016) [47]	Miandoab plain, Iran	WA-ANFIS, WA-ANN	GWL, P, Q	Monthly	2000–2009	R^2, RMSE
26	Ebrahimi and Rajaee, (2017) [194]	Qom plain, Iran	WA-ANN, WA-SVR, ANN, SVR	GWL	Monthly	2002–2013	RMSE, E
27	Huang et al. (2017) [165]	Gorges Reservoir Area, China	PSO-SVM, PSO-BPNN	GWL	Daily	2013–2014	R^2, RMSE, NSE
28	Barzegar et al. (2017) [195]	Azarbaijan, Iran	WA-ANN	GWL	Monthly	2001–2018	REVIEW
29	Zare and Koch, (2018) [98]	Miandarband plain, Iran	WA-ANFIS, AI	GWL, P	Yearly	1991–2013	RMSE, R^2
30	Balavalikar et al. (2018) [167]	Brahmavar, Kundapur and Hebri In Udupi district, India	POS-ANN, ANN	GWL	Monthly	2000–2015	R^2, RMSE, R, MAE, MAPE
31	Rakhshandehroo et al. (2018) [166]	USA	WA, DE, PSO, RBFNN, MLP	GWL	Daily	2000–2005	RMSE, MAE,PCC,NSE
32	Malekzadeh et al. (2019) [176]	Kabodarahang region, Iran	WA-SAELM, WA-ANN, WA-SVM.	GWL	Monthly	1990–2015	RMSE, R, MAE, MAPE, RSMRE, BIAS, NSC
33	Supreetha et al. (2019) [177]	Karnataka, India	PSO-ANN, ABC-ANN	GWL, P	Monthly	2000–2013	RMSE, MAE, MAPE
34	Roshni et al. (2019) [162]	Shikoku Island of Japan	GT-WANN	GWL, P	Monthly	1998–2004	BIAS, RMSE, R, NSE
35	Tang et al. (2019) [130]	Northern United Kingdom	SVM, ANN, random forest, k-NN	GWL	Hourly	2016–2017	MAE, MAPE, MSE, RMSE
36	Kombo et al. (2020) [147]	Rwanda	KNN-RF	T, P, GWL, Max. RH	Daily	2016–2018	R^2, RMSE, MSE, MAE
37	Moravej et al. (2020) [85]	Karaj plain, Iran	GA-ISA, GP, ISA-LSSVR	GWL	Monthly	2002–2008	R^2, RMSE, NS
38	Roshni, (2020) [178]	Konan groundwater basin, Japan	EANN-GA, EANN, GRNN, FFNN	P, GWL	Monthly	1998–2004	NSE, RMSE,Bias

(continued on next page)

Table 5 (*continued*)

No.	Author (year)	Location of study	Hybrid AI models	Input Combination	Frequency	Data Span	Performance metrics
39	Banadkooki et al. (2020) [179]	Yazd, Iran	RBF-WOA, MLP-WOA	R, T, GWL	Monthly	2000–2012	NSE, MAE, RSR
40	Natarajan and Sudheer, (2020) [154]	Andhra Pradesh, India	SVM-QPSO, ANN, SVM, GP, ELM	GWL	Monthly	1997–2013	RMSE, PCC, MAE, R^2
41	Seifi et al. (2020) [180]	Ardebil plain, Iran	CSO, PSO, WDA, GA, KA, AI	GWL	Monthly	2000–2012	RMSE, MAE, NSE, PBIAS

2.6.1. Gaussian process regression (GPR)

A Gaussian Process is a collection of random variables, where limited numbers of them are compatible with Gaussian distributions. A Gaussian process is determined completely by an average function, $(m(x))$, and a covariance function, $(k(x, x\prime))$. This process is a natural generalization from the Gaussian distribution with mean vector and covariance matrix, as shown in Eq. (1):

$$f \sim GP(m, k) \tag{1}$$

regression models of the Gaussian process are based on this hypothesis that adjustment observations must include information about each other. This process clarifies priorities on function space, which is called a natural extension of Gaussian function with mean vector and covariance matrix. It should be noted that Gaussian distribution is on vector; however, the Gaussian process goes on functions. As a result, Gaussian processes models owing to prior knowledge concerning data and functional dependencies, do not require any validation technique for generalizing. Moreover, Gaussian process regression models can predict distribution corresponding to inputs [210]. In Gaussian processes, X and Y denote inputs and outputs ranges, there are n pair of (x_i, y_i) independently and similarly. In regression, if $y \in R_e$ then a Gaussian process on x with mean function $\mu : Y \to R_e$ and Covariance function $k : X * X \to R_e$ would be defined. The main assumption of GPR is based on this equation:

Regression models of the Gaussian process are based on the hypothesis that adjustment observations must include information about each other. This process directly clarifies priorities on the function space, which is called a natural extension of the Gaussian function with mean vector and covariance matrix. It should be noted that the Gaussian distribution applies to vectors, while the Gaussian process applies to functions. As a result, Gaussian process models, due to prior knowledge concerning data and functional dependencies, do not require any validation technique for generalizing. Moreover, Gaussian process regression models can predict the distributions corresponding to inputs [210]. In Gaussian processes, X and Y denote inputs and outputs ranges, and there are n (x_i, y_i) pairs, which independently and identically distributed. In the regression, if $y \in R_e$ then a Gaussian process on x with mean function $\mu : Y \to R_e$ and Covariance function $k : X * X \to R_e$ is defined. The main assumption of GPR is based on Eq. (2):

$$y = f(x) + \epsilon, \epsilon \sim N(0, \sigma^2) \tag{2}$$

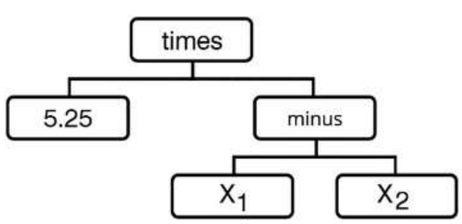

Fig. 11. An example of a gene (genome) expressing a function $5.25(X_1 - X_2)$.

2.6.2. GPR implementation in the hydrology

Koo et al. [211] stated that the primary benefit of using GPR models is that the model provides not only future predictions, but also the associated uncertainty. This distinguishes GPR models from other statistical models, yielding original high-fidelity results and a probabilistic estimate of the approximate uncertainties [212], as well as its simple structure [213], flexibility [214], and the ability to incorporate prior knowledge of the outputs in the meta-model construction process [211]. The application of GPR has been reported in several investigations associated with hydrology, such as the proficiency of GPR in forecasting Monthly streamflow [215], construction of data-driven hydrological models [216], prediction of short-term soil moisture [217], Modeling Pan EP [218], estimating chlorophyll concentrations in sub-surface waters [219], Assessment of infiltration models [220], modeling of infiltration of sandy soil [221], forecasting of reference EVP [222,223], prediction of water temperature of rivers [224], forecasting short-term WS [225] and seepage through earth dams [226], monitoring and fault detection of wastewater treatment processes (Samuelsson et al., 2017 [227]), Predictive Control of Drinking

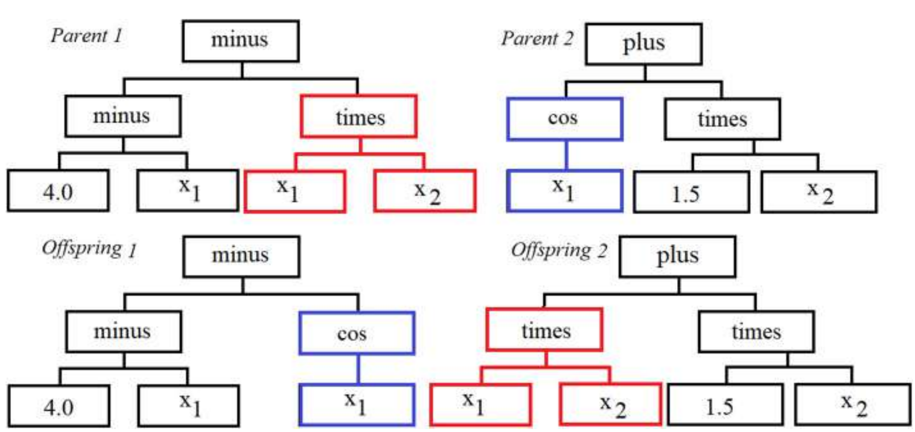

Fig. 12. An example of crossover operation acting on two parents and producing two offspring.

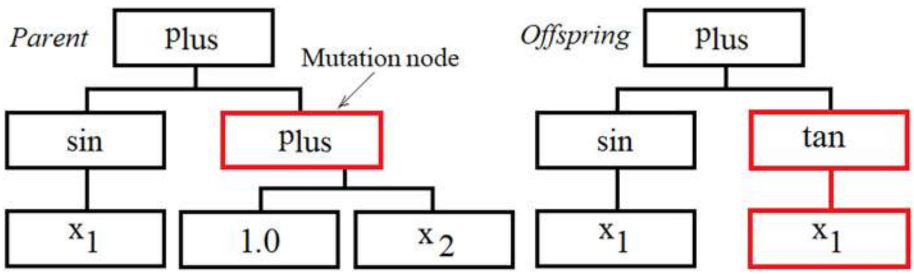

Fig. 13. Mutation operation acts on genetic programming (GP) chromosome.

Table 6
List of the researches on the developed evolutionary computing predictive models for GWL modeling.

Research	Applied AI models	Case study	Data span	Input parameters	Output parameter	Performance metrics	Time scale
Fallah-Mehdipour et al. (2013) [104]	GP, ANFIS	Karaj aquifers, Iran	7-year (84-month)	GWL, P, EP	GWL	RMSE, NSE, R^2	monthly
Kasiviswanathan et al. (2016) [38]	GP	Amarawathi basin, India	30 years (1980–2009)	Raf GWL	GWL,	CC,NE, RMSE,MBE	monthly
Sadat-Noori et al. 2020 [206]	GP	Tabriz plain, Iran	8-year (96-months)	GWL, P	GWL,	R^2 and RMSE	monthly

Water Networks [228], prediction of sulfate content in lakes of China [229], water demand forecasting [230], seawater intrusion prediction [231], modeling adsorption equilibrium of water on zeolite Li-LSX [232], and oceanic chlorophyll prediction [233].

2.6.3. Applications in GWT

The application of linear regression in the prediction of GWL has been assessed by Maatta [234]. In this survey, the importance of the combination of statistical models in predicting GWL was reported. Aburub and Hadi [235] applied several data mining techniques to predict GWL. Their findings indicated that the SVM algorithm outperformed other algorithms in terms of classification accuracy.

The high proficiency of GPR in forming reasonable predictions of groundwater quality data for the majority of linear trend cases, with a few exceptions of severely non-Gaussian data, has been reported by Koo et al. [211]. The efficiency of GPR in producing maps of GWL variability and identifying GWL patterns for the island of Crete has been investigated by Varouchakis and P Karatzas [236]. Kolli and Seshadri [237] relayed the ability of data mining techniques for the assessment of groundwater quality.

In some studies, the accuracies of other statistical models have been found to be better than that of GPR. For instance, Colchester et al. [238] compared three methods for representing accelerometry data (wavelets, splines, and Gaussian processes) with two systems for estimating GWL (SVR and GPR). Their results showed that the method using splines and a SVR model provided the lowest overall errors. Dolat Kordestani et al. [239] applied evidential belief function and boosted regression tree (EBF-BRT) algorithms for groundwater potential mapping. Their findings demonstrated that the combination of the two techniques could increase the efficacy of these methods in groundwater potential mapping. Similarly, Pourghasemi and Beheshtirad [240] combined EBF and GIS for groundwater potential mapping. Azimi et al. [241] exploited Gaussian process classification (GPC) to address the association analysis of climate-related drought and a decline in groundwater level. Kim et al. [242] utilized the capacity of the GPR model for long-term predictions of GWL. Comparing the GPR and ANFIS models in multi-step lead time forecasting of GWL revealed that the GPR model provided reasonably accurate predictions compared to those of ANFIS [90]. Zhang et al. [243] integrated Gaussian process (GP) and Markov Chain Monte Carlo (MCMC) to adaptively construct locally accurate surrogates for Bayesian experimental design in groundwater contaminant source identification problems. In this survey, without sacrificing estimation accuracy, the new approach achieved about 200 times of speed-up compared to MCMC. Bozorg-Haddad et al. [244] utilized a GA-SVR hybrid algorithm for the simulation and prediction of GWL. Rajabi and Ketabchi [245] applied GP emulation as a valuable tool for solving the computational challenges of uncertainty- based simulation–optimization schemes in coastal groundwater management. Their results indicated that GP emulation can provide an acceptable level of accuracy with no bias and low statistical dispersion. Lal and Datta [246] compared the capacity of GP and GPR models for groundwater salinity prediction. The GPR model outperformed the GP model. A list of articles using Gaussian Process Regression Models for GWL modeling are tabulated in Table 7.

2.7. Complementary AI models applications

The GWL is particularly non-stationary, and noisy GWL time-series may not be properly simulated by AI-based models [39,248]. The hybridization of ML techniques, developed based on wavelet-decomposed data, has become a very active research area to address this issue. It has shown better performance in simulating the raw GWL data sets than their simple model counterparts [249]. A representation of the local time-series data using scaling and wavelet coefficients at various resolutions attained through the Mallats pyramidal algorithm has been shown to provide the discrete wavelet decomposition [249] Generally, wavelet-based ML models are more precise, as the discrete wavelet transform (DWT) can improve discrimination against the non-stationary and non-linear trends that occur at different time-series scales of input variables [249].

Wavelets are a type of mathematical function (waveform) that, with an average of about zero, may oscillate and decay within a short time [249]. In order to denoise non-linear and non-stationary time-series and extract information that is hidden in the signal, WTs provide efficient optical signal processing techniques [195,248]. They were conceived as the continuous wavelet transform (CWT) [250]. The discrete wavelet transform (DWT) has been proposed for practical applications, as hydrologists and modelers generally only have access to discrete-time signals [39]. In the DWT, a signal is decomposed to an approximation at the first

Table 7
The conducted researches using Gaussian Process Regression Model for GWL modeling.Abbreviations: Gaussian process (GP), Genetic Algorithm (GA), Support Vector Regression (SVR), Naïve Bayes (NB), K-Nearest Neighbor (kNN), Classification Based on Association Rule (CBA), evidential belief function and boosted regression tree (EBF-BRT), receiver operating characteristics (ROC), Gaussian process classification (GPC), artificial neural network (ANN), Groundwater Resources Index (GRI), Standardized Precipitation Index (SPI), Adaptive Neuro Fuzzy Inference System (ANFIS), Correlation Coefficient (CC) Root Mean Squared Error (RMSE), Nash–Sutcliffe Efficiency (NSE)

Research	Applied AI models	Case study	Data span	Input parameters	Output parameter	Performance metrics
M. M. Rajabi and Ketabchi [245]	Gaussia GP emulation	Kish Island (Persian Gulf)	the period of the simulated dataset	KL, aL and RNet	quantities of	
interest (QoI).	Time saving ratio (TSR)					
OmidBozorg Haddad et al. [244]	GA-SVR hybrid algorithm	Karaj plain aquifer (Iran)	2002–2008	EP, prediction, groundwater and surface data	groundwater level	R^2 and RMSE
KamakKolli and Seshadri [237]	Data mining technique on Arc/View software	Tadepalle, Guntur district	–	physico-chemical		
parameters like TDS, TH, Cl						
and NO3	Water Quality Index	–				
[211]	GPR	Pyeongchang Yuchyeon	2007–2012	groundwater level (GWL), pH, Total dissolved solid (TDS), T, CL- SO4, NO3-N, and NH4	Groundwater Quality	confidence intervals
Farah Colchester et al. [238]	SVR, GPR	Kenya	April and November, 2014	S,V	groundwater depth	median error
Aburub and Hadi [247]	SVM, NB, KNN, CBA.	Jordan	–	elevation, faults, Raf, slope, T, wadis and outcrop	groundwater areas	Accuracy, Precision and F1
Emman Varouchakis et al. [236]	GPR	island of Crete, Greece			groundwater level spatio- temporal variability	
Dolat Kordestani et al. [239]	EBF-BRT algorithms	Lordegan aquifer (Iran)	2014	EBF values of the groundwater- conditioning factors (GCFs)	groundwater potential mapping.	ROC test
Azimi et al. [241]	GPC, ANN	609 study plains in Iran	2017 to 2019	pair of a statistical average of the value of each SPI and GRI for each		
plain.	groundwater drought					
Kim et al. [211]	GPR	Han River Basin	2004 to 2015	monthly averaged groundwater level	Groundwater Level Trend	confidence intervals
Raghav and Deka [90]	GPR, ANFIS	Sullia Taluk, India	2000 to 2013	Monthly ground water level time series up to previous Four time steps	multistep lead time forecasting of groundwater levels	CC, RMSE, NSE

decomposition level, which is then iteratively applied to subsequent decompositions [250].

The DWT is considered to be a sampled version of the CWT. In association with a specific dyadic scale and time, any time-series can be commonly re-expressed in terms of the DWT coefficient [249]. It divides a given function into different scale components, where a frequency range can also be allocated to each scale component, allowing the time-series to be viewed at multiple resolutions, thus enabling hydrologists to analyze each component with a resolution suited to its scale [39,195,248,249]. The scale here refers to the time interval of that specified time series, while the number of recurring oscillations over a unit of time is denoted as the frequency [249]. A signal (time-series) is decomposed by the DWT into non-sinusoidal components that provide adequate information for both synthesis and analysis of the raw signal (i.e., the time-series). It is possible to select or build the wavelet form to fit the time-series signal outline [249]. To improve the accuracy of AI-based models, the WT is usually suggested as a method to pre-process the time-series [39]. Barzegar et al. [195], on the other hand, used the maximal overlap discrete wavelet transform (MODWT) for time-series decomposition without a dyadic duration. The MODWT is comparable to the DWT, in that the input signal at each step is added to low- and high-pass filters. Here, the coefficients are not decimated by the MODWT, and the number of wavelets and scaling coefficients are similar to the number of sample observations at each transformation step. Although an accurate orthogonal decomposition of the time-series is not given by MODWT, it is more effective than the simple DWT, as it can be performed for any sample size [195].

WT relies on a fully adaptable window function (named the mother wavelet), which can be adjusted over time, depending on the compactness and shape of the signal [195]. In the literature, many mother wavelets exist and their choice depends on the data set(s) to be examined [19]. The type of time-series is the key criterion for choosing a mother wavelet [39]. The key elements of a mother wavelet comprise the support area, the association with the length of the wavelet period, and the number of missing moments, which regulate the wavelet's ability to display information in a time-series [39].

Numerous researchers have employed the WT for GWL modeling, as shown in the literature provided in Table 8. In predicting multi-step lead time GWLs across two neighboring micro-watersheds-namely, Pavanje and Gurpura-along the coastline of Karnataka, Rezaie-balf et al. [249] employed the WT to develop hybrid Wavelet-M5 Model Trees (W-MT) and Wavelet-Multivariate Adaptive Regression Splines (W-MARS) models. To decompose the input time-series, they utilized Haar, Daubechies, Dmey, and Coiflets as mother wavelets. The W-MARS and W-MT models were found to provide accurate forecasting, as opposed to the standard MARS and MT models. In improving the forecasting

Table 8
The literature review researches on the complementary ML models for GWL modeling

	AI models	Case study	Data span	Input parameters	Output parameter	Performance metrics
[249]	W-MARS, W-MT	Karnataka, India	August 1996 - July 2006	GWL, Raf, T	GWL	R^2, RMSE, NNSE
[39]	WGEP, WM5	Lorestan Province, Iran.	2002–2012	GWL, T, P	GWL	R^2, RMSE, rRMSE, BIAS, rBIAS, AIC
[252]	EEMD-GEP, EEMD-M5, CEEMD-GEP, CEEMD-M5	Delfan plain, Iran	2002 to 2012	GWL, P, T	GWL	R^2, RMSE, rRMSE, BIAS, rBIAS
[195]	WA-GMDH, WA-ELM	Maragheh- Bonab, Iran	Sep 1985- Mar 2016	GWL	GWL	R^2, RMSE, NSC
[248]	WP-SVR	Mangalore, India	1996–2006	GWL, Raf, T, Tidal Level	GWL	NRMSE, Normalized Mean Bias, Absolute Relative Error, NSC, Threshold Statistics, R^2
[194]	wavelet-ANN, wavelet-MLR, wavelet-SVR	Qom plain, Iran	April 2002 - March 2013	GWL	GWL	E, RMSE
[107]	LSSVM, ANFIS, NARX	Shabestar Plain, Iran	Climate Data (1951–2016) GWL (April 2002- March 2016)	P, T	Future ground-water level	R^2, RMSE
[254]	EMD, PSR, PSO, ELM, PSO-ELM, EMD-PSR-PSO-ELM	Heilongjiang Province, China	1998 to 2014	groundwater depth	ground-water depth prediction	posterior error ratio (C), small error frequency (p), relative mean square error (E1), fitting accuracy ratio (E2), test forecast effect index (E3).
[176]	SAELM, WA-SAELM	Kabodarahang region, Iran	August 1990 to September 2015	GWL	GWL	R, RMSE, NSC
[255]	ANN, ANFIS, Wavelet-ANN, Wavelet-ANFIS	Mashhad, Khorasan Razavi province, Iran	1992 to 2007	total P, EP, discharge, GWL	GWL	R^2, RMSE, NSC
[191]	FFNN, WT-FFNN, ARIMAX	Ardabil, north-western Iran		GWL	GWL	RMSE, R^2
[256]	XGBT, XGBL, WT-XGBT, WT-XGBL, WT-RF	Kumamoto City, Kyushu Island, Japan	1980–2017	GWL	GWL	MSE, MAE, RMSE, RSR, R^2, NSE, KGE
[185]	WA-SVR	Visakhapatnam, India	May 2001- February 2012	groundwater depth, P, T_{max}, T_{mean}	GWL	R^2, NSC, NMSE, RMSE, MAPE
[257]	EEMD-ANN, EEMD-SVM, EEMD-ANFIS	Lake Okeechobee, Florida	1997 to 2012	GWL	GWL	R, NMSE, RMSE, NSC, AIC
[258]	WA-ANN	Zhangye basin, China	June 2003- December 2010	GWL, P, EP, T_{mean}	GWL	R, MAE, RMSE, NSC, RSR
[259]	wavelet- SAELM	Kermanshah, Iran (Sarab Qanbar),	2002–2015	GWL	GWL	R, RMSE, MAE, MAPE, NSC
[98]	Wavelet-ANFIS	Miandarband plain, Kermanshah province, Iran	October 1991- June 2013	P, piezometric head data	GWL	R^2, RMSE

efficacy, the W-MARS models outperformed the W-MT and their respective simple corresponding models. Furthermore, compared with the other models, the W-MARS models provided relatively good six-month lead-time forecasts for GWL. Two hybrid models have been developed by Bahmani et al. [39]-wavelet gene expression programming (WGEP) and WMT-in order to simulate monthly GWL at three groundwater wells in Iran. To decompose the time signals, Haar, Coif1, Sym3, Db4, and Db2 wavelets, which have been widely used in hydrological studies, were adopted. The study revealed that the hybrid models-WGEP and WM5-showed an improved performance over their simple models-GEP and M5-while the performance was comparable between the hybrid models. It was also reported that the choice of an appropriate level of decomposition significantly affects the hybrid model's accuracy. The use of WGEP to pre-process a time-series and simulate GWL, compared to the hybridization of GEP with Ensemble Empirical Mode Decomposition (EEMD) [251] and Complementary Ensemble Empirical Mode Decomposition (CEEMD), was also supported in another study by Bahmani and Ouarda [252]. The study by Barzegar et al. [195] demonstrated the effectiveness of the hybrid wavelet-group data handling (WA-GMDH) and WA-EL models, with high-level wavelet filters, which delivered more reliable forecasts than those obtained using low-level wavelet filters. They also observed that, when using the least-squares boosting (LSBoost) algorithm, ensemble multi-wavelet models can improve the performance of the single wavelet-based model and lessen the forecast uncertainty. Sujay Raghavendra and Deka [248] demonstrated that the Wavelet packet-SVR (WP-SVR) model performs better than the classic SVR model for forecasting monthly GWL fluctuations. They also found that better results were produced by the wavelet packet coefficients of the Daubechies 4 wavelet with level 4 decomposition. Use of the hybrid wavelet-neural network (WNN), wavelet-linear regression (WLR), and wavelet-SVR (WSVR) models for monthly GWL simulation was tested by Ebrahimi and Rajaee [194] for two wells in the Qom plain, Iran. They reported that, by analyzing information at two decomposition levels, the wavelet- transformed data enhanced the training of the TDNN, MLR, and SVR models. They also found that wavelet types, such as Meyer's mother wavelet, showed a similar behavior at different well locations. The results of Jeihouni et al. [107] revealed that the hybrid technique of the wavelet Non-linear Autoregressive Network with Exogenous inputs (wavelet-NARX) gave the best results, in most cases, in comparison with wavelet-ANFIS (WA-ANFIS) and other models. For daily water level prediction in reservoirs, Seo et al. [253] researched the efficiency of the combination of WT with ANN and ANFIS. They discovered that the efficiency of the hybrid models was higher than that of their corresponding simple models. The details of other studies that have demonstrated the capability of hybridization of WT with other models are given in Table 8.

Several other researchers used this approach of transforming input signal using wavelet decomposition [47,107,105]. These examples highlight how wavelet transform has the potential to be used for improving the ANFIS performances used for GWL prediction. Nourani and Mousavi [47] compared all possible combinations of P; Q and GWL decomposed using wavelet transform coherence and combined for predicting monthly GWL data acquired over the period ranging between 2001 and 2011 in the Miandoab plain, northwest of Iran. The decomposed signal was used as input for the ANFIS and FFNN models and the best accuracy was obtained using hybrid WANFIS with R^2 and RMSE of 0.940 and 0.084, respectively, compared with the 0.93 and 0.095 obtained using the hybrid WFFNN. Jeihouni et al. [107] tested the importance of the wavelet decomposition in improving the prediction accuracy of AI models by comparingANFIS, LSSVM, and NARX models, and the same architecture coupled with the wavelet decomposition, i.e., WANFIS, W-LSSVM, and W-NARX. The six models were developed using P and T_{mean}. Tt was reported that both models were able to predict GWL accurately; however, the W-NARX was more accurate and exhibited high R^2($\sim$0.99) and low RMSE ($\sim$0.03) values. Wen et al. [105] analyzed the importance of the wavelet transform in improving the accuracy of the ANFIS model used for predicting weakly GWL in the Laizhou bay, China, and found that both ANFIS and WANFIS can provide good prediction accuracy. They also reported the superiority of the WANFIS compared the FFNN and ANFIS having a R^2, RMSE and MARE of 0.983, 0.062, and 2.48, respectively. More recently, some interesting research has been conducted by combining ANFIS with wavelet transform. Sridharam et al. [106] used several input variables namely, IL, P, T_{mean}, GWL, and EVP for modelling GWL at daily times step. They compared he performance of two AI models: the ANFIS and a hybrid WANFIS combining wavelet transform and ANFIS. The two models were evaluated and compared using several performances metrics, i.e., RMSE, MAE and R^2, and it was found that hybridizing the ANFIS using a wavelet decomposition method contributed significantly to the improvement of the models performances for which the RMSE and MAE were significantly decreased and the R^2 was increased from 0.924 to 0.962 during the testing phase.

Based on a recent review on the employment of WT to develop a hybrid model to simulate GWL, we found that the WT hybrid models, in all cases, performed better than their corresponding simple counterparts. This is due to the capability of the WT to act as a pre-processing tool in discriminating the non-linear and non-stationary trends in the time-series which usually persist in hydrological and climatological input variables. The WT hybrid models are also able to take in any sample size, with the ability to view the scaled component of the time-series at multiple resolutions. As a wide selection of mother wavelets exists, a further comparative study is needed to improve the wavelet selection in the development of WT hybrid models. Previous findings have also stressed the importance of selecting a suitable decomposition level, as it may affect the model's accuracy.

2.8. Statistical models applications

Statistical models have been widely used in various aspects of hydrological modeling [260,261]. In this type of modeling, the relationships between one or more variables are mathematically embodied, in order to mimic the behavior of the real system. These relationships are mainly set using function minimization procedures, which minimizes the sum of squared residuals between the observed and modeled target variables. As such, in statistical modeling, regression analysis and time-series analysis are two methods that employ such a minimization process. The bivariate analysis of time-series differs from that of regression analysis, in which the time is used as the independent or predictor variable. Meanwhile, in regression, the bivariate analysis is represented between two or more statistically associated variables. Further, independence among the individual measurements are assumed in the bivariate form of regression. In other words, the order of the predictor-predictand data pairs is not important in bivariate regression; whereas, in time-series analysis, the time dependence is recognized and used to improve the understanding of the underlying physical processes and/or the prediction accuracy [262].

A time-series model is stochastically handled without considering the inherited physical nature of the time-series [263,264]; that is to say, it conceptualizes the physical process of any time-series into a mathematical model. Thus, it requires adequate knowledge of the mathematical approaches for identifying time-series patterns. Autoregressive (AR), moving average (MA), ARMA, ARIMA, and SARIMA are commonly used methods for time-series modeling. In the following, the individual description of each model is presented:

2.8.1. Autoregressive process $AR(p)$

The serial dependence of data points in time series is represented by AutoRegressive process $AR(p)$. $AR(p)$ (Eq. 3) describes the linear combination of the highest autoregression order (p) coefficients of consecutive data points of the time series [265]:

$$x_t = \bar{x} + \phi_1 x_{(t-1)} + \phi_2 x_{(t-2)} + \cdots + \phi_p x_{(t-p)} + \epsilon_t \tag{3}$$

where, x_t is the variable value of x at time t; $\bar{x}$ is the sample variable means; ϕ_1, ϕ_2, ϕ_p are the autoregressive model parameters; ϵ_t is the white noise error; p refers to the order of the autoregression. The AR model is used when the time series is stationary. Therefore, it is worth to assess stationary where the AR model parameters should be within ± 1, hence the influence of antecedent values is hindered. Otherwise, the accumulated error from the previous values shifts the time series into a non-stationary one.

2.8.2. Moving average process $MA(q)$

Besides the serial dependence of data points considered in the autoregressive process, the time series might be influenced by the antecedent random error (white noise error) involved in prior data points. This could be accounted for through the moving average (MA)(q) process (4) which is made of the random error component and a linear combination of random shocks of the antecedent values [266].

$$x_t = \bar{x} + \epsilon_t - \theta_1 \epsilon_{(t-1)} - \theta_2 \epsilon_{(t-2)} - \cdots - \theta_q \epsilon_{(t-q)} \tag{4}$$

where, $\theta_1, \theta_2, \theta_q$ are the moving average parameters; $\epsilon_t, \epsilon_{(t-1)}, \epsilon_{(t-q)}$ are the random error components at $(t-1), (t-2), (t-q)$, respectively; q is the order highest moving average process. The MA model parameters require to invert to overcome the duality of the moving average process and the autoregressive process [267]. The inevitability condition of a moving average process is analogous to the stationarity condition of an autoregressive process.

2.8.3. Autoregressive moving average $ARMA(p, q)$

The real stochastic process of a random variable x_t is represented by the ARMA process. The ARMA model is a combination of AR and MA of order p and q, respectively [268]. The general form of ARMA is as follows (5):

$$\begin{aligned} x_t = \bar{x} + \phi_1 x_{(t-1)} + \phi_2 x_{(t-2)} + \cdots + \phi_p x_{(t-p)} + \epsilon_t - \theta_1 \epsilon_{(t-1)} \\ - \theta_2 \epsilon_{(t-2)} - \cdots - -\theta_q \epsilon_{(t-q)} \end{aligned} \tag{5}$$

An ARMA model with $(p, 0)$ is an autoregressive process only. While an ARMA of $(0, q)$ is a purely moving average process.

2.8.4. Autoregressive integrated moving average $ARIMA(p, q, d)$

An ARIMA model is presented as combined process of AR and MA. In contrast to ARMA, the differencing step is applied in the ARIMA model once or more to eliminate the non-stationarity in the time-series points. Differencing, in statistics, is a transformation applied to a non-stationary time-series to make it stationary and to remove the non-constant trend. Therefore, the ARIMA model has three specific parameters, p, q, and d, where d represents the number of differencing passes [269].

2.8.5. Seasonal Autoregressive integrated moving average $SARIMA(p, q, d)(ps, qs, ds)$

SARIMA is the generalized form of the ordinary ARIMA model. It is used when there is a seasonal pattern in the time-series. The seasonal parameters in SARIMA are estimated once they are identified through the model identification phase, along with non-seasonal ones. The seasonal differencing is applied to a seasonal time-series to remove the seasonal component. Therefore, the SARIMA model is typically denoted as $ARIMA(p, d, q)(ps, qs, ds)$, where ps, qs, and ds are the seasonal AR, MA, and differencing parameters, respectively [103].

The Box–Jenkins method, developed by Box and Jenkins [264], is used to identify the best fit of the time-series model on past observation values for the five stochastic models (AR, MA, ARMA, ARIMA, and SARIMA). The methodology of time-series modeling can be summarized as follows [264].

- Model identification: in this step, the ACF and PACF functions are employed to determine the order of AR and MA parameters.
- Parameter estimation: in this step, the computation algorithms are employed to find the model parameters coefficients that best fit the model. Generally, the minimization function of the sum of squares of the residuals is employed using either the approximate maximum likelihood method [270], the approximate maximum likelihood method with backcasting, or the exact maximum likelihood method [271].
- Model-checking: when the model structure and estimation parameters values are completed, it is of critical importance to check whether the built model conforms to the stationary univariate process. In other words, the reliable model should produce statistically independent residuals that contain only white noise error and no systematic error. Besides, the model should provide accurate forecasts sufficiently. The portmanteau lack-of-fit test-statistic [272] is typically used for the diagnostic purposes of the built model where the behavior of the estimated residual is checked to confirm that the realizations are approximately from a white noise process. A comparison of the forecasts with the measured data points can be further used to check the accuracy of generated forecasts.
- Forecasting: In the last step, the model is employed to compute new data points, which beyond those included in the input time series.

2.8.6. Literature review

In the literature, many successful applications of statistical models, including logistic regression [273], k-NN [274], linear discriminant analysis [274], quadratic discriminate analysis [275], multivariate adaptive regression spline (MARS) [276], and regression trees [275], in hydrology have been reported. However, time-series models such as autoregressive, Moving average, autoregressive moving average, autoregressive integrated moving average, and seasonal autoregressive integrated moving averages have been extensively applied to predict the present and to forecast future values in GWL series.

Mirza and Ghazavi [277] applied the five time-series models of AR, MA, ARMA, ARIMA, and SARIMA to predict the monthly GWL of 36 wells located in Isfahan province, Iran. The monthly GWL from 1990 to 2004 were first clustered using the Vard algorithm of the hierarchy method to classify the true groups of piezometric wells into five groups, according to their similarities to each other. The performance of the five models was investigated through 11 different structures, according to the lag time and differencing processes. They concluded that time-series models are one of the appropriate methods which could be of use to forecast the GWL. The AR with 2-lag showed the best forecasting of GWL for 60 months ahead for the five clusters.

Choubin and Malekian [278] compared the results of ANN and ARIMA models for GWL forecasting 4 months ahead in the Shiraz basin, southwestern Iran. The monthly time-series of GWL over the period 1993 to 2010, in addition to that of total P, monthly average streamflow, T, and EP, were employed to set up the models. Gamma and M tests were used to identify the optimal input parameters and the length of the training data, respectively. They reported the superior performance of ARIMA with p, q, and d values of 2, 1, and 2, respectively, in predicting GWL one month ahead. Gibrilla et al. [279] applied the ARIMA model to measure GWLt every six hours in seven monitoring wells from 2005 to 2014 in the Upper East Region of Ghana. The results revealed that the current demand in the region could be sustained under the current and predicted GWL trends. Sakizadeh et al. [280] investigated the performance of SARIMA and Holt-Winters Exponential Smoothing (HWES) methods using GWL records from 28 representative piezometers between 1984 and 2012 in the Malayer Aquifer. They concluded that the SARIMA technique provides further improvements over HWES. Therefore, the optimized SARIMA model was used to predict the time-series for the next 4 years (i.e., from 2012 to 2016). Takafuji et al. [281] compared the performance of ARIMA and a geostatistical method using sequential Gaussian simulation (SGS) for predicting GWL at 49 wells in the Bauru Aquifer System domain in Sao Paulo State, Brazil. They found that, for monitoring the aquifer, the ARIMA models performed more favorably than SGS, as they achieved the same accuracy level as SGS and a higher precision for all periods. Furthermore, they reported that time-series models can be optimized automatically by using the Akaike information criterion, which provides a precise and accurate trade-off to choose among the models. Goodarzi [282] evaluated the prediction of monthly GWL data at 58 piezometric wells for the period of 1995 to 2010 using ANN, HARTT, and SARIMA models in the Najafabad plain, Iran. They concluded that, though the three models were capable of predicting the GWL, the SARIMA models were more appropriate than the other evaluated methods, as they showed lower error. Therefore, it can be summarized that time-series models are capable of estimating the GWL with relatively good accuracy. A list of articles proposing applied statistical models for groundwater level modeling is given in Table 9.

2.9. Non-linear auto-regressive network with exogenous input (NARX) model for GWL modeling

FFN is one of the most common types of ANN model. An FFN consists of one input layer, several hidden layers, and one output layer. A distinctive feature of an FFN model is that the connections between layers permit forward information flow only [283,284]. The NARX model is a special type of RNN model, and is an important class within the discrete-time non-linear group models. NARX networks have several advantages; for example, they are computationally powerful and are useful for modeling an extensive variety of dynamic systems [285]. NARX networks are recurrent dynamic neural networks which have feedback connections. Based on previous studies, it was noted that the gradient descent learning algorithm may be more efficient within NARX, compared to other networks [286]. NARX networks can be modeled using two different types of architectures: Parallel and series–parallel [287,288]. The latter type of architecture is purely feed-forward and, thus, it can utilize static back-propagation during the training phase. The series–parallel architecture is generally expected to provide more accurate results with the use of accurate inputs. Meanwhile, in the parallel architecture, the past predicted output is utilized as part of the input combination to predict the output value at the next step [289]. As part of the current research, we report previous studies that have employed the NARX model for GWL prediction.

The groundwater information is an important issue for decision-makers in the agricultural area of Mississippi. Therefore, [288] applied a new model, called NARX, for simulating daily GWL in the Mississippi River Valley Alluvial (MRVA) aquifer in the southeastern United States. Two different algorithms-namely, LM and Bayesian Regularization (BR)-were employed to train the NARX network. Several modeling architectures were created, utilizing different hidden node combinations and delays (5, 25, 50, 75, and 100). A comparison between the obtained results was carried out to find the optimal network. Daily historical time series for P and GWL over eight years were considered for GWL forecasting, up to three months ahead. The results showed that NARX-BR learning was better than the NARX-LM network for daily GWL forecasting, according to several statistical indicators. The most accurate forecasting results were attained by BR with two hidden nodes and 100 time delays.

The performance of the NARX model has been investigated to forecast GWL by [290]. The proposed model was applied to forecast GWLs at several wells located in southwest Germany. Two different parameters, P and T, were considered as predictors. Several statistical indicators, such as RMSE, Nash, and R^2, were utilized to evaluate the performance of proposed models. The results indicated the outstanding efficiency of the NARX model for GWL forecasting under a small set of input parameters.

In 2019, [287] employed an autoregressive neural network (NNARx) for GWL forecasting in an aquifer system. The accuracy of the proposed model was compared with the autoregressive with

Table 9
The applied statistical models for groundwater level modeling.

Research	Applied AI models	Case study	Data span	Input parameters	Output parameter	Performance metrics
Mirzavand and Ghazavi [277]	AR, MA, ARMA, ARIMA, SARIMA	Isfahan province, Iran	1990–2004	Antecedent values of GWL	Present value of GWL	R^2, AIC
Choubin and Malekian [278]	ANN, ARIMA	Shiraz basin, southwestern Iran	1993–2010	Antecedent values of GWL	Present value of GWL	RMSE, MAE, R
Gibrilla et al. [279]	ARIMA	Upper East Region of Ghana	2005–2014	Antecedent values of GWL	Present value of GWL	R^2, RMSE, MAPE, MAE, MaxPE, MaxAE, Ljung-Box Q statistics
Sakizadeh et al. [280]	SARIMA, HWES	Malayer Aquifer	1984–2012	Antecedent values of GWL	Present value of GWL	ME, RMSE, MAE, MPE, MAPE, MASE, ACF1
Takafuji et al. [281]	ARIMA, a geostatistical method using sequential Gaussian simulation	Bauru Aquifer System domain in Sao Paulo State, Brazil	September 2014 until 30, 2015).	Antecedent values of GWL	Present value of GWL	RMSE
Goodarzi [282]	the artificial neural networks, HARTT model, SARIMA	Najafabad plain, Iran	1995–2010	Antecedent values of GWL	Present value of GWL	RMSE, R^2

Table 10
The established research on the implementation of NARX model for GWL prediction.

	Models	Case Study Location	Data Span	Time Scale	Input Parameters	Output Parameter	Perform- ance Metrics	Best Model
Guzman et al. (2017) [288]	NARX-LM, NARX-BR	USA	1987–1994	Daily	P, GWL	GWL	MSE, R^2, NSE	NARX-BR
Wunsch et al. (2018) [290]	NARX, ANN	Germany	1948–2008	Weekly	P, T	GWL	RMSE, R^2, NSE, RMSEr	NARX
Zanotti et al. (2019) [287]	NNARx, ARx	Italy	Not reported	Daily	P, T	GWL	MSE, RMSE, NSE, KGE, AIC	NNARx
Di Nunno and Granata (2020) [291]	NARX, NARX-BR	Italy	2008–2012	Daily	Raf, Evapotran-spiration	GWL	RMSE, R^2, MAE, RAE	NARX-BR
Al Jami et al. (2020) [292]	NARX, ANN	Bangladesh	1980–2013	Monthly	P, T, H%	GWL	MSE, NSE, R^2	NARX

exogenous input (ARx) model. Early stopping and Bayesian regularization methods, as well as a combination of both, were utilized for training the forecasting models to avoid over-fitting. The results showed that, for short-term forecasting, the performances of NNARx and ARx models were comparable, with a slightly better performance of ARx model. However, For the long-term, the NNARx model which was trained by the Bayesian regularization method was superior to ARx and other NNARx models. The authors concluded that the linear model needs less time and does not require high computational power. They found that suitable and reliable models for short- and long-term GWL forecasting are linear and neural network methods, respectively.

Daily GWL prediction was carried out, using the NARX method [291], at 76 wells located in the Apulian territory. Several input parameters, including Raf, EVP, and input time delay, were considered for modeling. A comprehensive analysis of the results was carried out to discern the optimal predictive model. The results supported the reliability of the NARX-BR model to predict GWL. The performance of NARX model, in terms of monthly GWL prediction, was examined in [292]. Three different algorithms were used to train NARX and a comparison between their results was conducted by utilizing several statistical indicators. The results revealed that combining Bayesian Regularization as a training algorithm with NARX could provide good prediction ability. Such a model can provide important information for GWL prediction. The established research on the implementation of NARX models for GWL prediction are tabulated in Table 10.

2.10. Other ML models applied for GWL prediction

Naghibi et al. (2015) [293] developed three different machine learning models-BRT, classification and regression tree (CART), and RF models-for mapping groundwater spring potential in the Kohrang Watershed, Iran. To perform this study, a large set of factors, including hydrological, geological, and physiographical factors, were selected as critical factors affecting spring occurrence. A GIS-based spring location map was prepared, using the topographic maps obtained from the National Cartographic Center of Iran (NCCI), which included 864 spring locations in the study area. The data was divided with a ratio of 70% and 30% for the training and model validation sets, respectively. The model performance was evaluated using the receiver operating characteristic (ROC) curve. The results showed that the BRT model had higher accuracy than the CART and RF models, considering the model performance evaluation results. Based on the discussion of the authors, the RF model was not superior to the others, although the RF has shown superior performance in the previous literature. It was also reported that factors such as altitude, drainage density, and slope degree were the most effective factors for predicting spring occurrence.

Nalarajan and Mohandas (2015) [294] presented an M5-MT model to predict monthly GWL in Jones Island, New Jersey, USA. A historical data series of GWL values were collected from monitoring wells between 1970 and 2010. The data from 1995–2009 was used to train the developed model, whereas the remaining were used to validate the model. Previous values of monthly GWL (up to 12 months) were selected as the appropriate input combinations. Observed and predicted results were compared using R^2 and RMSE. The results showed that the developed M5-MT model has strong accuracy in predicting the GWL. However, the authors indicated that the effects of some other parameters, such as P, the permeability of the soil, soil moisture, and soil temperature, are important for GWL prediction.

Zhao et al. (2016) [295] presented a methodology to predict GWL, in which a CART model was developed with the lagged value of Raf, reservoir level, and change of GWL as input variables. The required data were collected between 2005–2007 for the Three Gorges Dam Reservoir area. An SVM model was also developed for the same purpose, in order to compare the performance of the proposed CART model. Absolute error (AE) and relative error (RE) metrics were used to evaluate the model performance. Based on the comparison of observed and predicted values of the two models, it was concluded that the proposed CART model could predict GWL better than the SVM model.

Kaya et al. (2018) [296] proposed an M5-MT model and a feed-forward back-propagation ANN model to predict GWL in the Reyhanlí region, Turkey. Historical GWL data were collected from a well located in the study area between 2000 and 2015. Monthly P and T data were taken from Antakya Meteorological Station, which is governed by the DSI (General State of Hydraulic Work). Evaluation of the proposed model's performance was carried out using R, MSE, and MAE. The results showed that the proposed ANN method had a similar accuracy as the M5-tree model.

Wang et al. (2018) [297] proposed a hybrid model to predict GWL, which combines the canonical correlation forest algorithm with random features, referred to as the CCA-CRF model. The performance of the proposed model was compared with the random forest regression (RFR) and LS-SVR models. Historical daily G and T measurements collected for the Daguhe River in Qingdao, China were used as predictors of GWL. Several input combinations were examined, in order to find the best time lags to predict 1-, 3-, 5-, 7-, and 10-day-ahead GWL. The results of the models were evaluated using the R, RMSE, and MAE metrics. It was observed that the LS-SVR model had higher performance for 1-day ahead prediction, while the proposed CCA-CRF model was superior in predicting GWL in the longer-term. Furthermore, the authors indicated that the proposed CCA-CRF model was faster than the others.

Sharafati et al. (2020) [298] predicted GWL over the Rafsanjan aquifer, Iran, using a gradient boosted regression (GBR) model. Satellite-based products, including hydro-geological and climatic factors, were derived as predictors and several input combinations

Table 11
The applied other ML models for GWL modeling

Research	Applied AI models	Case study	Data span	Input parameters	Output parameter	Performance metrics	Data mode
Naghibi et al. (2015) [293]	BRT, CART, RF	Koohrang Watershed, Chaharmahal-e- Bakhtiari Province, Iran	NONE	A huge set of hydrological, geological, and physiographical factors.	Potential Ground water spring	ROC	NONE
Nalarajan and Mohandas (2015) [294]	M5 - MT	Jones Island, New Jersey, USA.	15 years (1995–2010)	GWL	GWL	R^2, RMSE	monthly
Zhao et al. (2016) [295]	CART, SVM	Three Gorges Dam Reservoir, China.	2005–2007	Raf, Reservoir Level, GWL change	Landslide GWL	AE, RE	Both daily and monthly
Kaya et al. (2018) [296]	M5 - MT	Reyhanli region, Turkey	15-years (2000–2015)	Raf, T, GWL	GWL	R, RMSE, MAE	monthly
Wang et al. (2018) [297]	CCA-CRF, LS-SVR, RFR	Daguhe River, Qingdao, China	1 year (2013 –2014)	Raf, T, GWL	GWL	R, RMSE, MAE	daily
Sharafati et al. (2020) [298]	GBR	Rafsanjan aquifer, Iran	9 years (2007 –2016)	Satellite-based products of hydro-geological, climatic factors.	GWL	R^2, NRMSE	monthly
Javadinejad et al. (2020) [299]	MLPNN, M5-MT	Micro-watershed, Gurpura River Basin, Ganjimatta Region, India	10-year (1996–2006)	Raf, T, GWL	GWL	R, RMSE, RAE	monthly

were selected using the gamma test (GT) method. The developed GBR model was used to predict 1-, 3-, and 6-month-ahead GWL in the study area. Thus, both short- and long-term values were predicted. The R2 and normalized RMSE (NRMSE) metrics were used to evaluate model performance, by comparing observed and predicted GWL values. It was observed that the developed model can be accurately used for GWL studies.

Javadinejad et al. (2020) [299] developed two different machine learning techniques-MLP-NN and M5-MT models-to predict the monthly GWL fluctuations for a micro-watershed of the Gurpura river basin, India. For this purpose, first, monthly GWL values during the period of 1996–2006 were collected from a well in the Ganjimatta region. Then, two different scenarios were applied, in order to determine appropriate input combinations of the MLP-NN model. Based on these scenarios, the one lagged time and present values of monthly GWL, T, and Raf were found to be the appropriate predictors of the MLPNN model. Similarly, an investigation was performed to determine the best input combinations, using linear rules to develop the M5-MT model. The observed and predicted values were compared in terms of R^2, RMSE, NSE, and RE. The results showed that the developed M5-MT model was superior to the MLP-NN model to predict GWL fluctuations. A list of articles discussing other applied ML models for GWL modeling is given in Table 11.

3. Literature review assessment

It is important for survey research to assess and evaluate the established literature and provide a comprehensive debate that can benefit the interested readers. In this section, several essential points are abstracted and discussed, in light of the reported review on machine learning-based models for GWL modeling.

- All tables (Tables 1–11) summarize the details of the reviewed papers, including author names, type of model, case study location, data span, time scale, input and output parameters, performance criteria, and best model. It can be noted that the researchers were often concerned with selecting the proper input combination for GWL prediction. It can be observed that most of the previous studies have used GWL, P, and T as input variables to predict GWL. It was also found that the majority of the authors considered the monthly and daily time scale for GWL modeling.
- ANN models can easily be extended from univariate to multivariate cases, compared to other conceptual models. Moreover, the complexity of ANN models can be varied simply, through changing the learning algorithms, transfer functions, and model structure. Similar to regression models, the input variables might be assigned by using correlation analyses or empirical proof. In accordance with the reviewed papers, the results showed that ANN models can efficiently predict the GWL and capture the non-linear behaviors of the GWL in different regions and case studies, compared to other models such as ARMA and GM(1, 1).
- Based on the reviewed papers collected from 2008 to 2020, MLP has been much more popular than other modeling approaches, such as RBFNN and ELM, in GWL modeling. The most interesting observation from these studies is that the LM algorithm is more popular than other algorithms in training ANNs for forecasting GWL. The LM algorithm is one of the most efficient learning algorithms, as it can interpolate between the Gauss–Newton algorithm and the gradient descent method. The robustness of the LM algorithm, in many cases, comes from its capability to reach an optimal solution, even if starts very far off the final minimum. The LM algorithm has many other advantages, such as faster convergence and lower probability to become stuck in local minima than other learning algorithms used to train MLP.
- In modeling GWL using MLP with a single hidden layer, researchers most frequently used the sigmoid transfer function in the output layer. It is important to mention that other researchers have also used the hyperbolic tangent sigmoid transfer function in the hidden layer; however, it is not as frequently used as the sigmoid transfer function. Moreover, during the development phase of ANN models, scholars generally use trial-and-error methods to select the number of hidden nodes in the hidden layer(s). The assessment process of ANN models for assessing the qualification of the suggested models was carried out by using statistical measures. Moreover, very limited published papers have used parameters that had a significant

effect on the fluctuation of GWL, such as groundwater abstraction quantity. Researchers usually used error metrics such as RMSE, MAE, R^2, R and NASH.

- ELM was presented, in the last decade, as an alternative algorithm to train a single feedforward neural network or MLP. Few studies have been conducted to forecast GWL using ELM. The main advantages of the ELM are its ability to train faster, its capability to obtain more accurate results even when a larger number of hidden nodes is used, and its good generalizability.
- The input data used is very important in developing GWL predictive models over a certain period. Some researchers have used only the lags of GWL to establish their models for predicting GWL. However, other researchers combined past GWL values and hydrological variables, such as Raf, EP, EVP, T, relative H%, flow discharge of a river, and so on. Based on the present review, only a few researchers have used only meteorological or hydrological parameters for GWL forecasting.
- The cited literature reported that GWL predicted using statistical ARIMA models are more accurate, in comparison to other applied AI models. Despite requiring a great deal of experience, due to their complexity, time-series models have been inherently identified as very powerful techniques with great flexibility, as they are more likely to deal with non-stationary time-series more effectively. Besides, these models can be used for short-term GWL prediction without the need for other input data. This might be an advantageous feature in an area where the availability of hydrological data is lacking. The monthly time step of collected GWL was used in most of the cited papers; this might be attributed to the high availability of monthly GWL records, in comparison to other time scales.
- According to the reviewed papers, the input parameters that have been used in GWL modeling are mostly antecedent values (auto-correlated input variables) without any other exogenous hydrological variables. However, in some other models (e.g., ANNs), data such as T, river discharge (surface runoff), EVP, surface water (lake) level, pumping rates (extraction from wells), and H% have been used as input variables and the results were compared with those of time-series models. However, the outcomes of time-series models were superior, compared with multi-input variables models.
- A review of the previous studies utilizing NARX networks for GWL forecasting was also conducted, in order to enrich the review process. The main points highlighted from the related studies can be summarized in three points: (i) NARX networks suffer from several limitations, such as over-fitting problems and local minima; (iii) The Bayesian algorithm can be considered as a reliable training method to avoid over-fitting problem, but its performance may be reduced when coupling it with early stopping; and (iii) the literature has reported that linear models (ARX) could be a useful and easily applicable tool for short-term GWL forecasting.
- With the advances in computational power and internet technology, deep learning applications in hydrology are expected to grow significantly in the long-term. Indeed, the application of deep learning in groundwater prediction is still relatively low, as compared to other hydrological variables such as water level and discharge [134]. It is no surprise that more deep learning groundwater-related articles will become available in the near future. As stated in the United Nation's Sustainable Development Goal 6 of Clean Water and Sanitation, more than 1.7 billion people live in river basins where the water usage exceeds water supply. In many parts of the world, groundwater is still unexplored and can provide an alternative solution to reduce water stress issues, if used wisely. Reliable groundwater information and forecasting are essential for groundwater resource management. In the future, collaborations among researchers and local stakeholders need to be strengthened, in order to develop a more practical framework, such that deep learning-extracted GWL information can be fully utilized by local governments; for instance, the development of tools with user-friendly graphical user interfaces may encourage the usage of deep learning in GWL simulation and forecasting by local stakeholders and users with little programming background.
- The Internet of Things (IoT) paradigm allows groundwater information to be gathered and analyzed more smartly with broader user communities. Advances in computational power, internet speed, and coverage, together with rapid development in software technologies, such as cloud storage systems and service-oriented architecture (SOA), have stimulated the development of smart water quantity and quality monitoring systems [300,301]. Approximately 1.6 million monitoring wells are available worldwide to measure GWL; however, most of them are not recorded automatically [302,303]. Therefore, the implementation of IoT is expected to reduce the difficulty in obtaining GWL data. The integration of IoT and deep learning can provide more accurate real-time GWL data collection, transfer, and analysis at low-cost. For instance, Su et al. [303] developed deep learning algorithms that combine both IoT and groundwater model using a groundwater-related web GIS platform, in order to enhance groundwater data management.
- The literature review presented and discussed above highlights the great capabilities of the ANFIS model as a robust tool for GWL prediction. ANFIS can provide high accuracy and precision for nearly all cases (i.e., monthly, daily, or weekly time steps). However, an important conclusion that can be drawn, based the above analysis, is that the selection of the variables used as inputs for the ANFIS model is an important factor controlling the accuracy of the model. It has been demonstrated that, in some cases, the inclusion of a large number of climate variables is required for an accurate GWL estimation. As shown above, most research regarding the application of the ANFIS model has been conducted without metaheuristic optimization algorithms, such as PSO, firefly optimization algorithm (FFA), or Grey wolf optimizer (GWO), among others. These algorithms remain relatively underexplored and they can certainly contribute to the advancement of methods for GWL prediction, helping to overcome some specific difficulties encountered during the training of the ANFIS model, especially rapid convergence and local minima.
- The employment of the wavelet technique to develop complementary models can enhance the predictability efficiency and, in all cases, hybrid methods involving wavelets performed better than their regular counterparts. In general, wavelet-based machine learning models are more accurate, as the DWT provides better discrimination of the non-linear and non-stationary trends that exist at various scales in the time-series of the input variables [249]. It has also been found to be useful for other aquifers and basins with different characteristics [194]. The generated wavelet models are simpler and more interpretable, making it possible to understand which independent variables have a greater effect in simulating the dependent variable [39].
- An optimal number of lag times for the input values must be identified, as it plays an important role in GWL simulation [39]. Furthermore, selecting a suitable decomposition level affects the accuracy of hybrid models [39]. This is because a high level of decomposition is not always helpful in increasing the model's accuracy. Further research needs to be conducted, in order to improve higher lead-time forecasting. The selection of significant hydrological variables as inputs for the models must also be considered, which is very specific to the region

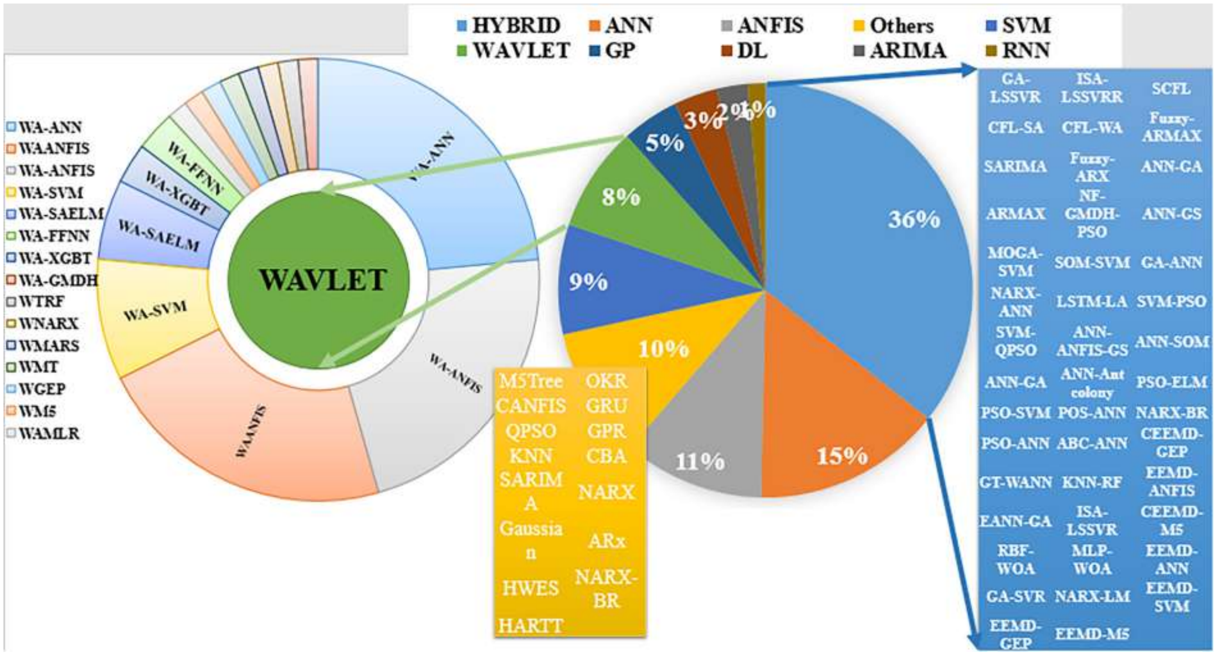

Fig. 14. Applied AI models for GWL modelling: Pie-chart demonstration of the various AI models with extended view of the three most widely preferred AI model types including Hybrid-type models, Wavelet assimilated models and others.

of study and the climate in question, as it significantly affects the performance of the models [39,194]. Therefore, it is recommended to carry out exhaustive studies in the future to evaluate the effects of other hydrological variables on groundwater simulation and to understand the dynamics involved to find suitable variables for groundwater modeling in different climates and conditions. The employed model can be used for monitoring seasonal GWL fluctuations by dividing the data, according to monsoon and non-monsoon periods. More comparative studies to investigate the performance of the models at different stages of modeling, as well as comparisons with other time-series pre-processing tools, need to be explored. In future works, the hybrid models should able to explain the physical phenomena involved, which are currently lacking in the previous and current literature. The effects of the various inherent parameters in the various employed models also need further investigation.

- In our review of the numerous studies carried out in the field of GWL, it was observed that there has been a significant increase in the number of published works over the years. It is evident that increases in groundwater contamination, the dependence of groundwater utilization, changes in water level, and advancement in machine learning and AI tools have led to more prominent research using AI-based models in this field, as shown in Fig. 2. As per Fig.2 a slow growth was observed during 2008–2011; however, the number of publications doubled during 2011–2013, while steady progress was detected in the subsequent years. Furthermore, an exponential growth can be observed from 2017–2020 due to an increase in the popularity of AI models. Even though 2020 was a difficult year for everyone, 28 papers were still published in the field, thus demonstrating that such computational tools are the need of the hour, allowing for the progress of such important research.

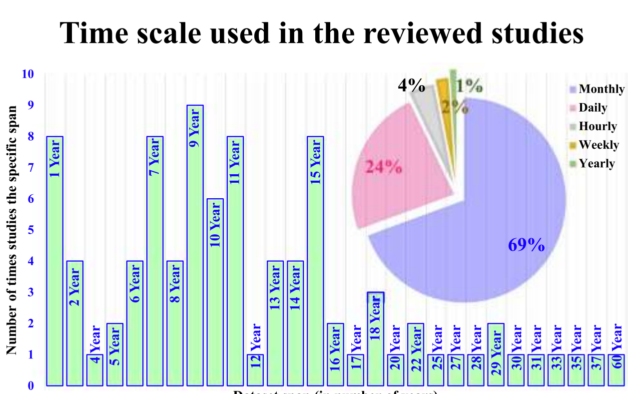

Fig. 15. Time scale analysis: Pie-chart demonstration of the usage of the dataset time scale for GWL modelling and bar chart presenting the application of the specified time scale in total number of studies.

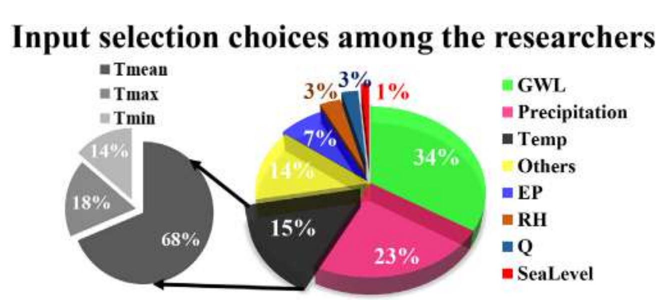

Fig. 16. Depiction of the preferred input selection for GWL modeling.

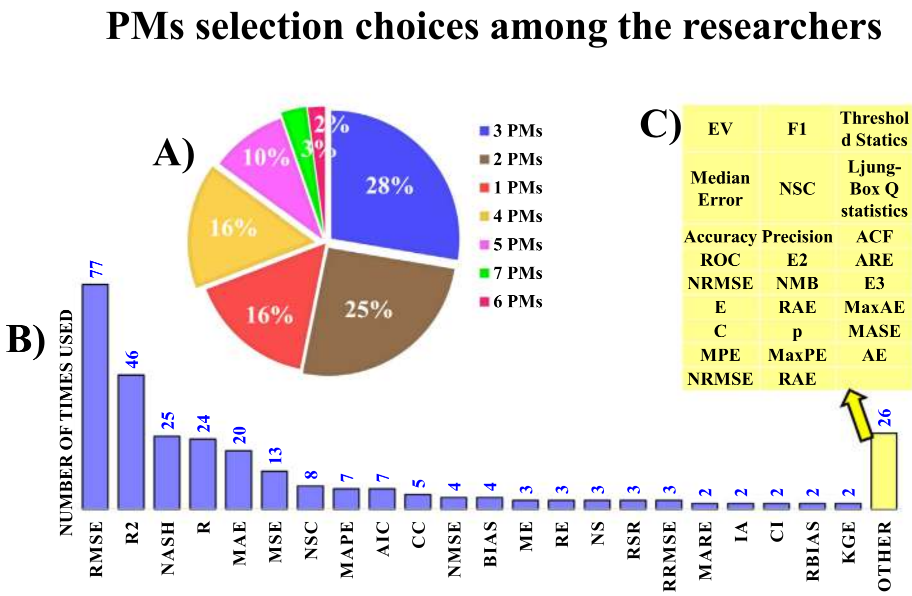

Fig. 17. Statistical analysis of applied performance metrics (PMs): A. Combination of PMs utilized in total studies. B. Individual PMs examined. C. presenting the other PMs examined except the prevalent PMs.

- Over the period of the survey, AI models have advanced, leading to more complex and integrated type of models, which have given researchers the means to develop more accurate and robust models. A similar conclusion was drawn after visualization of the various models applied to GWL modeling in the past decade. Fig. 14 presents an in-depth description of the most applied model types in GWL simulation, in pie-chart form. It can be seen, from the chart, that the most implemented were hybrid-type (36%) models, mostly consisting of the base models such as ANN, SVM, fuzzy-based models, and tree-based models (presented in the blue box). Their popularity can be explained based on their higher accuracy, efficiency, and ability to deal with non-linear data sets. The second extended pie-chart from the main chart denotes the wavelet-type models, which consist of the integration of wavelet tools with the base models (secondary pie-chart). The ability of wavelets to reduce data noise has played an important role in their widespread application (8%). The third most applied model was distinguished as others, as it covered various other types of models which, apparently, are difficult to place in other groups (presented in the orange box). This also indicates that there is a lot more to be explored in this area.
- AI models has been proven to be effective tools when provided with systematic and consistent data over a continuous time period. Moreover, the time scale also plays a vital role in the model performance; thus, a visual representation of the time scales used in the published papers is presented in Fig. 15. The pie chart depicts that the most applied data collection was monthly data (69%), followed by daily data (24%). Studies that applied yearly data (1%) can be utilized for GWL capacity change studies but may be rendered insignificant when studying seasonal changes. Similarly, depending on the type of study, hourly data (4%) can also be used. However, hourly data collection can be expensive and may not be a preferable choice for low-budget research projects. When considering the duration of the data utilized for the study, 1 year (8 studies) seemed to be the smallest duration which allowed the model to work efficiently. Following that, 7- (8 studies), 9- (9 studies), 11- (8 studies), and 15-year data sets (8 studies) have also been majorly applied. It should be considered that larger data sets can reveal the time-series pattern trend changes, whereas smaller data sets cannot. A total of 10 research papers used larger data sets (between 20–60 years), which are important in understanding long-term trend changes; however, such data may be ineffective for near-future prediction, as recent data are more useful for prediction analyses.
- The selection of input was mostly based on the influence of those variables on the selected output. Fig. 16 presents such preferred input variables for GWL modeling. As per this figure (Fig. 16), GWL (34%), precipitation, and temperature were the most preferable input variables. Most studies utilized a combination of these input variables, as mentioned in the figure; however, most researchers chose GWL in those combinations. In addition, 1% also included sea level, in order to consider possible seawater intrusion into a permeable aquifer. Such considerations depend on the geographical location, which may affect (either directly or indirectly) the GWL.
- Performance metrics (PMs) help to understand the performance of models, where each PM can reveal different information of the model, leading to a wide range of PMs being applied, as shown in Fig. 17. Fig. 17a shows the combination of PMs applied in the studies, which indicates that most preferred combination was 3 and least preferred was 6. However, it is always beneficial to utilize various PMs to overcome the limitations of individual PMs. Fig. 17b shows the most applied PM; among all, the RMSE (77) was the most-used error type PM, while R^2 (46) was the most-used accuracy assessment PM. Fig. 17c is an extension of Fig. 17b, showing the other PMs applied.
- The literature review also emphasised on the integration climate change on watershed GWL and more research shall be adopted for this kind of modeling interaction between climate and geo-science water behaviour [304]. Climate change has been remarkably observed especially in tropical region and has substantial influence on ground temperature in which lead for the GWL fluctuation [305].

4. Future research direction

Based on the presented literature review and the gaps identified in the previous section, recommendations of possible future research directions to improve the accuracy of GWL prediction models and to enhance the related knowledge are outlined in this section.

- Exogenous parameters, such as sea level and groundwater abstraction, have vital influences on the GWL in different regions around the world. Increased attention should be paid to the rapid changes in sea level rise when simulating GWL in coastal aquifers. Global warming has undeniably major effects on sea level by melting large quantities of ice, thus leading to a rise in sea and ocean water levels in some areas over the world. Consequently, the amount of seawater that will seep into the aquifer increases, which has a great impact on the sharp fluctuations in changing GWL, especially in coastal areas. On the other hand, the rise in global temperatures leads to evaporation of large quantities of water, which may lead to a decrease in the GWL in wells. The other important parameter is groundwater abstraction quantity, which should also be taken into account in future studies. In arid and semi-arid areas, which depend largely on groundwater for irrigation, agriculture, and other purposes, the groundwater that is extracted may not be replaced until after long periods of groundwater recharge, due to natural factors such as less rainfall. Therefore, abstraction has a great impact on GWL fluctuations.
- The selection of GWL lags should be given more attention in the development of the AI modeling approaches. Among different mathematical and statistical approaches, ACF and PACF have been considered efficient methods to select the best GWL lags as inputs. Based on the reviewed papers collected in this study, few studies used ACF and/or PACF to select the most proper preceding GWL variables. The ACF and PACF approaches provide much more information on the main characteristics of the time-series of groundwater fluctuations over a certain period. The fluctuations of the GWL provide a direct measure of the effects of groundwater development and valuable knowledge about the dynamics of an aquifer in GWL time-series data. Therefore, there is a high possibility to accurately forecast future GWL from its previous data.
- To obtain more precise GWL predictions, many studies have used antecedent data of GWL, as well as hydrological and meteorological information, such as Raf, H%, T, EVP, and so on. However, increasing the number of input variables could hinder the process of developing reliable and accurate models. In future research, the researchers may have to apply feature selection techniques to select the most significant input parameters and to get rid of redundant information [306,307]. Moreover, the selection of the most appropriate variables can enhance the model learning process, save time, and reduce computational costs [54]. Thus, applying a feature selection approach prior to the learning phase of AI models may help to achieve more precise and reliable GWL prediction models.
- A majority of researchers have developed predictive models at monthly and daily time scales. More attention should be paid to the prediction of yearly GWL, as it is considered very significant for water resource management and planning in the long-term. Moreover, long-term GWL forecasting could help decision-makers to develop strategic plans and policies for water management and to ensure water sustainability, especially in dry areas.
- Our review showed that, among the genetic programming techniques, Classic GP, MGGP, and GEP have been successfully used for GWL prediction to date. Future studies could be designed to assess the efficiency of other GP variants, such as Linear GP [308] or multi-stag GP [309], for GWL prediction.
- Further studies should take into consideration the filling in (i.e., imputation) of missing groundwater values using deep learning techniques [310–313]. Groundwater observations are usually sparse and the existence of missing values (e.g., due to instrument failure or poor monitoring management systems) are common. These missing values may degrade the data quality and increase the uncertainty in spatio-temporal groundwater analysis and simulation [314]. Hence, reliable groundwater data filling algorithms are needed, in order to reproduce the actual conditions for groundwater forecasting. As the groundwater pattern is usually non-linear or non-stationary, imputing the missing values is a complex issue. For this task, deep learning could provide a powerful tool to extract the non-linear spatio-temporal groundwater patterns without considering their explicit forms [315]. The LSTM is specifically designed for long-term period data prediction, being equipped with memory cells that retain important information regarding historical events [316]. Therefore, the improvement of LSTM models in groundwater missing value imputation is foreseen to be a popular topic. Furthermore, groundwater sensors can employ deep learning methods to detect and correct some unreasonable or outlier readings; in this way, only useful information will be transmitted to the central system.
- Hybrid versions of ML models that incorporate nature inspired algorithms for tuning the hyperparameters standalone ML models are highly empathised to be explored in this research domain. As the optimization of the internal models parameters is influencing the learning process and the prediction capacity [317,318].

5. Conclusions

The current survey was established to provide an informative milestone on the implementation of machine learning models in the simulation of GWL. The survey covered the period of 2008–2020, where all the gathered studies were obtained from indexed journals in the Web of Science. Based on the reported review, ten versions of ML models have been applied for GWL modeling over the globe. The survey identified several essential elements in the existing GWL simulation models, including the applied algorithms, input parameters, target parameters, investigated regions, data span, and performance metrics. The surveyed studies were assessed and evaluated scientifically, and numerous findings were discussed in detail. In accordance with the current status of the conducted literature, various possible future research directions were recognized for the interested readers and practitioners in this domain.

Abbreviations

The list of abbreviations used in this paper are tabulated in Table 12.

Table 12
The list of abbreviations used in this paper.

ACF	Autocorrelation Function	AE	Absolute Error
AI	Artificial Intelligence	ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks	AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average	ARMA	Autoregressive-Moving-Average
ARMAX	Auto Regressive Moving Average With External Model	ARX	Auto-Regressive With External Model
BA	Bat Algorithm	BNN	Bayesian Neural Networks
BP	Backpropagation	BR	Bayesian Regularization
BRT	Boosted Regression Tree	CANFIS	Co-Adaptive Neuro-Fuzzy Inference Systems
CART	Classification And Regression Tree	CBA	Classification Based On Association Rule
CC	Correlation Coefficient	CEEMD	Complementary Ensemble Empirical Mode Decomposition
CFL-WA	Committee Fuzzy Logic Weighted Averaging	CFN	Cascade Forward Network
CSO	Cat Swarm Optimization	CWT	Continuous Wavelet Transform
DE	Differential Evolution	DL	Deep Learning
DWT	Discrete Wavelet Transform	EANN	Emotional ANN
EBF	Evidential Belief Function	EEMD	Ensemble Empirical Mode Decomposition
ELM	Extreme Learning Machine	EP	Evaporation
EVP	Evapotranspiration	EV	Error Variation
FFA	Firefly Optimization Algorithm	FFBPNN	Feed-Forward Back-Propagation Neural Network
FFNN	Feed Forward Neural Network	FL	Fuzzy Logic
GA	Genetic Algorithm	GB	Gradient Boosting
GBR	Gradient Boosted Regression	GEP	Gene Expression Programming
GIS	Geographic Information System	GMDH	Group Method Of Data Handling
GOA	Grasshopper Optimization Algorithm	GP	Genetic Programming
GP	Gaussian Process	GPC	Gaussian Process Classification
GPR	Aussian Process Regression	GR	Gridded Rainfall
GRACE	Gravity Recovery And Climate Experiment	GRI	Groundwater Resources Index
GRNN	Generalized Regression Neural Network	GSA	Gravitational Search Algorithm
GSM	Grey Self-Memory Model	GT	Gamma And M-Tests
GWA-GWHP	Groundwater Abstraction Associated With Operation Of The GWHP System	GWF	Groundwater Fluctuation
GWA-WCC	Groundwater Abstraction Associated With Operation Of The WCC System	GWL	Groundwater Level
GWO	Grey Wolf Optimizer	H%	Humidity
HBSA	Hybrid Bat-Swarm Algorithm	HIS	Improved Harmony Search
HS	Harmony Search	HWES	Holt-Winters Exponential Smoothing
IA	Index Of Agreement	IL	Infiltration Loss
IoT	Internet Of Things	ISA	Interior Search Algorithm
KA	Krill Algorithm	kNN	K Nearest Neighbor
LAT	Latitude	LFL	Larsen Fuzzy Logic
LM	Levenberg–Marquardt	LNG	Longitude
LSBoost	Last Squares Boosting	LSSVM	East-Squares Support Vector Machine
LSTM	Long Short-Term Memory	LSTM-LA	Long Short-Term Memory-Lion Algorithm
M5tree	M5 Model Tree	MA	Moving Average
MAE	Mean Absolute Error	MAPE	Mean Absolute Percentage Error
MARS	Multivariate Adaptive Regression Spline	MCMC	Markov Chain Monte Carlo
ME	Mean Error	MF	Membership Functions
MFL	Mamdani Fuzzy Logic	MGGP	Multigene GP
ML	Machine Learning	MLP	Multilayer Perceptron
MLR	Multiple Linear Regression	MODWT	Maximal Overlap Discrete Wavelet Transform
MOGA	Multi-Objective Genetic Algorithm	MRVA	Mississippi River Valley Alluvial
NB	Naïve Bayes	NCCI	National Cartographic Center Of Iran
NF	Neuro-Fuzzy	NMSE	Normalized Mean Square Error
NRMSE	Normalized Root Mean Square Error	NS	Nash–Sutcliffe Efficiency Coefficient
NSE	Nash–Sutcliffe Efficiency	OK	Ordinary Kriging
P	Precipitation	PACF	Partial Autocorrelation Function
PSO	Particle Swarm Optimization	Q	Discharge
QPSO	Quantum Behaved Particle Swarm Optimization Function	R	Pearson'S Correlation Coefficient
Raf	Rainfall	RBFNN	Radial Basis Function Neural Network
RE	Reduction Of Error Statistics	RE	Relative Error
RF	Random Forest	RFR	Random Forest Regression
RMSE	Root Mean Square Error	RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristics	RS	River Stage
SARIMA	Seasonal Autoregressive Integrated Moving Average	SCFL	Simple Committee Fuzzy Logic
SD	Sunshine Duration	SFL	Ugeno Fuzzy Logic
SFR	Stream Flow Rate	SGS	Sequential Gaussian Simulation
SM	Soil Moisture	SMO	Sequential Minimal Optimization
SOA	Service-Oriented Architecture	SOM	Self-Organizing Map
SPI	Standardized Precipitation Index	SVD	Singular Value Decomposition
SVM	Support Vector Machines	SVR	Support Vector Regression
SWL	Surface Water Level	T	Temperature
T_{max}	Maximum Temperature	T_{mean}	Mean Air Temperature
T_{min}	Minimum Temperature	WA	Whale Algorithm
WA	Weed Algorithm	WANFIS	Wavelet-Adaptive Neuro-Fuzzy Inference System
WEF	Weighted Error Function	WGEP	Wavelet Gene Expression Programming
WL	Water Level	WLR	Wavelet-Linear Regression
WMT	Wavelet-M5 Model Tree	WNN	Wavelet- Neural Network
WS	Wind Speed	WSVR	Wavelet-SVR
WT	Wavelet Transform		

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

The authors would like to thank Al-Mustaqbal University College for providing technical support for this research.

References

[1] M. Qadir, B.R. Sharma, A. Bruggeman, R. Choukr-Allah, F. Karajeh, Non-conventional water resources and opportunities for water augmentation to achieve food security in water scarce countries, Agricult. Water Manage. 87 (1) (2007) 2–22.
[2] Y. Wada, L.P. Van Beek, C.M. Van Kempen, J.W. Reckman, S. Vasak, M.F. Bierkens, Global depletion of groundwater resources, Geophys. Res. Lett. 37 (20).
[3] H. Afzaal, A.A. Farooque, F. Abbas, B. Acharya, T. Esau, Groundwater estimation from major physical hydrology components using artificial neural networks and deep learning, Water 12 (1) (2020) 5.
[4] S. Sadeghi-Tabas, S. Samadi, B. Zahabiyoun, et al., Application of bayesian algorithm in continuous streamflow modeling of a mountain watershed, European Water 57 (2017) 101–108.
[5] P.K. Gupta, B. Yadav, B.K. Yadav, Assessment of lnapl in subsurface under fluctuating groundwater table using 2d sand tank experiments, J. Environ. Eng. 145 (9) (2019) 04019048.
[6] A. Izady, K. Davary, A. Alizadeh, A.N. Ziaei, A. Alipoor, A. Joodavi, M.L. Brusseau, A framework toward developing a groundwater conceptual model, Arab. J. Geosci. 7 (9) (2014) 3611–3631.
[7] J. Xue, Z. Huo, F. Wang, S. Kang, G. Huang, Untangling the effects of shallow groundwater and deficit irrigation on irrigation water productivity in arid region: New conceptual model, Sci. Total Environ. 619 (2018) 1170–1182.
[8] P.J. Omar, S. Gaur, S. Dwivedi, P. Dikshit, Groundwater modelling using an analytic element method and finite difference method: An insight into lower ganga river basin, J. Earth Syst. Sci. 128 (7) (2019) 195.
[9] P. Jamin, M. Cochand, S. Dagenais, J.-M. Lemieux, R. Fortier, J. Molson, S. Brouyère, Direct measurement of groundwater flux in aquifers within the discontinuous permafrost zone: an application of the finite volume point dilution method near umiujaq (nunavik, canada), Hydrogeol. J. (2020) 1–17.
[10] C. Ukpaka, S.N.-A. Adaobi, C. Ukpaka, Development and evaluation of trans-amadi groundwater parameters: The integration of finite element techniques, Chem. Int. 3 (2017) 306.
[11] T. Pathania, A. Bottacin-Busolin, A. Rastogi, T. Eldho, Simulation of groundwater flow in an unconfined sloping aquifer using the element-free galerkin method, Water Resour. Manage. 33 (8) (2019) 2827–2845.
[12] B. Barnett, L. Townley, V. Post, R. Evans, R. Hunt, L. Peeters, S. Richardson, A. Werner, A. Knapton, A. Boronkay, Australian groundwater modelling guidelines, National Water Commission, Canberra.
[13] F. Jiang, Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen, Y. Wang, Artificial intelligence in healthcare: past, present and future, Stroke Vascul. Neurol. 2 (4) (2017) 230–243.
[14] M. Zounemat-Kermani, O. Kisi, J. Piri, A. Mahdavi-Meymand, Closure to "assessment of artificial intelligence–based models and metaheuristic algorithms in modeling evaporation" by mohammad zounemat-kermani, ozgur kisi, jamshid piri, and amin mahdavi-meymand, J. Hydrol. Eng. 25 (9) (2020) 07020015.
[15] S.K. Bhagat, T.M. Tung, Z.M. Yaseen, Development of artificial intelligence for modeling wastewater heavy metal removal: State of the art, application assessment and possible future research, J. Cleaner Prod. 250 (2020) 119473.
[16] T. Hai, A. Sharafati, A. Mohammed, S.Q. Salih, R.C. Deo, N. Al-Ansari, Z.M. Yaseen, Global solar radiation estimation and climatic variability analysis using extreme learning machine based predictive model, IEEE Access 8 (2020) 12026–12042.
[17] S.Q. Salih, A.A. Alsewari, Z.M. Yaseen, Pressure vessel design simulation: Implementing of multi-swarm particle swarm optimization, in: Proceedings of the 2019 8th International Conference on Software and Computer Applications, 2019, pp. 120–124.
[18] U. Beyaztas, S.Q. Salih, K.-W. Chau, N. Al-Ansari, Z.M. Yaseen, Construction of functional data analysis modeling strategy for global solar radiation prediction: application of cross-station paradigm, Eng. Appl. Comput. Fluid Mech. 13 (1) (2019) 1165–1181.
[19] T.M. Tung, Z.M. Yaseen, et al., A survey on river water quality modelling using artificial intelligence models: 2000–2020, J. Hydrol. 585 (2020) 124670.
[20] M. Fadaee, A. Mahdavi-Meymand, M. Zounemat-Kermani, Suspended sediment prediction using integrative soft computing models: On the analogy between the butterfly optimization and genetic algorithms, Geocarto International (just-accepted) (2020) 1–14.
[21] Z.M. Yaseen, M. Fu, C. Wang, W.H.M.W. Mohtar, R.C. Deo, A. El-Shafie, Application of the hybrid artificial neural network coupled with rolling mechanism and grey model algorithms for streamflow forecasting over multiple time horizons, Water Resour. Manage 32 (5) (2018) 1883–1899.
[22] Omeje, Otitodilichukwu Excel, Hamza Sabo Maccido, Yusuf Abdullahi Badamasi, and Sani Isah Abba. "Performance of Hybrid Neuro-Fuzzy Model for Solar Radiation Simulation at Abuja, Nigeria: A Correlation Based Input Selection Technique." *Knowledge-Based Engineering and Sciences* 2, no. 3 (2021): 54-66.
[23] M. Jamei, I. Ahmadianfar, X. Chu, Z.M. Yaseen, Prediction of surface water total dissolved solids using hybridized wavelet-multigene genetic programming: New approach, J. Hydrol. 589 (2020) 125335.
[24] Y. Zhu, Y. Liu, W. Wang, V.P. Singh, X. Ma, Z. Yu, Three dimensional characterization of meteorological and hydrological droughts and their probabilistic links, J. Hydrol. 578 (2019) 124016.
[25] M. Zounemat-Kermani, M. Scholz, Computing air demand using the takagi–sugeno model for dam outlets, Water 5 (3) (2013) 1441–1456.
[26] Z.M. Yaseen, S.O. Sulaiman, R.C. Deo, K.-W. Chau, An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction, J. Hydrol. 569 (2019) 387–408.
[27] R.M. Adnan, Z. Liang, S. Heddam, M. Zounemat-Kermani, O. Kisi, B. Li, Least square support vector machine and multivariate adaptive regression splines for streamflow prediction in mountainous basin using hydro-meteorological data as inputs, J. Hydrol. 586 (2020) 124371.
[28] S.K. Bhagat, T.M. Tung, Z.M. Yaseen, Heavy metal contamination prediction using ensemble model: Case study of bay sedimentation, australia, J. Hazard. Mater. 403 (2020) 123492.
[29] A. Mahdavi-Meymand, M. Zounemat-Kermani, A new integrated model of the group method of data handling and the firefly algorithm (gmdh-fa): application to aeration modelling on spillways, Artif. Intell. Rev. 53 (4) (2020) 2549–2569.
[30] I.N. Daliakopoulos, P. Coulibaly, I.K. Tsanis, Groundwater level forecasting using artificial neural networks, J. Hydrol. 309 (1–4) (2005) 229–240.
[31] J. Adamowski, H.F. Chan, A wavelet neural network conjunction model for groundwater level forecasting, J. Hydrol. 407 (1–4) (2011) 28–40.
[32] S. Ranjithan, J. Eheart, J. Garrett Jr, Neural network-based screening for groundwater reclamation under uncertainty, Water Resour. Res. 29 (3) (1993) 563–574.
[33] L.L. Rogers, F.U. Dowla, Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling, Water Resour. Res. 30 (2) (1994) 457–481.
[34] S. Lallahem, J. Mania, A. Hani, Y. Najjar, On the use of neural networks to evaluate groundwater levels in fractured media, J. Hydrol. 307 (1–4) (2005) 92–111.
[35] A.A. Nadiri, K. Naderi, R. Khatibi, M. Gharekhani, Modelling groundwater level variations by learning from multiple models using fuzzy logic, Hydrol. Sci. J. 64 (2) (2019) 210–226.
[36] T. Zhou, F. Wang, Z. Yang, Comparative analysis of ann and svm models combined with wavelet preprocess for groundwater depth prediction, Water 9 (10) (2017) 781.
[37] D.D. Moghaddam, O. Rahmati, A. Haghizadeh, Z. Kalantari, A modeling comparison of groundwater potential mapping in a mountain bedrock aquifer: Quest, garp, and rf models, Water 12 (3) (2020) 679.
[38] K. Kasiviswanathan, S. Saravanan, M. Balamurugan, K. Saravanan, Genetic programming based monthly groundwater level forecast models with uncertainty quantification, Model. Earth Syst. Environ. 2 (1) (2016) 27.
[39] R. Bahmani, A. Solgi, T.B. Ouarda, Groundwater level simulation using gene expression programming and m5 model tree combined with wavelet transform, Hydrol. Sci. J. (2020) 1–13.
[40] H. Afzaal, A.A. Farooque, F. Abbas, B. Acharya, T. Esau, Groundwater estimation from major physical hydrology components using artificial neural networks and deep learning, Water 12 (1) (2020) 5.
[41] M. Alizamir, O. Kisi, M. Zounemat-Kermani, Modelling long-term groundwater fluctuations by extreme learning machine using hydro-climatic data, Hydrol. Sci. J. 63 (1) (2018) 63–73.
[42] B.D. Bowes, J.M. Sadler, M.M. Morsy, M. Behl, J.L. Goodall, Forecasting groundwater table in a flood prone coastal city with long short-term memory and recurrent neural networks, Water 11 (5) (2019) 1098.
[43] B.T. Pham, A. Jaafari, I. Prakash, S.K. Singh, N.K. Quoc, D.T. Bui, Hybrid computational intelligence models for groundwater potential mapping, Catena 182 (2019) 104101.
[44] P.T. Nguyen, D.H. Ha, A. Jaafari, H.D. Nguyen, T. Van Phong, N. Al-Ansari, I. Prakash, H.V. Le, B.T. Pham, Groundwater potential mapping combining artificial neural network and real adaboost ensemble technique: the daknong province case-study, Vietnam, Int. J. Environ. Res. Public Health 17 (7) (2020) 2473.
[45] G.-B. Kim, A study on the establishment of groundwater protection area around a saline waterway by combining artificial neural network and gis-based ahp, Environ. Earth Sci. 79 (5) (2020) 1–17.
[46] T. Rajaee, H. Ebrahimi, V. Nourani, A review of the artificial intelligence methods in groundwater level modeling, J. Hydrol. 572 (2019) 336–351.
[47] V. Nourani, S. Mousavi, Spatiotemporal groundwater level modeling using hybrid artificial intelligence-meshless method, J. Hydrol. 536 (2016) 10–25.
[48] C. Chen, W. He, H. Zhou, Y. Xue, M. Zhu, A comparative study among machine learning and numerical models for simulating groundwater dynamics in the heihe river basin, northwestern china, Sci. Rep. 10 (1) (2020) 1–13.

[49] C. Chen, W. He, H. Zhou, Y. Xue, M. Zhu, A comparative study among machine learning and numerical models for simulating groundwater dynamics in the heihe river basin, northwestern china, Sci. Rep. 10 (1) (2020) 1–13.
[50] N. Bisoyi, H. Gupta, N.P. Padhy, G.J. Chakrapani, Prediction of daily sediment discharge using a back propagation neural network training algorithm: A case study of the narmada river, india, Int. J. Sediment Res. 34 (2) (2019) 125–135.
[51] M.K. AlOmar, M.M. Hameed, M.A. AlSaadi, Multi hours ahead prediction of surface ozone gas concentration: Robust artificial intelligence approach, Atmosp. Pollut. Res. 11 (9) (2020) 1572–1587.
[52] M. Hameed, S.S. Sharqi, Z.M. Yaseen, H.A. Afan, A. Hussain, A. Elshafie, Application of artificial intelligence (ai) techniques in water quality index prediction: a case study in tropical region, malaysia, Neural Comput. Appl. 28 (1) (2017) 893–905.
[53] Z.M. Yaseen, A. El-Shafie, H.A. Afan, M. Hameed, W.H.M.W. Mohtar, A. Hussain, Rbfnn versus ffnn for daily river flow forecasting at johor river, malaysia, Neural Comput. Appl. 27 (6) (2016) 1533–1542.
[54] S.K. Bhagat, T. Tiyasha, S.M. Awadh, T.M. Tung, A.H. Jawad, Z.M. Yaseen, Prediction of sediment heavy metal at the australian bays using newly developed hybrid artificial intelligence models, Environ. Pollut. 268 (2020) 115663.
[55] R.C. Deo, M. Şahin, Application of the artificial neural network model for prediction of monthly standardized precipitation and evapotranspiration index using hydrometeorological parameters and climate indices in eastern australia, Atmosph. Res. 161 (2015) 65–81.
[56] H.B. Abarghouei, M.R. Kousari, M.A.A. Zarch, Prediction of drought in dry lands through feedforward artificial neural network abilities, Arab. J. Geosci. 6 (5) (2013) 1417–1433.
[57] H.A. Afan, A. El-Shafie, Z.M. Yaseen, M.M. Hameed, W.H.M.W. Mohtar, A. Hussain, Ann based sediment prediction model utilizing different input scenarios, Water Resour. Manage. 29 (4) (2015) 1231–1245.
[58] G.R. Rakhshandehroo, M. Vaghefi, M.A. Aghbolaghi, Forecasting groundwater level in shiraz plain using artificial neural networks, Arab. J. Sci. Eng. 37 (7) (2012) 1871–1883.
[59] X. Meng, M. Yin, L. Ning, D. Liu, X. Xue, A threshold artificial neural network model for improving runoff prediction in a karst watershed, Environ. Earth Sci. 74 (6) (2015) 5039–5048.
[60] M.M. Hameed, M.K. AlOmar, Prediction of compressive strength of high-performance concrete: Hybrid artificial intelligence technique, in: International Conference on Applied Computing to Support Industry: Innovation and Technology Springer, 2019, pp. 323–335.
[61] S. Nacar, M.A. Hınıs, M. Kankal, Forecasting daily streamflow discharges using various neural network models and training algorithms, KSCE J. Civil Eng. 22 (9) (2018) 3676–3685.
[62] S. Ali, M. Shahbaz, Streamflow forecasting by modeling the rainfall–streamflow relationship using artificial neural networks, Model. Earth Syst. Environ. 6 (3) (2020) 1645–1656.
[63] Z.M. Yaseen, M. Fu, C. Wang, W.H.M.W. Mohtar, R.C. Deo, A. El-Shafie, Application of the hybrid artificial neural network coupled with rolling mechanism and grey model algorithms for streamflow forecasting over multiple time horizons, Water Resour. Manage. 32 (5) (2018) 1883–1899.
[64] A. Jalalkamali, H. Sedghi, M. Manshouri, Monthly groundwater level prediction using ann and neuro-fuzzy models: a case study on kerman plain, iran, J. Hydroinform. 13 (4) (2011) 867–876.
[65] S.S. Nair, G. Sindhu, Groundwater level forecasting using artificial neural network, Int. J. Sci. Res. Publ. 6 (1) (2016) 2250–3153.
[66] A. Lohani, G. Krishan, Groundwater level simulation using artificial neural network in southeast punjab, india, J. Geol. Geosci. 4 (3) (2015) 206.
[67] M. Derbela, I. Nouiri, Intelligent approach to predict future groundwater level based on artificial neural networks (ann), Euro-Mediterranean J. Environ. Integr. 5 (3) (2020) 1–11.
[68] M. Iqbal, U.A. Naeem, A. Ahmad, U. Ghani, T. Farid, et al., Relating groundwater levels with meteorological parameters using ann technique, Measurement 166 (2020) 108163.
[69] S.M. Guzman, J.O. Paz, M.L.M. Tagert, A. Mercer, Artificial neural networks and support vector machines: Contrast study for groundwater level prediction., in: 2015 ASABE Annual International Meeting, Am. Soc. Agricul. Biol. Eng. 2015 (2015) 1.
[70] Y.-M. Hong, Feasibility of using artificial neural networks to forecast groundwater levels in real time, Landslides 14 (5) (2017) 1815–1826.
[71] G.N. Kouziokas, A. Chatzigeorgiou, K. Perakis, Multilayer feed forward models in groundwater level forecasting using meteorological data in public management, Water Resour. Manage 32 (15) (2018) 5041–5052.
[72] S. Lee, K.-K. Lee, H. Yoon, Using artificial neural network models for groundwater level forecasting and assessment of the relative impacts of influencing factors, Hydrogeol. J. 27 (2) (2019) 567–579.
[73] Z. Li, Q. Yang, L. Wang, J.D. Martín, Application of rbfn network and gm (1, 1) for groundwater level simulation, Appl. Water Sci. 7 (6) (2017) 3345–3353.
[74] M.K.N. Shamsuddin, F.M. Kusin, W.N.A. Sulaiman, M.F. Ramli, M.F.T. Baharuddin, M.S. Adnan, Forecasting of groundwater level using artificial neural network by incorporating river recharge and river bank infiltration, in: MATEC Web of Conferences, Vol. 103, EDP Sciences, 2017, p. 04007.
[75] S. Evans, G.P. Williams, N.L. Jones, D.P. Ames, E.J. Nelson, Exploiting earth observation data to impute groundwater level measurements with an extreme learning machine, Remote Sens. 12 (12) (2020) 2044.
[76] B. Yadav, S. Ch, S. Mathur, J. Adamowski, Assessing the suitability of extreme learning machines (elm) for groundwater level prediction, J. Water Land Develop. 32 (1) (2017) 103–112.
[77] A. Sharafati, A. Tafarojnoruz, D. Motta, Z.M. Yaseen, Application of nature-inspired optimization algorithms to anfis model to predict wave-induced scour depth around pipelines, J. Hydroinform. 22 (6) (2020) 1425–1451.
[78] J.-S. Jang, Anfis: adaptive-network-based fuzzy inference system, IEEE Trans. Syst., Man, Cybern. 23 (3) (1993) 665–685.
[79] L. Penghui, A.A. Ewees, B.H. Beyaztas, C. Qi, S.Q. Salih, N. Al-Ansari, S.K. Bhagat, Z.M. Yaseen, V.P. Singh, Metaheuristic optimization algorithms hybridized with artificial intelligence model for soil temperature prediction: Novel model, IEEE Access 8 (2020) 51884–51904.
[80] T.M. Tung, Z.M. Yaseen, et al., A survey on river water quality modelling using artificial intelligence models: 2000–2020, J. Hydrol. 585 (2020) 124670.
[81] A. Azad, H. Karami, S. Farzin, S.-F. Mousavi, O. Kisi, Modeling river water quality parameters using modified adaptive neuro fuzzy inference system, Water Sci. Eng. 12 (1) (2019) 45–54.
[82] S. Maroufpoor, E. Maroufpoor, O. Bozorg-Haddad, J. Shiri, Z.M. Yaseen, Soil moisture simulation using hybrid artificial intelligent model: Hybridization of adaptive neuro fuzzy inference system with grey wolf optimizer algorithm, J. Hydrol. 575 (2019) 544–556.
[83] V. Nourani, G. Elkiran, J. Abdullahi, Multi-step ahead modeling of reference evapotranspiration using a multi-model approach, J. Hydrol. 581 (2020) 124434.
[84] F.B. Banadkooki, M. Ehteram, F. Panahi, S.S. Sammen, F.B. Othman, E.-S. Ahmed, Estimation of total dissolved solids (tds) using new hybrid machine learning models, J. Hydrol. 124989 (2020).
[85] M. Moravej, P. Amani, S.-M. Hosseini-Moghari, Groundwater level simulation and forecasting using interior search algorithm-least square support vector regression (isa-lssvr), Groundwater Sustain. Devel. 11 (2020) 100447.
[86] G.-M. Bak, Y.-C. Bae, Groundwater level prediction using anfis algorithm, J. Korea Inst. Electron. Commun. Sci. 14 (6) (2019) 1235–1240.
[87] A.-A. Jahanara, S.R. Khodashenas, Prediction of ground water table using nf-gmdh based evolutionary algorithms, KSCE J. Civil Eng. 23 (12) (2019) 5235–5243.
[88] N. Zhang, C. Xiao, B. Liu, X. Liang, Groundwater depth predictions by gsm, rbf, and anfis models: a comparative assessment, Arab. J. Geosci. 10 (8) (2017) 189.
[89] Y. Gong, Y. Zhang, S. Lan, H. Wang, 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 Resour. Manage. 30 (1) (2016) 375–391.
[90] N.S. Raghavendra, P.C. Deka, Multistep ahead groundwater level time-series forecasting using gaussian process regression and anfis, in: Advanced Computing and Systems for Security Springer, 2016, pp. 289–302.
[91] M. Khaki, I. Yusoff, N. Islami, Simulation of groundwater level through artificial intelligence system, Environ. Earth Sci. 73 (12) (2015) 8357–8367.
[92] N. Djurovic, M. Domazet, R. Stricevic, V. Pocuca, V. Spalevic, R. Pivic, E. Gregoric, U. Domazet, Comparison of groundwater level models based on artificial neural networks and anfis, Sci. World J. (2015).
[93] S. Samantaray, A. Sahoo, D.K. Ghose, Infiltration loss affects toward groundwater fluctuation through canfis in arid watershed: A case study, in: Smart Intelligent Computing and Applications, Springer, 2020, pp. 781–789.
[94] S. Maiti, R. Tiwari, A comparative study of artificial neural networks, bayesian neural networks and adaptive neuro-fuzzy inference system in groundwater level prediction, Environ. Earth Sci. 71 (7) (2014) 3147–3160.
[95] S. Emamgholizadeh, H. Kashi, I. Marofpoor, E. Zalaghi, Prediction of water quality parameters of karoon river (iran) by artificial intelligence-based models, Int. J. Environ. Sci. Technol. 11 (3) (2014) 645–656.
[96] V. Moosavi, M. Vafakhah, B. Shirmohammadi, N. Behnia, A wavelet-anfis hybrid model for groundwater level forecasting for different prediction periods, Water Resour. Manage. 27 (5) (2013) 1301–1321.
[97] V. Moosavi, M. Vafakhah, B. Shirmohammadi, M. Ranjbar, Optimization of wavelet-anfis and wavelet-ann hybrid models by taguchi method for groundwater level forecasting, Arab. J. Sci. Eng. 39 (3) (2014) 1785–1796.
[98] M. Zare, M. Koch, Groundwater level fluctuations simulation and prediction by anfis-and hybrid wavelet-anfis/fuzzy c-means (fcm) clustering models: Application to the miandarband plain, J. Hydro-environment Res. 18 (2018) 63–76.
[99] O. Kisi, J. Shiri, Wavelet and neuro-fuzzy conjunction model for predicting water table depth fluctuations, Hydrol. Res. 43 (3) (2012) 286–300.
[100] J. Shiri, O. Kisi, H. Yoon, K.-K. Lee, A.H. Nazemi, Predicting groundwater level fluctuations with meteorological effect implications–a comparative study among soft computing techniques, Comput. Geosci. 56 (2013) 32–44.
[101] M. Kholghi, S. Hosseini, Comparison of groundwater level estimation using neuro-fuzzy and ordinary kriging, Environ. Model. Assessment 14 (6) (2009) 729.
[102] P. Sreekanth, P. Sreedevi, S. Ahmed, N. Geethanjali, Comparison of ffnn and anfis models for estimating groundwater level, Environ. Earth Sci. 62 (6) (2011) 1301–1310.
[103] B. Shirmohammadi, M. Vafakhah, V. Moosavi, A. Moghaddamnia, Application of several data-driven techniques for predicting groundwater level, Water Resour. Manage 27 (2) (2013) 419–432.
[104] E. Fallah-Mehdipour, O.B. Haddad, M. Mariño, Prediction and simulation of monthly groundwater levels by genetic programming, J. Hydro-Environ. Res. 7 (4) (2013) 253–260.

[105] X. Wen, Q. Feng, H. Yu, J. Wu, J. Si, Z. Chang, H. Xi, Wavelet and adaptive neuro-fuzzy inference system conjunction model for groundwater level predicting in a coastal aquifer, Neural Comput. Appl. 26 (5) (2015) 1203–1215.
[106] S. Sridharam, A. Sahoo, S. Samantaray, D.K. Ghose, Estimation of water table depth using wavelet-anfis: A case study, in: Communication Software and Networks, Springer, pp. 747–754.
[107] E. Jeihouni, M. Mohammadi, S. Eslamian, M.J. Zareian, Potential impacts of climate change on groundwater level through hybrid soft-computing methods: a case study–shabestar plain, iran, Environ. Monit. Assess. 191 (10) (2019) 620.
[108] V. Vapnik, The nature of statistical learning theory, Springer Science & Business Media, 2013.
[109] B. Scholkopf, A.J. Smola, Learning with kernels: support vector machines, regularization, optimization, and beyond, Adaptive Computation and Machine Learning series (2018).
[110] S.K. Bhagat, T. Tiyasha, T.M. Tung, R.R. Mostafa, Z.M. Yaseen, Manganese (mn) removal prediction using extreme gradient model, Ecotoxicol. Environ. Saf. 204 (2020) 111059.
[111] J.C. Principe, N.R. Euliano, W.C. Lefebvre, Innovating adaptive and neural systems instruction with interactive electronic books, Proc. IEEE 88 (1) (2000) 81–95.
[112] V. Vapnik, The nature of statistical learning theory, Springer Science & Business Media, 2013.
[113] S. Kim, Y. Seo, V.P. Singh, Assessment of pan evaporation modeling using bootstrap resampling and soft computing methods, J. Comput. Civil Eng. 29 (5) (2015) 04014063.
[114] S. Haykin, Neural Networks and Learning Machines, 3/E, Pearson Education India, 2010.
[115] Y. Tikhamarine, D. Souag-Gamane, A.N. Ahmed, S.S. Sammen, O. Kisi, Y.F. Huang, A. El-Shafie, Rainfall-runoff modelling using improved machine learning methods: Harris hawks optimizer vs. particle swarm optimization, J. Hydrol. (2020) 125133.
[116] M. Kwon, H.-H. Kwon, D. Han, A hybrid approach combining conceptual hydrological models, support vector machines and remote sensing data for rainfall-runoff modeling, Remote Sensing 12 (11) (2020) 1801.
[117] A. Malik, A. Kumar, S. Kim, M.H. Kashani, V. Karimi, A. Sharafati, M.A. Ghorbani, N. Al-Ansari, S.Q. Salih, Z.M. Yaseen, et al., Modeling monthly pan evaporation process over the indian central himalayas: application of multiple learning artificial intelligence model, Eng. Appl. Comput. Fluid Mech. 14 (1) (2020) 323–338.
[118] J.-L. Chen, H. Yang, M.-Q. Lv, Z.-L. Xiao, S.J. Wu, Estimation of monthly pan evaporation using support vector machine in three gorges reservoir area, china, Theoret. Appl. Climatol. 138 (1–2) (2019) 1095–1107.
[119] M.Y. Chia, Y.F. Huang, C.H. Koo, Support vector machine enhanced empirical reference evapotranspiration estimation with limited meteorological parameters, Comput. Electron. Agricul.s 175 (2020) 105577.
[120] L.B. Ferreira, F.F. da Cunha, R.A. de Oliveira, E.I. Fernandes Filho, Estimation of reference evapotranspiration in brazil with limited meteorological data using ann and svm–a new approach, J. Hydrol. 572 (2019) 556–570.
[121] M. Behzad, K. Asghari, E.A. Coppola Jr, Comparative study of svms and anns in aquifer water level prediction, J. Comput. Civil Eng. 24 (5) (2010) 408–413.
[122] S.-Y. Liong, C. Sivapragasam, Flood stage forecasting with support vector machines 1, JAWRA J. Am. Water Resour. Assoc. 38 (1) (2002) 173–186.
[123] N.D. Bokde, Z.H. Ali, M.T. Al-Hadidi, A.A. Farooque, M. Jamei, A.A. Al Maliki, B. H. Beyaztas, H. Faris, Z.M. Yaseen, Total dissolved salt prediction using neurocomputing models: Case study of gypsum soil within iraq region, IEEE Access 9 (2021) 53617–53635.
[124] H.-T. Fang, B.-C. Jhong, Y.-C. Tan, K.-Y. Ke, M.-H. Chuang, A two-stage approach integrating som-and moga-svm-based algorithms to forecast spatial-temporal groundwater level with meteorological factors, Water Resour. Manage. 33 (2) (2019) 797–818.
[125] S.M. Guzman, J.O. Paz, M.L.M. Tagert, A.E. Mercer, Evaluation of seasonally classified inputs for the prediction of daily groundwater levels: Narx networks vs support vector machines, Environ. Model. Assess. 24 (2) (2019) 223–234.
[126] S. Nie, J. Bian, H. Wan, X. Sun, B. Zhang, Simulation and uncertainty analysis for groundwater levels using radial basis function neural network and support vector machine models, J. Water Supply: Res. Technol.–AQUA 66 (1) (2017) 15–24.
[127] M. Sahoo, A. Kasot, A. Dhar, A. Kar, On predictability of groundwater level in shallow wells using satellite observations, Water Resour. Manage. 32 (4) (2018) 1225–1244.
[128] S.R. Naganna, B.H. Beyaztas, N. Bokde, A.M. Armanuos, On the evaluation of the gradient tree boosting model for groundwater level forecasting, Knowledge-Based Eng. Sci. 1 (01) (2020) 48–57.
[129] M.T. Sattari, R. Mirabbasi, R.S. Sushab, J. Abraham, Prediction of groundwater level in ardebil plain using support vector regression and m5 tree model, Groundwater 56 (4) (2018) 636–646.
[130] Y. Tang, C. Zang, Y. Wei, M. Jiang, Data-driven modeling of groundwater level with least-square support vector machine and spatial–temporal analysis, Geotech. Geol. Eng. 37 (3) (2019) 1661–1670.
[131] H. Yoon, Y. Hyun, K. Ha, K.-K. Lee, G.-B. Kim, A method to improve the stability and accuracy of ann-and svm-based time series models for long-term groundwater level predictions, Comput. Geosci. 90 (2016) 144–155.
[132] A. Wunsch, T. Liesch, S. Broda, Groundwater level forecasting with artificial neural networks: a comparison of long short-term memory (lstm), convolutional neural networks (cnns), and non-linear autoregressive networks with exogenous input (narx), Hydrol. Earth Syst. Sci. 25 (3) (2021) 1671–1687.
[133] S. Sengupta, S. Basak, P. Saikia, S. Paul, V. Tsalavoutis, F. Atiah, V. Ravi, A. Peters, A review of deep learning with special emphasis on architectures, applications and recent trends, Knowl.-Based Syst. 105596 (2020).
[134] M. Sit, B.Z. Demiray, Z. Xiang, G.J. Ewing, Y. Sermet, I. Demir, A comprehensive review of deep learning applications in hydrology and water resources, Water Sci. Technol.
[135] D. Kumar, T. Roshni, A. Singh, M.K. Jha, P. Samui, Predicting groundwater depth fluctuations using deep learning, extreme learning machine and gaussian process: a comparative study, Earth Sci. Inf. (2020) 1–14.
[136] B. Supreetha, N. Shenoy, P. Nayak, Lion algorithm-optimized long short-term memory network for groundwater level forecasting in udupi district, india, Appl. Computat. Intell. Soft Comput. (2020).
[137] C. Park, I.-M. Chung, Evaluating the groundwater prediction using lstm model, J. Korea Water Resour. Assoc. 53 (4) (2020) 273–283.
[138] M.-J. Shin, S.-H. Moon, K.G. Kang, D.-C. Moon, H.-J. Koh, Analysis of groundwater level variations caused by the changes in groundwater withdrawals using long short-term memory network, Hydrology 7 (3) (2020) 64.
[139] A. Dax, M. Zilberbrand, Imputing missing groundwater observations, Hydrol. Res. 49 (3) (2018) 831–845.
[140] M. Vu, A. Jardani, N. Massei, M. Fournier, Reconstruction of missing groundwater level data by using long short-term memory (lstm) deep neural network, J. Hydrol. 125776 (2020).
[141] A.Y. Sun, B.R. Scanlon, Z. Zhang, D. Walling, S.N. Bhanja, A. Mukherjee, Z. Zhong, Combining physically based modeling and deep learning for fusing grace satellite data: Can we learn from mismatch?, Water Resour. Res. 55 (2) (2019) 1179–1195.
[142] J. Zhang, Y. Zhu, X. Zhang, M. Ye, J. Yang, Developing a long short-term memory (lstm) based model for predicting water table depth in agricultural areas, J. Hydrol. 561 (2018) 918–929.
[143] J. Jeong, E. Park, H. Chen, K.-Y. Kim, W.S. Han, H. Suk, Estimation of groundwater level based on the robust training of recurrent neural networks using corrupted data, J. Hydrol. 582 (2020) 124512.
[144] J. Jeong, E. Park, Comparative applications of data-driven models representing water table fluctuations, J. Hydrol. 572 (2019) 261–273.
[145] Z.M. Yaseen, I. Ebtehaj, S. Kim, H. Sanikhani, H. Asadi, M.I. Ghareb, H. Bonakdari, W.H.M. Wan Mohtar, N. Al-Ansari, S. Shahid, Novel hybrid data-intelligence model for forecasting monthly rainfall with uncertainty analysis, Water 11 (3) (2019) 502.
[146] Z.M. Yaseen, M.F. Allawi, H. Karami, M. Ehteram, S. Farzin, A.N. Ahmed, S.B. Koting, N.S. Mohd, W.Z.B. Jaafar, H.A. Afan, et al., A hybrid bat–swarm algorithm for optimizing dam and reservoir operation, Neural Comput. Appl. 31 (12) (2019) 8807–8821.
[147] O.H. Kombo, S. Kumaran, Y.H. Sheikh, A. Bovim, K. Jayavel, Long-term groundwater level prediction model based on hybrid knn-rf technique, Hydrology 7 (3) (2020) 59.
[148] K.-H. Chang, G. Lin, Optimal design of hybrid renewable energy systems using simulation optimization, Simul. Model. Pract. Theory 52 (2015) 40–51.
[149] Q.B. Pham, S.I. Abba, A.G. Usman, N.T.T. Linh, V. Gupta, A. Malik, R. Costache, N.D. Vo, D.Q. Tri, Potential of hybrid data-intelligence algorithms for multi-station modelling of rainfall, Water Resour. Manage. 33 (15) (2019) 5067–5087.
[150] V. Nourani, A.H. Baghanam, J. Adamowski, O. Kisi, Applications of hybrid wavelet–artificial intelligence models in hydrology: a review, J. Hydrol. 514 (2014) 358–377.
[151] G.P. Zhang, Time series forecasting using a hybrid arima and neural network model, Neurocomputing 50 (2003) 159–175.
[152] M. Ghorbani, R.C. Deo, Z.M. Yaseen, M.H. Kashani, B. Mohammadi, Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (mlp-ffa) model: case study in north iran, Theor. Appl. Climatol. 133 (3–4) (2018) 1119–1131.
[153] T. Kashiwao, K. Nakayama, S. Ando, K. Ikeda, M. Lee, A. Bahadori, A neural network-based local rainfall prediction system using meteorological data on the internet: A case study using data from the japan meteorological agency, Appl. Soft Comput. 56 (2017) 317–330.
[154] N. Natarajan, C. Sudheer, Groundwater level forecasting using soft computing techniques, Neural Comput. Appl. 32 (12) (2020) 7691–7708.
[155] A. Jain, A.M. Kumar, Hybrid neural network models for hydrologic time series forecasting, Appl. Soft Comput. 7 (2) (2007) 585–592.
[156] V. Nourani, A.H. Baghanam, J. Adamowski, O. Kisi, Applications of hybrid wavelet–artificial intelligence models in hydrology: a review, J. Hydrol. 514 (2014) 358–377.
[157] F. Fahimi, Z.M. Yaseen, A. El-shafie, Application of soft computing based hybrid models in hydrological variables modeling: a comprehensive review, Theor. Appl. Climatol. 128 (3–4) (2017) 875–903.
[158] A. Sharafati, M. Haghbin, M.S. Aldlemy, M.H. Mussa, A.W. Al Zand, M. Ali, S.K. Bhagat, N. Al-Ansari, Z.M. Yaseen, Development of advanced computer aid model for shear strength of concrete slender beam prediction, Appl. Sci. 10 (11) (2020) 3811.

[159] S.Q. Salih, M. Habib, I. Aljarah, H. Faris, Z.M. Yaseen, An evolutionary optimized artificial intelligence model for modeling scouring depth of submerged weir, Eng. Appl. Artif. Intell. 96 (2020) 104012.
[160] S. Ardabili, A. Mosavi, A.R. Várkonyi-Kóczy, Advances in machine learning modeling reviewing hybrid and ensemble methods, in: International Conference on Global Research and Education Springer, 2019, pp. 215–227.
[161] A.Y. Sun, D. Wang, X. Xu, Monthly streamflow forecasting using gaussian process regression, J. Hydrol. 511 (2014) 72–81.
[162] T. Roshni, M.K. Jha, R.C. Deo, A. Vandana, Development and evaluation of hybrid artificial neural network architectures for modeling spatio-temporal groundwater fluctuations in a complex aquifer system, Water Resour. Manage 33 (7) (2019) 2381–2397.
[163] S. Mathur, Groundwater level forecasting using svm-pso, International Journal of Hydrology, Sci. Technol. 2 (2) (2012) 202–218.
[164] F.-J. Chang, L.-C. Chang, C.-W. Huang, I.-F. Kao, Prediction of monthly regional groundwater levels through hybrid soft-computing techniques, J. Hydrol. 541 (2016) 965–976.
[165] F. Huang, J. Huang, S.-H. Jiang, C. Zhou, Prediction of groundwater levels using evidence of chaos and support vector machine, J. Hydroinform. 19 (4) (2017) 586–606.
[166] G. Rakhshandehroo, H. Akbari, M. Afshari Igder, E. Ostadzadeh, Long-term groundwater-level forecasting in shallow and deep wells using wavelet neural networks trained by an improved harmony search algorithm, J. Hydrol. Eng. 23 (2) (2018) 04017058.
[167] S. Balavalikar, P. Nayak, N. Shenoy, K. Nayak, Particle swarm optimization based artificial neural network model for forecasting groundwater level in udupi district, in: AIP Conference Proceedings, Vol. 1952, AIP Publishing LLC, 2018, p. 020021.
[168] K. Muralitharan, R. Sakthivel, R. Vishnuvarthan, Neural network based optimization approach for energy demand prediction in smart grid, Neurocomputing 273 (2018) 199–208.
[169] J. Wu, J. Long, M. Liu, Evolving rbf neural networks for rainfall prediction using hybrid particle swarm optimization and genetic algorithm, Neurocomputing 148 (2015) 136–142.
[170] H.M. Hasanien, Performance improvement of photovoltaic power systems using an optimal control strategy based on whale optimization algorithm, Electric Power Syst. Res. 157 (2018) 168–176.
[171] B.S. Yıldız, A.R. Yıldız, Comparison of grey wolf, whale, water cycle, ant lion and sine-cosine algorithms for the optimization of a vehicle engine connecting rod, Mater. Testing 60 (3) (2018) 311–315.
[172] N.B. Dash, S.N. Panda, R. Remesan, N. Sahoo, Hybrid neural modeling for groundwater level prediction, Neural Comput. Appl. 19 (8) (2010) 1251–1263.
[173] A. Jalalkamali, N. Jalalkamali, Groundwater modeling using hybrid of artificial neural network with genetic algorithm, Afr. J. Agric. Res. 6 (26) (2011) 5775–5784.
[174] J. Adamowski, H.F. Chan, A wavelet neural network conjunction model for groundwater level forecasting, J. Hydrol. 407 (1–4) (2011) 28–40.
[175] E. Tapoglou, G.P. Karatzas, I.C. Trichakis, E.A. Varouchakis, A spatio-temporal hybrid neural network-kriging model for groundwater level simulation, J. Hydrol. 519 (2014) 3193–3203.
[176] M. Malekzadeh, S. Kardar, K. Saeb, S. Shabanlou, L. Taghavi, A novel approach for prediction of monthly ground water level using a hybrid wavelet and non-tuned self-adaptive machine learning model, Water Resour. Manage. 33 (4) (2019) 1609–1628.
[177] B. Supreetha, K.P. Nayak, K.N. Shenoy, Hybrid artificial intelligence based abc-pso system for ground water level forecasting in udupi region, J. Eng. Sci. Technol. 14 (2) (2019) 797–809.
[178] T. Roshni, M.K. Jha, J. Drisya, Neural network modeling for groundwater-level forecasting in coastal aquifers, Neural Comput. Appl. (2020) 1–18.
[179] F.B. Banadkooki, M. Ehteram, A.N. Ahmed, F.Y. Teo, C.M. Fai, H.A. Afan, M. Sapitang, A. El-Shafie, Enhancement of groundwater-level prediction using an integrated machine learning model optimized by whale algorithm, Nat. Resour. Res. (2020) 1–20.
[180] A. Seifi, M. Ehteram, V.P. Singh, A. Mosavi, Modeling and uncertainty analysis of groundwater level using six evolutionary optimization algorithms hybridized with anfis, svm, and ann, Sustainability 12 (10) (2020) 4023.
[181] V. Nourani, R.G. Ejlali, M.T. Alami, Spatiotemporal groundwater level forecasting in coastal aquifers by hybrid artificial neural network-geostatistics model: a case study, Environ. Eng. Sci. 28 (3) (2011) 217–228.
[182] V. Moosavi, M. Vafakhah, B. Shirmohammadi, N. Behnia, A wavelet-anfis hybrid model for groundwater level forecasting for different prediction periods, Water Resour. Manage. 27 (5) (2013) 1301–1321.
[183] R. Maheswaran, R. Khosa, Long term forecasting of groundwater levels with evidence of non-stationary and nonlinear characteristics, Comput. Geosci. 52 (2013) 422–436.
[184] S. Emamgholizadeh, K. Moslemi, G. Karami, Prediction the groundwater level of bastam plain (iran) by artificial neural network (ann) and adaptive neuro-fuzzy inference system (anfis), Water Resour. Manage. 28 (15) (2014) 5433–5446.
[185] C. Suryanarayana, C. Sudheer, V. Mahammood, B.K. Panigrahi, An integrated wavelet-support vector machine for groundwater level prediction in visakhapatnam, india, Neurocomputing 145 (2014) 324–335.
[186] E. Tapoglou, I.C. Trichakis, Z. Dokou, I.K. Nikolos, G.P. Karatzas, Groundwater-level forecasting under climate change scenarios using an artificial neural network trained with particle swarm optimization, Hydrol. Sci. J. 59 (6) (2014) 1225–1239.
[187] Z. He, Y. Zhang, Q. Guo, X. Zhao, Comparative study of artificial neural networks and wavelet artificial neural networks for groundwater depth data forecasting with various curve fractal dimensions, Water Resour. Manage. 28 (15) (2014) 5297–5317.
[188] M.K. Jha, S. Sahoo, Efficacy of neural network and genetic algorithm techniques in simulating spatio-temporal fluctuations of groundwater, Hydrol. Processes 29 (5) (2015) 671–691.
[189] T.-H. Yang, W.-H. Shi, P.-T. Wang, H.-L. Liu, Q.-L. Yu, Y. Li, Numerical simulation on slope stability analysis considering anisotropic properties of layered fractured rocks: a case study, Arab. J. Geosci. 8 (8) (2015) 5413–5421.
[190] B. Khalil, S. Broda, J. Adamowski, B. Ozga-Zielinski, A. Donohoe, Short-term forecasting of groundwater levels under conditions of mine-tailings recharge using wavelet ensemble neural network models, Hydrogeol. J. 23 (1) (2015) 121–141.
[191] V. Nourani, M.T. Alami, F.D. Vousoughi, Wavelet-entropy data pre-processing approach for ann-based groundwater level modeling, J. Hydrol. 524 (2015) 255–269.
[192] J.-C. Han, Y. Huang, Z. Li, C. Zhao, G. Cheng, P. Huang, Groundwater level prediction using a som-aided stepwise cluster inference model, J. Environ. Manage. 182 (2016) 308–321.
[193] Z. Hosseini, S. Gharechelou, M. Nakhaei, S. Gharechelou, Optimal design of bp algorithm by aco r model for groundwater-level forecasting: A case study on shabestar plain, iran, Arab. J. Geosci. 9 (6) (2016) 436.
[194] H. Ebrahimi, T. Rajaee, Simulation of groundwater level variations using wavelet combined with neural network, linear regression and support vector machine, Global Planet. Change 148 (2017) 181–191.
[195] R. Barzegar, E. Fijani, A.A. Moghaddam, E. Tziritis, Forecasting of groundwater level fluctuations using ensemble hybrid multi-wavelet neural network-based models, Sci. Total Environ. 599 (2017) 20–31.
[196] A.D. Mehr, An improved gene expression programming model for streamflow forecasting in intermittent streams, J. Hydrol. 563 (2018) 669–678.
[197] J. Shiri, Ö. Kişl, Comparison of genetic programming with neuro-fuzzy systems for predicting short-term water table depth fluctuations, Comput. Geosci. 37 (10) (2011) 1692–1701.
[198] M. Cobaner, B. Babayigit, A. Dogan, Estimation of groundwater levels with surface observations via genetic programming, J.-Am. Water Works Assoc. 108 (6) (2016) E335–E348.
[199] A.D. Mehr, V. Nourani, E. Kahya, B. Hrnjica, A.M. Sattar, Z.M. Yaseen, Genetic programming in water resources engineering: A state-of-the-art review, J. Hydrol. 566 (2018) 643–667.
[200] J.R. Koza, J.R. Koza, Genetic programming: on the programming of computers by means of natural selection, vol. 1, MIT Press, 1992.
[201] B. Hrnjica, A. Danandeh Mehr, Optimized Genetic Programming Applications: Emerging Research and Opportunities, Emerging Research and Opportunities, IGI global (2018).
[202] A.D. Mehr, V. Nourani, Season algorithm-multigene genetic programming: a new approach for rainfall-runoff modelling, Water Resour. Manage 32 (8) (2018) 2665–2679.
[203] B. Hrnjica, A.D. Mehr, Š. Behrem, N. Ağıralioğlu, Genetic programming for turbidity prediction: hourly and monthly scenarios, Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi 25 (8) (2019) 992–997.
[204] R. Tür, Maximum wave height hindcasting using ensemble linear-nonlinear models, Theoret. Appl. Climatol. 141 (2020) 1434–4483.
[205] A. Rahmani-Rezaeieh, M. Mohammadi, A.D. Mehr, Ensemble gene expression programming: a new approach for evolution of parsimonious streamflow forecasting model, Theoret. Appl. Climatol. 139 (1–2) (2020) 549–564.
[206] M. Sadat-Noori, W. Glamore, D. Khojasteh, Groundwater level prediction using genetic programming: the importance of precipitation data and weather station location on model accuracy, Environ. Earth Sci. 79 (2020) 37.
[207] T. Hastie, R. Tibshirani, J. Friedman, The elements of statistical learning: data mining, inference, and prediction, Springer Science & Business Media, 2009.
[208] X. Liang, Y. Liang, Applications of data mining in hydrology, in: Proceedings 2001 IEEE International Conference on Data Mining IEEE, 2001, pp. 617–620.
[209] D. Karthik, K. Vijayarekha, Multivariate data mining techniques for assessing water potability, Rasayan J. Chem. 7 (3) (2014) 256–259.
[210] M. Pal, S. Deswal, Modelling pile capacity using gaussian process regression, Comput. Geotech. 37 (7–8) (2010) 942–947.
[211] M.-H. Koo, E. Park, J. Jeong, H. Lee, H.G. Kim, M. Kwon, Y. Kim, S. Nam, J.Y. Ko, J.H. Choi, et al., Applications of gaussian process regression to groundwater quality data, J. Soil Groundwater Environ. 21 (6) (2016) 67–79.
[212] C.E. Rasmussen, Gaussian processes in machine learning, in: Summer School on Machine Learning, Springer, 2003, pp. 63–71.
[213] P. Moonen, J. Allegrini, Employing statistical model emulation as a surrogate for cfd, Environ. Modell. Software 72 (2015) 77–91.
[214] N.E. Owen, P. Challenor, P.P. Menon, S. Bennani, Comparison of surrogate-based uncertainty quantification methods for computationally expensive simulators, SIAM/ASA J. Uncertainty Quantif. 5 (1) (2017) 403–435.
[215] A.Y. Sun, D. Wang, X. Xu, Monthly streamflow forecasting using gaussian process regression, J. Hydrol. 511 (2014) 72–81.
[216] Y. Wang, C. Ocampo-Martínez, V. Puig, J. Quevedo, Gaussian-process-based demand forecasting for predictive control of drinking water networks, in: International Conference on Critical Information Infrastructures Security Springer, 2014, pp. 69–80.

[217] M. Liu, C. Huang, L. Wang, Y. Zhang, X. Luo, Short-term soil moisture forecasting via gaussian process regression with sample selection, Water 12 (11) (2020) 3085.
[218] S. Shabani, S. Samadianfard, M.T. Sattari, A. Mosavi, S. Shamshirband, T. Kmet, A.R. Várkonyi-Kóczy, Modeling pan evaporation using gaussian process regression k-nearest neighbors random forest and support vector machines; comparative analysis, Atmosphere 11 (1) (2020) 66.
[219] L. Pasolli, F. Melgani, E. Blanzieri, Gaussian process regression for estimating chlorophyll concentration in subsurface waters from remote sensing data, IEEE Geosci. Remote Sens. Lett. 7 (3) (2010) 464–468.
[220] P. Sihag, M. Kumar, B. Singh, Assessment of infiltration models developed using soft computing techniques, Geol., Ecol., Landscapes (2020) 1–11.
[221] P. Sihag, N. Tiwari, S. Ranjan, Modelling of infiltration of sandy soil using gaussian process regression, Model. Earth Syst. Environ. 3 (3) (2017) 1091–1100.
[222] M. Karbasi, Forecasting of multi-step ahead reference evapotranspiration using wavelet-gaussian process regression model, Water Resour. Manage. 32 (3) (2018) 1035–1052.
[223] D. Holman, M. Sridharan, P. Gowda, D. Porter, T. Marek, T. Howell, J. Moorhead, Gaussian process models for reference et estimation from alternative meteorological data sources, J. Hydrol. 517 (2014) 28–35.
[224] R. Grbić, D. Kurtagić, D. Slišković, Stream water temperature prediction based on gaussian process regression, Expert Syst. Appl. 40 (18) (2013) 7407–7414.
[225] J. Hu, J. Wang, Short-term wind speed prediction using empirical wavelet transform and gaussian process regression, Energy 93 (2015) 1456–1466.
[226] K. Roushangar, S. Garekhani, F. Alizadeh, Forecasting daily seepage discharge of an earth dam using wavelet–mutual information–gaussian process regression approaches, Geotech. Geol. Eng. 34 (5) (2016) 1313–1326.
[227] O. Samuelsson, A. Björk, J. Zambrano, B. Carlsson, Gaussian process regression for monitoring and fault detection of wastewater treatment processes, Water Sci. Technol. 75 (12) (2017) 2952–2963.
[228] Y. Wang, C. Ocampo-Martínez, V. Puig, J. Quevedo, Gaussian-process-based demand forecasting for predictive control of drinking water networks, in: International Conference on Critical Information Infrastructures Security Springer, 2014, pp. 69–80.
[229] J. Zhao, H. Guo, M. Han, H. Tang, X. Li, Gaussian process regression for prediction of sulfate content in lakes of china, J. Eng. Technol. Sci. 51 (2) (2019) 198–215.
[230] P. Vijai, P.B. Sivakumar, Performance comparison of techniques for water demand forecasting, Procedia Comput. Sci. 143 (2018) 258–266.
[231] G. Kopsiaftis, E. Protopapadakis, A. Voulodimos, N. Doulamis, A. Mantoglou, Gaussian process regression tuned by bayesian optimization for seawater intrusion prediction, Comput. Intell. Neurosci. (2019).
[232] A. Desai, V. Schwamberger, T. Herzog, J. Jaanchen, F.P. Schmidt, Modeling of adsorption equilibria through gaussian process regression of data in dubinin's representation: Application to water/zeolite li-lsx, Ind. Eng. Chem. Res. 58 (37) (2019) 17549–17554.
[233] K. Blix, G. Camps-Valls, R. Jenssen, Gaussian process sensitivity analysis for oceanic chlorophyll estimation, IEEE J. Selected Top. Appl. Earth Observ. Remote Sens. 10 (4) (2017) 1265–1277.
[234] S. Maatta, Predicting groundwater levels using linear regression and neural networks, Ground Water 3 (2011) 3–5.
[235] F. Aburub, W. Hadi, A new associative classification algorithm for predicting groundwater locations, J. Inform. Knowl. Manage. 17 (04) (2018) 1850043.
[236] E.A. Varouchakis, G.P. Karatzas, Gaussian process regression for spatiotemporal analysis of groundwater level variations, EGU General Assembly Conference Abstracts (2020) 6665.
[237] K. Kolli, R. Seshadri, Ground water quality assessment using data mining techniques, Int. J. Comput. Appl. 76 (15).
[238] F.E. Colchester, H.G. Marais, P. Thomson, R. Hope, D.A. Clifton, Accidental infrastructure for groundwater monitoring in africa, Environ. Modell. Software 91 (2017) 241–250.
[239] M.D. Kordestani, S.A. Naghibi, H. Hashemi, K. Ahmadi, B. Kalantar, B. Pradhan, Groundwater potential mapping using a novel data-mining ensemble model, Hydrogeol. J. 27 (1) (2019) 211–224.
[240] H.R. Pourghasemi, M. Beheshtirad, Assessment of a data-driven evidential belief function model and gis for groundwater potential mapping in the koohrang watershed, iran, Geocarto Int. 30 (6) (2015) 662–685.
[241] S. Azimi, M.A. Moghaddam, S.A.H. Monfared, Large-scale association analysis of climate drought and decline in groundwater quantity using gaussian process classification (case study: 609 study area of iran), J. Environ. Health Sci. Eng. 16 (2) (2018) 129–145.
[242] H.G. Kim, E. Park, J. Jeong, W.S. Han, K.-Y. Kim, Groundwater level trend analysis for long-term prediction basedon gaussian process regression, J. Soil Groundwater Environ. 21 (4) (2016) 30–41.
[243] J. Zhang, W. Li, L. Zeng, L. Wu, An adaptive gaussian process-based method for efficient bayesian experimental design in groundwater contaminant source identification problems, Water Resour. Res. 52 (8) (2016) 5971–5984.
[244] O. Bozorg-Haddad, M. Delpasand, H.A. Loáiciga, Self-optimizer data-mining method for aquifer level prediction, Water Supply 20 (2) (2020) 724–736.
[245] M.M. Rajabi, H. Ketabchi, Uncertainty-based simulation-optimization using gaussian process emulation: application to coastal groundwater management, J. Hydrol. 555 (2017) 518–534.
[246] A. Lal, B. Datta, Genetic programming and gaussian process regression models for groundwater salinity prediction: Machine learning for sustainable water resources management, in: 2018 IEEE Conference on Technologies for Sustainability (SusTech) IEEE, 2018, pp. 1–7.
[247] F. Aburub, W. Hadi, Predicting groundwater areas using data mining techniques: Groundwater in jordan as case study, Int. J. Comput. Inform. Eng. 10 (9) (2016) 1621–1624.
[248] N.S. Raghavendra, P.C. Deka, Forecasting monthly groundwater level fluctuations in coastal aquifers using hybrid wavelet packet–support vector regression, Cogent Eng. 2 (1) (2015) 999414.
[249] M. Rezaie-balf, S.R. Naganna, A. Ghaemi, P.C. Deka, Wavelet coupled mars and m5 model tree approaches for groundwater level forecasting, J. Hydrol. 553 (2017) 356–373.
[250] S.G. Mallat, A theory for multiresolution signal decomposition: the wavelet representation, IEEE Trans. Pattern Anal. Mach. Intell. 11 (7) (1989) 674–693.
[251] N. Bokde, A. Feijóo, D. Villanueva, K. Kulat, A review on hybrid empirical mode decomposition models for wind speed and wind power prediction, Energies 12 (2) (2019) 254.
[252] R. Bahmani, T.B. Ouarda, Groundwater level modeling with hybrid artificial intelligence techniques, J. Hydrol. 125659 (2020).
[253] Y. Seo, S. Kim, O. Kisi, V.P. Singh, Daily water level forecasting using wavelet decomposition and artificial intelligence techniques, J. Hydrol. 520 (2015) 224–243.
[254] D. Liu, G. Li, Q. Fu, M. Li, C. Liu, M.A. Faiz, M.I. Khan, T. Li, S. Cui, Application of particle swarm optimization and extreme learning machine forecasting models for regional groundwater depth using nonlinear prediction models as preprocessor, J. Hydrol. Eng. 23 (12) (2018) 04018052.
[255] V. Moosavi, M. Vafakhah, B. Shirmohammadi, N. Behnia, A wavelet-anfis hybrid model for groundwater level forecasting for different prediction periods, Water Resour. Manage. 27 (5) (2013) 1301–1321.
[256] A.S. Rahman, T. Hosono, J.M. Quilty, J. Das, A. Basak, Multiscale groundwater level forecasting: Coupling new machine learning approaches with wavelet transforms, Adv. Water Resour. 103595 (2020).
[257] Y. Gong, Z. Wang, G. Xu, Z. Zhang, A comparative study of groundwater level forecasting using data-driven models based on ensemble empirical mode decomposition, Water 10 (6) (2018) 730.
[258] X. Wen, Q. Feng, R.C. Deo, M. Wu, J. Si, Wavelet analysis–artificial neural network conjunction models for multi-scale monthly groundwater level predicting in an arid inland river basin, northwestern china, Hydrol. Res. 48 (6) (2017) 1710–1729.
[259] F. Yosefvand, S. Shabanlou, Forecasting of groundwater level using ensemble hybrid wavelet–self-adaptive extreme learning machine-based models, Nat. Resour. Res. (2020) 1–18.
[260] S.A. Naghibi, H.R. Pourghasemi, K. Abbaspour, A comparison between ten advanced and soft computing models for groundwater qanat potential assessment in iran using r and gis, Theoret. Appl. Climatol. 131 (3–4) (2018) 967–984.
[261] M. Al-Mukhtar, Random forest, support vector machine, and neural networks to modelling suspended sediment in tigris river-baghdad, Environ. Monitor. Assess. 191 (11) (2019) 673.
[262] R. McCuen, Modeling Hydrologic Change: Statistical Methods, CRC Press (2016), URL: https://books.google.dk/books?id=iI_MBQAAQBAJ.
[263] S. Mahdouh, H. van Oorschot, S. de Lange, et al., Statistical analysis in water resources engineering., Statistical analysis in water resources engineering.
[264] G.E. Box, G.M. Jenkins, G.C. Reinsel, G.M. Ljung, Time series analysis: forecasting and control, John Wiley & Sons, 2015.
[265] X. Yang, J. Zhou, W. Fang, Y. Wang, An ensemble flow forecast method based on autoregressive model and hydrological uncertainty processer, Water 12 (11) (2020) 3138.
[266] A. Katimon, S. Shahid, M. Mohsenipour, Modeling water quality and hydrological variables using arima: a case study of johor river, malaysia, Sustain. Water Resources Manage. 4 (4) (2018) 991–998.
[267] F. Cui, S.Q. Salih, B. Choubin, S.K. Bhagat, P. Samui, Z.M. Yaseen, Newly explored machine learning model for river flow time series forecasting at mary river, australia, Environ. Monit. Assess. 192 (12) (2020) 1–15.
[268] S. Mehdizadeh, Using ar, ma, and arma time series models to improve the performance of mars and knn approaches in monthly precipitation modeling under limited climatic data, Water Resour. Manage 34 (1) (2020) 263–282.
[269] P. Aghelpour, V. Varshavian, Evaluation of stochastic and artificial intelligence models in modeling and predicting of river daily flow time series, Stoch. Env. Res. Risk Assess. 34 (1) (2020) 33–50.
[270] A. McLeod, P.H. Sales, Algorithm as 191: An algorithm for approximate likelihood calculation of arma and seasonal arma models, Appl. Stat. (1983) 211–223.
[271] G. Melard, Algorithm as 197: A fast algorithm for the exact likelihood of autoregressive-moving average models, J. R. Stat. Soc. Ser. C (Appl. Stat.) 33 (1) (1984) 104–114.
[272] G.E. Box, D.A. Pierce, Distribution of residual autocorrelations in autoregressive-integrated moving average time series models, J. Am. Stat. Assoc. 65 (332) (1970) 1509–1526.
[273] H.-C. Chan, P.-A. Chen, J.-T. Lee, Rainfall-induced landslide susceptibility using a rainfall–runoff model and logistic regression, Water 10 (10) (2018) 1354.
[274] J. Ren, B. Ren, Q. Zhang, X. Zheng, A novel hybrid extreme learning machine approach improved by k nearest neighbor method and fireworks algorithm for flood forecasting in medium and small watershed of loess region, Water 11 (9) (2019) 1848.

[275] S. Janizadeh, M. Avand, A. Jaafari, T.V. Phong, M. Bayat, E. Ahmadisharaf, I. Prakash, B.T. Pham, S. Lee, Prediction success of machine learning methods for flash flood susceptibility mapping in the tafresh watershed, iran, Sustainability 11 (19) (2019) 5426.
[276] O. Rahmati, F. Falah, K.S. Dayal, R.C. Deo, F. Mohammadi, T. Biggs, D.D. Moghaddam, S.A. Naghibi, D.T. Bui, Machine learning approaches for spatial modeling of agricultural droughts in the south-east region of queensland australia, Sci. Total Environ. 699 (2020) 134230.
[277] M. Mirzavand, R. Ghazavi, A stochastic modelling technique for groundwater level forecasting in an arid environment using time series methods, Water Resour. Manage. 29 (4) (2015) 1315–1328.
[278] B. Choubin, A. Malekian, Combined gamma and m-test-based ann and arima models for groundwater fluctuation forecasting in semiarid regions, Environ. Earth Sci. 76 (15) (2017) 538.
[279] A. Gibrilla, G. Anornu, D. Adomako, Trend analysis and arima modelling of recent groundwater levels in the white volta river basin of ghana, Groundwater for, Sustain. Develop. 6 (2018) 150–163.
[280] M. Sakizadeh, M.M. Mohamed, H. Klammler, Trend analysis and spatial prediction of groundwater levels using time series forecasting and a novel spatio-temporal method, Water Resour. Manage 33 (4) (2019) 1425–1437.
[281] E.H. de Moraes Takafuji, M.M. da Rocha, R.L. Manzione, Groundwater level prediction/forecasting and assessment of uncertainty using sgs and arima models: A case study in the bauru aquifer system (brazil), Nat. Resour. Res. 28 (2) (2019) 487–503.
[282] M. Goodarzi, Application and performance evaluation of time series, neural networks and hartt models in predicting groundwater level changes, najafabad plain, iran, Sustain. Water Resour. Manage. 6 (4) (2020) 1–10.
[283] M.F. Allawi, O. Jaafar, M. Ehteram, F.M. Hamzah, A. El-Shafie, Synchronizing artificial intelligence models for operating the dam and reservoir system, Water Resour. Manage. 32 (10) (2018) 3373–3389.
[284] Q.A. Aljanabi, Z. Chik, M.F. Allawi, A.H. El-Shafie, A.N. Ahmed, A. El-Shafie, Support vector regression-based model for prediction of behavior stone column parameters in soft clay under highway embankment, Neural Comput. Appl. 30 (8) (2018) 2459–2469.
[285] Y. Raptodimos, I. Lazakis, Application of narx neural network for predicting marine engine performance parameters, Ships Offshore Struct. 15 (4) (2020) 443–452.
[286] A.A. Alsumaiei, A nonlinear autoregressive modeling approach for forecasting groundwater level fluctuation in urban aquifers, Water 12 (3) (2020) 820.
[287] C. Zanotti, M. Rotiroti, S. Sterlacchini, G. Cappellini, L. Fumagalli, G.A. Stefania, M.S. Nannucci, B. Leoni, T. Bonomi, Choosing between linear and nonlinear models and avoiding overfitting for short and long term groundwater level forecasting in a linear system, J. Hydrol. 578 (2019) 124015.
[288] S.M. Guzman, J.O. Paz, M.L.M. Tagert, The use of narx neural networks to forecast daily groundwater levels, Water Resour. Manage. 31 (5) (2017) 1591–1603.
[289] R. Ezzeldin, A. Hatata, Application of narx neural network model for discharge prediction through lateral orifices, Alexand. Eng. J. 57 (4) (2018) 2991–2998.
[290] A. Wunsch, T. Liesch, S. Broda, Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (narx), J. Hydrol. 567 (2018) 743–758.
[291] F. Di Nunno, F. Granata, Groundwater level prediction in apulia region (southern italy) using narx neural network, Environ. Res. 190 (2020) 110062.
[292] A. Al Jami, M.U. Himel, K. Hasan, S.R. Basak, A.F. Mita, Narx neural network approach for the monthly prediction of groundwater levels in sylhet sadar, bangladesh, J. Groundwater Sci. Eng. 8 (2) (2020) 118–126.
[293] S.A. Naghibi, H.R. Pourghasemi, B. Dixon, Gis-based groundwater potential mapping using boosted regression tree, classification and regression tree, and random forest machine learning models in iran, Environ. Monitor. Assess. 188 (1) (2016) 44.
[294] N.A. Nalarajan, C. Mohandas, Groundwater level prediction using m5 model trees, J. Inst. Eng. (India): Series A 96 (1) (2015) 57–62.
[295] Y. Zhao, Y. Li, L. Zhang, Q. Wang, Groundwater level prediction of landslide based on classification and regression tree, Geodesy Geodyn. 7 (5) (2016) 348–355.
[296] Y. Kaya, F. Üneş, M. Demirci, B. Taşar, H. Varçin, Groundwater level prediction using artificial neural network and m5 tree models, Aerul si Apa, Componente ale Mediului (2018) 195–201.
[297] X. Wang, T. Liu, X. Zheng, H. Peng, J. Xin, B. Zhang, Short-term prediction of groundwater level using improved random forest regression with a combination of random features, Appl. Water Sci. 8 (5) (2018) 125.
[298] A. Sharafati, S. Asadollah, A. Neshat, A new artificial intelligence strategy for predicting the groundwater level over the rafsanjan aquifer in iran, Journal of Hydrology 591, cited By 0. doi:10.1016/j.jhydrol.2020.125468. URL:https://www.scopus.com/inward/record.uri?eid=2-s2.0-85090282789& doi=10.1016 %2fj.jhydrol.2020.125468&partnerID=40&md5=f361fd8d18bc5bd44aa23db338e60ca7.
[299] S. Javadinejad, R. Dara, F. Jafary, Modelling groundwater level fluctuation in an indian coastal aquifer, Water SA 46 (4) (2020) 665–671, cited By 0. doi:10.17159/wsa/2020.v46.i4.9081. URL:https://www.scopus.com/inward/record.uri?eid=2-s2.0-85094923349&doi=10.17159%2fwsa%2f2020.v46.i4.9081&partnerID=40&md5=d146c404ee3e532056e679e64eadea92.
[300] A.A. Maroli, V.S. Narwane, R.D. Raut, B.E. Narkhede, Framework for the implementation of an internet of things (iot)-based water distribution and management system, Clean Technol. Environ. Policy (2020) 1–13.
[301] R. Martínez, N. Vela, A. e. Aatik, E. Murray, P. Roche, J.M. Navarro, On the use of an iot integrated system for water quality monitoring and management in wastewater treatment plants, Water 12 (4) (2020) 1096.
[302] Y. Fan, H. Li, G. Miguez-Macho, Global patterns of groundwater table depth, Science 339 (6122) (2013) 940–943.
[303] Y.-S. Su, C.-F. Ni, W.-C. Li, I.-H. Lee, C.-P. Lin, Applying deep learning algorithms to enhance simulation of large-scale groundwater flow in iots, Appl. Soft Comput. 106298 (2020).
[304] R. Dehghani, H.T. Poudeh, Z. Izadi, The effect of climate change on groundwater level and its prediction using modern meta-heuristic model, Groundwater Sustain. Devel. 16 (2022) 100702.
[305] B. Halder, M. Haghbin, A.A. Farooque, An assessment of urban expansion impacts on land transformation of rajpur-sonarpur municipality, Knowl.-Based Eng. Sci. 2 (3) (2021) 34–53.
[306] H.A. Afan, M.F. Allawi, A. El-Shafie, Z.M. Yaseen, A.N. Ahmed, M.A. Malek, S.B. Koting, S.Q. Salih, W.H.M.W. Mohtar, S.H. Lai, et al., Input attributes optimization using the feasibility of genetic nature inspired algorithm: Application of river flow forecasting, Sci. Rep. 10 (1) (2020) 1–15.
[307] S.Q. Salih, A. Sharafati, I. Ebtehaj, H. Sanikhani, R. Siddique, R.C. Deo, H. Bonakdari, S. Shahid, Z.M. Yaseen, Integrative stochastic model standardization with genetic algorithm for rainfall pattern forecasting in tropical and semi-arid environments, Hydrol. Sci. J. 65 (7) (2020) 1145–1157.
[308] A. Uyumaz, A. Danandeh Mehr, E. Kahya, H. Erdem, Rectangular side weirs discharge coefficient estimation in circular channels using linear genetic programming approach, J. Hydroinform. 16 (6) (2014) 1318–1330.
[309] A.D. Mehr, M.J.S. Safari, Multiple genetic programming: a new approach to improve genetic-based month ahead rainfall forecasts, Environ. Monit. Assess. 192 (1) (2020) 25.
[310] M. Das, S.K. Ghosh, A deep-learning-based forecasting ensemble to predict missing data for remote sensing analysis, IEEE J. Selected Top. Appl. Earth Observ. Remote Sens. 10 (12) (2017) 5228–5236.
[311] P.J. García-Laencina, J.-L. Sancho-Gómez, A.R. Figueiras-Vidal, Pattern classification with missing data: a review, Neural Comput. Appl. 19 (2) (2010) 263–282.
[312] J.M. Jerez, I. Molina, P.J. García-Laencina, E. Alba, N. Ribelles, M. Martín, L. Franco, Missing data imputation using statistical and machine learning methods in a real breast cancer problem, Artif. Intell. Med. 50 (2) (2010) 105–115.
[313] Q. Yu, Y. Miche, E. Eirola, M. Van Heeswijk, E. SéVerin, A. Lendasse, Regularized extreme learning machine for regression with missing data, Neurocomputing 102 (2013) 45–51.
[314] H. Ren, E. Cromwell, B. Kravitz, X. Chen, Using deep learning to fill spatio-temporal data gaps in hydrological monitoring networks, Hydrol. Earth Syst. Sci. Discuss. (2019) 1–20.
[315] M. Längkvist, L. Karlsson, A. Loutfi, A review of unsupervised feature learning and deep learning for time-series modeling, Pattern Recogn. Lett. 42 (2014) 11–24.
[316] X. Ma, Z. Tao, Y. Wang, H. Yu, Y. Wang, Long short-term memory neural network for traffic speed prediction using remote microwave sensor data, Transp. Res. Part C: Emerging Technol. 54 (2015) 187–197.
[317] F. Cui, Z.A. Al-Sudani, G.S. Hassan, H.A. Afan, S.J. Ahammed, Z.M. Yaseen, Boosted artificial intelligence model using improved alpha-guided grey wolf optimizer for groundwater level prediction: Comparative study and insight for federated learning technology, J. Hydrol. 127384 (2021).
[318] N. Shiri, J. Shiri, Z.M. Yaseen, S. Kim, I.-M. Chung, V. Nourani, M. Zounemat-Kermani, Development of artificial intelligence models for well groundwater quality simulation: Different modeling scenarios, Plos one 16 (5) (2021) e0251510.

Tao Hai, graduated with B.Sc at the Department of Computer and Information Science of Northwest University of Nationalities from 2000 to 2004. He completed his M.S at School of Mathematics and Statistics of Lanzhou University in 2009. From 2009 to 2012, he obtained his PhD at Faculty of Computer System and Software Engineering in University Malaysia Pahang. He is an associate professor in Baoji University of Arts and Sciences. His current research interests include machine learning, Internet of things and optimization computation.

Mr. Mohammed Majeed Hameed has received his master's degree from the National University of Malaysia in 2014. Currently, he is assigned as a lecturer at Al-Maarif university college, department of civil engineering. He is interested in water resources engineering, environment and water pollutants, water quality, and applying machine learning models to solve different engineering problems.

Dr. Haydar A. Marhoon holds a Bachelor in Control and System Engineering from University of Technology, Baghdad in 2003. His Master's degree and Ph.D in Information Technology are both from Universiti Utara Malaysia in 2012 and 2017 respectively. He works at the Computer Science, University of Kerbala and currently in Al-Ayen University, Iraq. Research interests are Computer Networks, Communication Engineering and computer graphics processing.

Dr. Mohammad Zounemat-Kermani is a university lecturer and researcher specializing in hydrosciences. His research areas are focused on developing soft computing techniques and machine learning models in hydraulics and hydrology applications.

Salim HEDDAM is a lecture and researcher in the field of water resources management and civil engineering. His current research interests include Modelling using Artificial Intelligence Technique, Hydrology, Water Resources Analysis Planning and management, Reservoir Water Quality Modeling, Application of statistical methods in Water and Environmental Resources, Environmental and Water Quality, Hydrologic forecasting and modelling; suspended sediment modelling; forecasting hydrological variables such as precipitation, streamflows, evaporation, evapotranspiration, groundwater, lake level; and also Hydro-Informatics. He is a Reviewer for more than 50 journals indexed in Science Citation Index (SCI) in the fields of hydrology, irrigation, water resources and hydro-informatics. He has authored more than 75 research articles, and 6 chapters (Web of Science h-index = 20, Scopus h-index 22), and a total number of citation over 1600 (Google Scholar h-index = 24).

Professor Dr. Sungwon KIM is currently a Full Professor in Department of Railroad Construction and Safety Engineering, Dongyang University, South Korea. He has conducted the international collaborative studies with renowned international researchers on the impact of geophysical modeling including rainfall-runoff, streamflow, water stage, evaporation, evapotranspiration, and meteorological variables using machine learning, deep learning, and data-driven techniques. He has developed efficient methods and models that can be used to characterize these natural processes. He has published over 250 research papers including leading international journals and total number of citation over 2100 (Google scholar H-Index=26). In addition, he has served as reviewer more than 135 international journals including hydrology, water resources, geophysics, artificial intelligence, and machine learning fields and so on.

Sadeq Oleiwi Sulaiman holds a Ph.D. degree in Civil Engineering from the University of Technology (Iraq). Currently, he is a Full Professor in the Department of Dams & Water Resources Engineering, University of Anbar, Iraq. He has also worked as a postdoctoral researcher at the Lulea University of Technology (Sweden). Dr. Sulaiman has published more than 30 refereed publications and collaborated as subject editor/reviewer for different international scholarly journals. His current research focuses on rainfall-runoff, streamflow, water stage, stochastic hydrology, optimization, hydrosystems engineering, sediment transport, and using machine learning and deep learning techniques to solve different problems in water resources engineering.

Dr. Mou Leong Tan is a senior lecturer in the field of physical geography. He has published more than published more than 70 scientific articles in predominantly Q1 and Q2 journals that have been cited over 1600 times based on citation data reported by Google scholar, with an H-index of 19. The impact of his research also extends across multiple disciplines, as confirmed by citing studies published in the fields of hydrologic, remote sensing, climatic, environmental engineering and others.

Dr Zulfaqar Sa'adi is postdoctoral researcher in the field of hydro-climatology and currently working at Centre for Environmental Sustainability and Water Security (IPASA), Universiti Teknologi Malaysia. The scope of his research is in the field of hydro-climatological modelling and climate change future projection for hydrologic resilience. He has published in various reputed international journal. He has served as a reviewer for more than 30 international journals.

Ali Danandeh Mehr holds Ph.D. degree in Civil Engineering from Istanbul Technical University (Turkey). Currently, he is an associate professor at Civil Engineering Department of Antalya Bilim University, Turkey. He has also worked as a postdoctoral researcher at University of Tabriz (Iran) and University of Oulu (Finland). Dr. Danandeh Mehr has published more than 50 refereed publications and collaborated as subject editor/reviewer for different international scholarly journals. His current research focuses on the stochastic hydrology, hydroinformatics, and developing evolutionary algorithms to solve different problems in water resources systems.

Dr. Mohammed Falah Allawi is a Lecturer and Researcher in the water resources engineering field. His research is focused on developing and optimizing machine learning methods for analyzing and processing patterns of hydrological variables. He is reviewer of many journals some of them are Journal of Hydrology, Water Resources Management Journal and Water Journal.

Dr S. I. Abba is a lecture and researcher in Civil Engineering with a specialization in water resource and environmental engineering. He received a B.Sc. degree from Bayero University Kano (BUK), the MTech. Degree from Sharda University, India, and from Near East University (NEU), Cyprus. He is currently a researcher with King Fahad University of Petroleum and Minerals and a lecturer at Baze University, Nigeria. His research interests include artificial intelligence, machine learning, hydrology, hydro-climatology, hydro-environmental modelling, computational engineering, soft computing, and optimization algorithm. In addition, he has excellent expertise in remote sensing, GIS, and advanced data analysis and classification.

Jasni Mohamad Zain received the bachelor's degree in computer science from the University of Liverpool, Liverpool, U.K., in 1989 and the Ph.D. degree from Brunel University, West London, U.K., in 2005., She started her career as a Tutor in 1997 with the University of Technology Malaysia, Johor Bahru, Malaysia. She is currently a Professor with the Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Malaysia, and was the Dean of the Faculty of Computer Systems and Software Engineering, University Malaysia Pahang, Pahang, Malaysia, for eight years. She has graduated 15 Ph.D. students and 6 master's students by research under her supervision. She has authored or co-authored over 100 refereed papers. She has a patent pending for digital watermarking. Her current research interests include digital watermarking and image processing, as well as data and network security. Dr. Zain has been actively presenting papers and keynote addresses at national and international conferences.

Dr. Mayadah Waheed Falah is a lecturer and researcher in the field of civil engineering. She has worked extensively with diverse civil engineering applications and published with multiple disciplines. She has more in data analytics and material engineering.

Mehdi Jamei received the M.Sc. and Ph.D. degrees in civil engineering from Shahid Chamran University of Ahvaz, Iran, in 2005 and 2015, respectively. He worked 12 years as a signor engineering and a project manager in the famous consulting companies in Iran. He is currently an Assistant Professor with the Department of Civil engineering, Shahd Chamran University of Ahvaz, Iran. His research contributions are in the domain of data mining topics, focused majorly on applied soft computing, numerical method in porous media, and prediction applications in hydrology, scouring, water quality, nanofluids, and energy.

Dr. Neeraj Dhanraj Bokde received the M.E. degree in embedded systems from the EEE Department, BITS Pilani, Pilani Campus, India, and the Ph.D. degree in data science from the Visvesvaraya National Institute of Technology, Nagpur, India. He is currently working as a Postdoctoral Researcher with the Department of Mechanical and Production Engineering - Renewable Energy and Thermodynamics, Aarhus University, Aarhus, Denmark. His major research contributions are in the domain of data science topics, focused majorly on time series analysis, software package development, and prediction applications in renewable energy. He is serving in editorial positions in Data in Brief, Frontiers in Energy Research, Energies, and Information journals.

Dr. Maryam Bayatvarkeshi is an Assistant Professor in the Department of Soil Science at the University of Malayer. She has majored in Irrigation and Drainage; however, is passionate about hydrology in particular modeling. Most of her researches focuses on the application of intelligent models for tackling complicated problems such as evapotranspiration, weather variables, soil physical and chemical properties in the hydrology and water resource management domain. She has published over 12 research manuscripts in high-ranked journals so that they have been cited in over 300 publications.

Dr. Mustafa Al-Mukhtar is working as associate professor of Water Resources Engineering at the Civil Engineering Department of the University of Technology-Baghdad. His research interests focus mainly on using the artificial intelligence methods in water resources management. He is interested in machine learning, statistical and stochastic modelling and he manipulated with variety of statistical software since 2011. He published several papers in peer reviewed international journals in this field. With respect to his academic experience profile, He started his academic job in 2006 as assistant lecturer at the University of Technology, Baghdad. In 2015, he completed his PhD degree from TU Freiberg in Germany. He taught several subjects related to the water resources and hydrological engineering such as water management, fluid mechanics, hydrology, dams engineering, and statistics. In addition, He was involved in some consultancy projects such as designing wastewater treatment plant, and Environmental Impact Assessment of several projects. He has supervised on many under and post graduate students. In 2017, he honorably was selected for the Fulbright Visiting Scholar Program.

TIYASHA successfully secured National eligibility test conducted by government of India. She awarded honors in master's degree in Environmental Engineering from the Rajasthan Technical University, India in 2014. She joined the Department of Civil Engineering, Institute of Technology, Ambo University, Ethiopia, as a Lecturer, where, she also led a funded project which won the Energy Globe Award, issued by Austrian energy pioneer Wolfgang Neumann. At present, She is pursuing a Ph.D. degree in Faculty of Civil Engineering from Ton Duc Thang University, Ho Chi Minh City, Vietnam.

SURAJ KUMAR BHAGAT received Gold Medal (First Rank in the University) during his master's degree in Environmental Engineering from the Rajasthan Technical University, India in 2014. He also earned a research fellowship at the Indian Institute of Technology (IIT Delhi), India in 2013. In 2014, He joined the Department of Civil Engineering, Institute of Technology, Ambo University, Ethiopia, as a Lecturer, where, he also led a funded project which won the Energy Globe Award at national level, issued by Austrian energy pioneer Wolfgang Neumann. At present, he is pursuing a Ph.D. degree in Faculty of Civil Engineering from Ton Duc Thang University, Ho Chi Minh City, Vietnam.

Dr. Khaled Mohamed Khedher is currently Assistant Professor in Civil Engineering Department, in College of Engineering at King Khalid University since 2018. Before, he worked as Assistant Professor in Civil Engineering for many years at the Universities (France, Tunisia, and Saudi Arabia). He has participated in many international and national conferences and symposiums linked to Civil Engineering and new technologies (GIS, Remote Sensing, and Geosciences). He has also worked on many articles and papers in ISI journals with high impact factor. Until now, more than 60 papers online published in the International publishers (Elsevier, Taylor & Francis, MDPI, Wiley, Springer, and more...).

Nadhir Al-Ansari obtained his BSc and MSC degrees from the University of Baghdad in 1968 and 1972 respectively. He obtained his PhD degree from Dundee University in Water Resources Engineering in 1976. Now he is a Professor at the department of Civil, Environmental and Natural Resources Engineering at Lulea Technical University Sweden. Previously worked at Baghdad University 1976-1995 then at Al-Bayt University in Jordan (1995- 2007). Research interests are mainly in Geology, Water Resources and Environment. Served several academic administrative post (Dean, Head of Department). Publications include more than 424 articles in international/national journals, chapters in books and 13 books. He executed more than 60 major research projects in Iraq, Jordan and UK. Awarded several scientific and educational awards, among them is the British Council on its 70th Anniversary awarded him top 5 scientists in Cultural Relations. One patent on Physical methods for the separation of iron oxides. Supervised more than 66 postgraduate students at Iraq, Jordan, UK Australia universities. Member of several scientific societies e.g., International Association of Hydrological Sciences, Chartered Institution of Water and Environment Management, Network of Iraqi Scientists Abroad, Founder and president of the Iraqi Scientific Society for Water Resources ... etc. Member of the editorial board of ten international journals.

DR. SHAMSUDDIN SHAHID is an Associate Professor in the Department of Hydraulic & Hydrology, Faculty of Civil Engineering, Universiti Teknologi Malaysia (UTM). He is also the head of the Integrated Water Resources Management (IWRM) research group of UTM. His major research interests include Water Resources Management, Climate Change Impacts and Adaptation to Water Resources, Statistical Hydrology, Hydrological Disasters, and Groundwater Hydrology. He uses statistical and mathematical tools for innovative solutions of hydrological problems for adaptation to global environmental changes. His major research achievements in recent years include forecasting water demand in a holistic way, downscaling climate using an alternative approach for better projection of climate change, modeling economical impacts of global warming induced changes in water resources, modeling droughts during crop-growing seasons, projection of drought severity-area-frequency curves for adaptation to climate change impacts on droughts and water stress, multi-criteria decision making for selection of adaptation and mitigation strategies, determination of unidirectional trends to distinguish global climate change from natural variability. Dr. Shahid has successfully completed about 10 national and international research projects as a principal investigator. He published about 100 research articles in internationally reputed indexed journals and 5 academic books.

Dr. Zaher Mundher Yaseen is a lecturer and researcher in the field of civil engineering. The scope of his research is quite abroad, covering water resources engineering, environmental engineering, knowledge-based system development, and the implementation of data analytic and artificial intelligence models. He has published over 260 research articles within international journals and total number of citations over 7500 (Google Scholar H-Index = 49). He has collaborated with over 45 international countries and more than 430 researchers. He has served as a reviewer for more than 135 international journals.