International Journal of Engineering Science Invention
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 6 Issue 3|| March 2017 || PP. 79-100

Journal on Ground Water Studies with the Application of Ai

Chitrabhanu Sahoo[1], Rojanil Senapati[2]
[1]*Assistant Professor, Department of Civil Engineering, Gandhi Institute For Technology (GIFT), Bhubaneswar*
[2]*Assistant Professor, Department of Civil Engineering, Gandhi Engineering College, Bhubaneswar*

Abstract: *This study is a review to the special issue on artificial intelligence (AI) methods for groundwater level (GWL) modeling and forecasting, and presents a brief overview of the most popular AI techniques, along with the bibliographic reviews of the experiences of the authors over past years, and the reviewing and comparison of the obtained results. Accordingly, 67 journal papers published from 2001 to 2018 were reviewed in the terms of the features and abilities of the modeling approaches, input data consideration, prediction time steps, data division, etc. From the reviewed papers it can be concluded that despite some weaknesses, if the AI methods properly be developed, they can successfully be used to simulate and forecast the GWL time series in diﬀerent aquifers. Since some of the stages of the AI modeling are based on the experience or trial-and-error procedures, it is useful to review them in the special application on GWL modeling. Many partial and general results were achieved from the reviewed papers, which can provide applicable guidelines for researchers who want to perform similar works in this field. Several new ideas in the related area of research are also presented in this study for developing innovativemethodsandforimprovingthequalityofthemodeling.*

I. Introduction

Measurement and analysis of the groundwater level (GWL) in aquifers is an important and useful task in the management of the groundwater resources, and the knowledge about the GWL variations can be used for quantifying the groundwater availability. The GWL variations in wells provide a direct measure of the impact of groundwaterdevelopment,andimportantinformationaboutaquiferdynamicsisoftenembeddedinthecontinuouslyreco rdedGWLtimeseries(Butleret al., 2013). Therefore, the modeling and predicting of GWL is neces- sary for water managers and engineers to qualify and quantify groundwater resources and to maintain a balance between supply and demands.

For GWL modeling, conceptual or physical based models are tradi- tionally the main tool; however they have some practical limitations,including the need for large amount of data and input parameters. In many cases, data is limited on one hand, and obtaining accurate pre- dictions is more important than understandingunderlyingmechanisms, on the other hand, and therefore, the black-box artificial intelligence (AI) models can be a suitable alternative. Although there are diﬀerent methods for modeling and predicting GW Linaquiferssuchas conceptual, physical, numerical, statistical, etc. methods, however in recent years, AI methods have been used for their simplicity and ac- ceptable results, and many researches have investigated the perfor- mance of AI models for GWL modeling in diﬀerent parts of the world. This study is a review of those papers that have used AI methods for modeling and forecasting GWL. Of course, these methods have some weaknesses, such as overtraining, low generalizability, risk of using unrelated data, incorrect modeling with inappropriate methods, and so on. However, their simplicity of use, high speed run and acceptable accuracywithouttheneedtoknowtheproblemsphysicshaveledmany researchers to apply them. It should be noted that it is the nature or perhaps the defect of the AI models that if they were developed for the prediction of a specified time series, the accurate results could not ne- cessarily be derived in the similar ones; but the major advantage of AI modelsisthenonlinearandcomplicatedphenomenamodelingwithout the need for full understanding underlying mechanisms (Rajaee andBoroumand, 2015). Therefore, the use of AI approaches in GWL mod- eling has steadily increased and attracted interest of many researchers in theworld.

In order to develop new and better AI approaches for GWL mod- eling, it is important to investigate what has been done with AI models and current researches, and there is a need for researchers to know whatotherscholarshavedoneinthisregard.Manyreviewpapershave been recently published that have explored using AI models in hy- drology (e.g., Solomatine (2005)), or in diﬀerent hydrological and water resources fields (e.g., Maier et al. (2010)in the field ofriver variables modeling, and Wu et al. (2014) in the field of water quality modeling), while, no review paper is find that has centered on the specific use of AI models for GWL modeling and forecasting. Each hy- drological phenomenon has its own characteristics, and it is reasonable thattheuseofAImodelsinGWLmodelingtobereviewedindividually. Nourani et al. (2014) have cited and reviewed some wavelet-AI studies in GWL modeling (5 papers); however, in the best knowledge of the authors,thereisnotyetanindividualandcomprehensivereviewpaper evaluating the application of AI methods in GWL modeling and for- casting.

The current review study presents and compares the details of the journal papers dealing with the AI methods for GWL modeling and forecasting, in the terms of the features and abilities of the modeling approaches, the input data consideration, the quantity and quality of used data, the study areas and aquifers, the prediction time steps, the data division, etc. 67 papers are reviewed in this study. These papers havebeenpublishedintheinternationaljournalsbelongstothefamous publications such as Elsevier, Springer, IWA, Wiley, ASCE, etc. during the period from 2001 to 2018. The papers were found from searching the web using the relevant key words, and were chosen because they were published in well-known international journals in the fields of hydrology, water resources and AI sciences. Based on the search, Journal of Hydrology (Elsevier) with 12 papers and Water Resources Management (Springer) with 11 papers are the journals that have been published the most papers in this regard. Also, Hydrological Processes (Wiley), Journal of Hydroinformatics (IWA), Hydrogeology Journal (Springer)andComputers&Geosciences(Elsevier),eachonehavebeen published three papers in this regard. The rest of the journals (a totalof 29 journals) that had papers in this regard have been published one or two papers so far (Table1).

Fig. 1shows number of published papers regarding AI in GWL modeling (reviewed in this study) with respect to year of publication. As can be seen, such publications have increased in recent years. Therefore, due to the interest of researchers in this field and given the difficulty of conceptual/numerical GWL modeling, this review was provided to help new researches in this field.

Details of the selected papers are given in Table 1, where thepapers on the subject of GWL modeling with AI methods are comparing re- garding to the authors and year of publication, journals and impact factor (IF), region of study, type of utilized AI methods, hydrological input variables, time steps and range of total data. The abbreviations used in the Table 1 have been explained in the end of thetable.

In the following, some very commonly used AI methods for mod- eling GWL are addressed. The methods include artificial neural net- works (ANN), adaptive neuro-fuzzy inference system (ANFIS),genetic programming (GP), support vector machine (SVM) and some hybrid models such as wavelet-AI models. Firstly, a brief description of each method is presented and thereafter the related conducted studies are cited and reviewed. This is followed by general results and discussion, conclusionsand recommendations for future avenues of research.

II. Artificial intelligence methods for GWL modeling

Introductory

ANNs are computational models inspired by biological neural net- works. They can be used to approximate functions that are generally unknown,ortopredictfuturevaluesofpossiblynoisytimeseriesbased on past histories. ANNs are composed of simple elements operating in parallel. As in nature, the connections between elements largely determine the network function (Beale et al., 2010). A common ANN comprised of multiple elements, called neurons (processing elements), and connection pathways that link them. The neurons having similar properties are grouped in one single layer. Typically, three separate layers exist in an ANN, namely input, hidden and output layers. The input layer takes input variables, which in the case of GWL forecasting are usually the precipitation, temperature, GWL, etc. time series. In the hidden and output layers, each neuron passes its weighted and biased input through a desired transfer (activation) function to produce a re- sult. ANNs are trained with a sample data, so that a particular input leads to a specific target output. Training means tuning the adjustable network parameters (called weights and biases) to optimize the net- work performance. The training process can be done with various training (learning) algorithms. The Levenberg-Marquardt (LM) algo- rithm, the back-propagation (BP) algorithm, the Bayesian regulariza- tion (BR) algorithm and the gradient descent with momentum and adaptivelearningrateback-propagation (GDX) algorithm areexamples of most used training algorithms inthe literature.

Diff erent ANN types have been widely described in the literature; however several types of them are briefly presented here. The feed- forward neural networks (FNNs) propagate input signal through the network in a forward direction, layer by layer. The multilayer percep- tron (MLP) network as a historical FNN consists of an input layer, one or more hidden layers, and one output layer. The recurrent neural networks (RNN) feed the outputs of the hidden layer back to itself. In the RNNs, an additional layer is interconnected with the hidden layer that plays the role of the network history. The radial basis function (RBF) networks are also feed-forward, but have only one hidden layer that uses Gaussian transfer function and a standard Euclidean distance to measure how far an input vector is from a specific center vector. The amount of Euclidean distance is transferred by the Gaussian function that determines the output of the layer. RBF networks tend to learn much faster than a FNN.

Theself-organizingmap(SOM)networkasakindofANNsconsists of one input layer and one output layer called 'Kohonen' layer. The input layer is fully connected to the output layer. The SOM is trained using an unsupervised competitive training algorithm. The n-dimen- sional input vector is sent through the network, and the Euclidean distance between the weight vector and the input vector is computed. The training process will be continued to select best neurons that re- duce the distance between the weights and inputs. An advantage ofthe SOM is to map high-dimensional input space into low dimensional space.

Regardless of the type of utilized ANN, they have some common modelingstages. Fig.2 shows the typicalstagesofusingANNsforGWL simulation andforecasting.

BIBLIOGRAPHICreview

RecentexperimentsinGWLmodelinghavereportedthatANNsmay offer a promising alternative for conceptual methods. In one of the first studies, Coulibaly et al. (2001)compared three types of ANN models using GWL, precipitation and temperature time series as the inputs of models to simulate average monthly GWL in the Gondo aquifer, Bur- kina Faso. Simulation results showed that the RNN is most efficient compared to the static structure input delay ANN and RBF-ANN. Lallahem et al. (2005) evaluated ANN for estimating the monthly GWL in an unconfined chalky aquifer in northern France. The input datawas the GWL of 13 piezometers, rainfall, mean temperature, precipitation and potential evapotranspiration, and the main objective was to si- mulate the GWL in a selected piezometer. The simulations revealed the merit of using MLP models. Daliakopoulos et al. (2005)tested seven different ANN models with various architectures and training algo- rithms for monthly GWL forecasting in the island of Crete, Greece. The input variables were the past GWL, temperature,precipitationandriver discharge.TheFNNtrainedwiththeLMalgorithmhadthebestresults. Nayaketal. (2006) investigatedthepotentialofMLPtrainedwithBP

No.	Author (year)	Journal (2016 IF)	Region of study	Used AI models	Input variables	Time step	Range of total data (Number of data)
1	Coulibaly et al. (2001)	Water Resources Research (4.397)	Gondo aquifer, Burkina Faso	ANN	GWL, P, T	Monthly average	1986–1996 (108 sets)
2	Lallahem et al. (2005)	Journal of Hydrology (3.483)	Chalky aquifer of northern France	ANN	GWL, R, mean T, e□ective R, potential ET	Monthly	1988–1999 (132 sets)
3	Daliakopoulos et al. (2005)	Journal of Hydrology (3.483)	Island of Crete, Greece	ANN	GWL, T, P, Q	Monthly	1988–2002 (160 sets)
4	Nayak et al. (2006)	Water Resources Management (2.848)	Central Godavari Delta System, India	ANN	GWL, neighboring wells GWL, R, canal releases	Monthly average	1981–1989 (108 sets)
5	Krishna et al. (2008)	Hydrological Processes (3.014)	Andhra Pradesh state, India	ANN	GWL, R, ET	Monthly average	1995–2004 (120 sets)
6	Mohammadi (2008)	Practical Hydroinformatics (Book)	Chamchamal plain, Iran	ANN	MODFLOW output parameters	Monthly	1986–1998 (144 sets)
7	Feng et al (2008)	Groundwater (2.067)	Shiyang river basin, northwest China	ANN	GWL, P, E, Q, population, irrigation ratio, irrigation area	Monthly	1980–1997 (216 sets)
8	Tsanis et al. (2014)	Journal of Hydroinformatics (1.634)	Messara Valley, Crete, Greece	ANN	P, T, runo□, GWL, specific yield	Monthly	1981–2002 (264 sets)
9	Nourani et al. (2008)	Hydrological Processes (3.014)	Tabriz aquifer, Iran	ANN	GWL, R, mean T, Q	Monthly	1995–2004 (120 sets)
10	Kholghi and hosseini (2009)	Environmental Modeling & Assessment (1.023)	Qazvin plain, Iran	ANFIS, Kriging	GWL	Spatial modeling	Spatial modeling
11	Banerjee et al. (2009)	Environmental geology (no IF)	Hyderabad, India	ANN	Not mentioned in the paper	Monthly	2005–2007 (23 sets)
12	Yang et al. (2009)	Journal of Arid Environments (1.835)	Western Jilin, China	ANN	GWL	Monthly average	1986–2004 (132 sets)
13	Mohanty et al. (2010)	Water Resources Management (2.848)	Orissa, India	ANN	GWL, R, E, River stage, SWL, Pumping rate	Weekly	2004–2007 (174 sets)

14	Chen et al. (2010)	Journal of Hydrologic Engineering (1.694)	Southern Taiwan	ANN	GWL, neighboring wells GWL	Monthly average	1997–2003 (63 sets)
15	Chen et al. (2011)	Journal of Water Resources Planning and Management (3.537)	Southern Taiwan	ANN	GWL, neighboring wells GWL	Monthly average	1998–2004 (76 sets)
16	Jalalkamali et al. (2011)	Journal of Hydroinformatics (1.634)	Kerman, Iran	ANFIS, ANN	GWL, T, R	Monthly	1988–2009 (264 sets)
17	Adamowski and Chan (2011)	Journal of Hydrology (3.483)	Quebec, Canada	WANN, ANN	GWL, P, T	Monthly average	2002–2009 (84 sets)
18	Yoon et al. (2011)	Journal of Hydrology (3.483)	Beach of the Donghae city, Korea	SVM, ANN	GWL, P, tide level	Six-hourly	2004–2006 (2370 sets)
19	Sreekanth et al. (2011)	Environmental Earth Science (1.569)	Maheshwaram watershed, India	ANN, ANFIS	GWL, R, E, T, H	Monthly	2000–2006 (84 sets)
20	Nourani et al. (2011)	Environmental Engineering Science (1.426)	Shabestar plain, Iran	ANN-GS	GWL, R, lake level	Monthly	1994–2006 (144 sets)
21	Trichakis et al. (2011)	Water Resources Management (2.848)	Edward's aquifer, Texas, USA	ANN	GWL, P, day number, pumping	Daily	Not mentioned in the paper
22	Rakhshandehroo et al. (2012)	Arabian Journal for Science and Engineering (0.865)	Shiraz plain, Iran	ANN	GWL, P, T, E, Q	Monthly	1993–2004 (138 sets)
23	Taormina et al. (2012)	Engineering Applications of Artificial Intelligence (2.894)	Lagoon of Venice, Italy	ANN	GWL, R, ET	Hourly	2005–2008 (23850 sets)
24	Kisi and Shiri (2012)	Hydrology Research (1.754)	Illinois State, USA	Wavelet-ANFIS, ANFIS	GWL	Daily	2001–2008 (2430 sets)
25	Shirmohammadi et al. (2013)	Water Resources Management (2.848)	Mashhad plain, Iran	ANFIS	P	Monthly	1992–2007 (180 sets)
26	Sahoo and Jha (2013)	Hydrogeology Journal (2.109)	Konan basin, Kochi, Japan	ANN	GWL, R, T, river stage, seasonal dummy variables	Monthly	1999–2004 (72 sets)
27	Shiri et al. (2013)	Computers & Geosciences (2.533)	Hoengchon, south Korea	GP, ANN, ANFIS, SVM	GWL, R, ET	Daily average	2001–2008 (2920 sets)
28	Fallah-Mehdipour et al. (2013)	Journal of Hydro-environment Research (1.429)	Karaj plain, Iran	GP, ANFIS	GWL, P, E	Monthly	7 years (84 sets)

Table 1 Details of the reviewed papers, where the AI methods were used to model the GWL. (continuedonnextPAGE)

Table 1 (continued)

No.	Author (year)	Journal (2016 IF)	Region of study	Used AI models	Input variables	Time step	Range of total data (Number of data)
36	Ying et al. (2014)	Journal of Water Supply Research and Technology-Aqua (0.824)	Jilin Province, China	ANN	GWL	Monthly	1986–2013 (about 336 sets)
37	Jha and Sahoo (2015)	Hydrological Processes (3.014)	Konan basin, Kochi, Japan	ANN-GA	GWL, R, T, river stage, seasonal dummy variables	Monthly	1999–2004 (72 sets)
38	Yang et al. (2015)	Arabian Journal of Geosciences (0.955)	Dongshan Island, Fujian, China	Wavelet-ANN, ANN	GWL	Monthly average	2000–2011 (144 sets)
39	Khalil et al. (2015)	Hydrogeology Journal (2.109)	Manitou mine site, Quebec, Canada	Wavelet-ensemble-ANN, Wavelet-ANN, ANN	Recharge, P, T	Daily	2009–2011 (900 sets)
40	Mirzavand et al. (2015)	Natural Hazards (1.833)	Kashan plain, Iran	ANFIS, SVR	R, E, Q, Aquifer discharge	Monthly	1990–2010 (240 sets)
41	Juan et al. (2015)	Journal of Hydrology (3.483)	Qinghai-Tibet Plateau, China	ANN	GWL, T, P	Daily	2010–2012 (653 sets)
42	Gholami et al. (2015)	Journal of Hydrology (3.483)	Caspian southern coasts, Iran	ANN	P, tree-rings	Annually	1970–2013 (44 sets)
43	Khaki et al. (2015)	Environmental Earth Sciences (1.569)	Langat basin, Malaysia	ANFIS, ANN	R, H, E, min and max T	Monthly average	2007–2013 (79 sets)
44	Nourani et al. (2015)	Journal of Hydrology (3.483)	Ardabil plain, Iran	Wavelet-ANN, ANN	GWL, R, runo	Monthly	1988–2012 (300 sets)
45	Mohanty et al. (2015)	Water Resources Management (2.848)	Mahanadi delta of Odisha, India	ANN	GWL, R, E, river stage, SWL, pumping rates	Weekly	2004–2007 (174 sets)
46	Gong et al. (2015)	Water Resources Management (2.848)	shore of Lake Okeechobee, Florida, USA	ANFIS, SVM, ANN	GWL,SWL, P, T	Monthly	1998–2009 (144 sets)
47	Sun et al. (2016)	Hydrology and Earth System Sciences (4.437)	Nee Soon swamp forest , Singapore	ANN	SWL, P	Daily	2012–2013 (730 sets)
48	Chang et al. (2016)	Journal of Hydrology	Zhuoshui River	ANN (SOM-NARX)	GWL, Q, R	Monthly	2000–2013 (168 sets)

Abbreviations: P, precipitation; T, temperature; R, rainfall; H, humidity; E, evaporation; ET, evapotranspiration; Q, river flow/discharge/runoff ; SWL, surface water level; GS, geostatistics

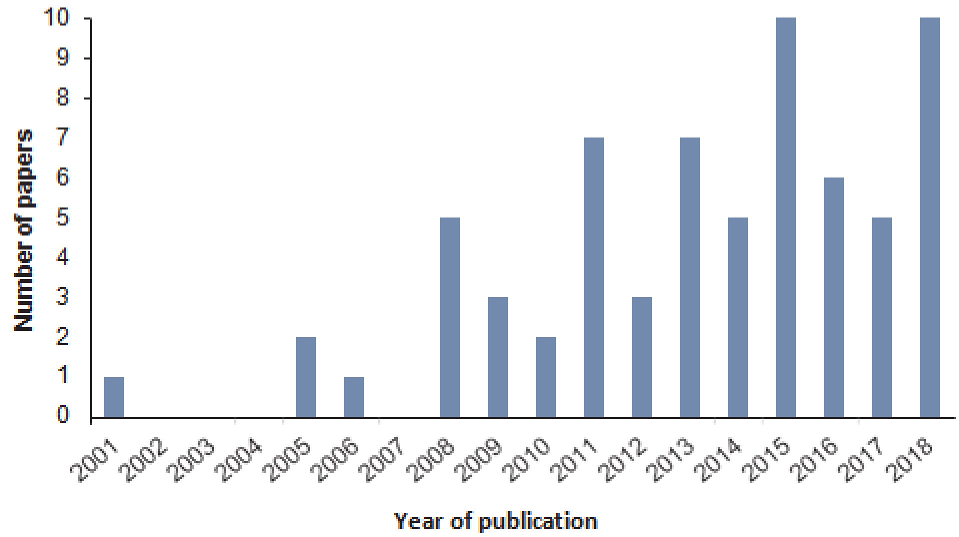


Fig. 1. Number of published papers regarding AI methods in GWL modeling (used in this study) with respect to year of publication.

algorithm in forecasting the monthly GWL in an unconfined coastal aquifer in India. The inputvariables were selected as precipitation, canal releases and GWL of the observation well and two neighboring wells. The performance was good for 1 and 2-month ahead forecasting, but was deteriorated after 2-month.

Krishna et al. (2008)applied several ANN training algorithms to predict monthly GWL in an urban coastal aquifer in Andhra Pradesh state, India. It was found that the FNN trained with LM algorithm is a good choice, compared to BR and RBF algorithms. In their study, GWL were also predicted in neighboring wells using model parameters from the best network of a well. Mohammadi (2008) tested MODFLOW and twotypesofANN,i.e.,MLPandRNNtosimulatethemonthlyGWLofa karstic aquifer, located in Iran. He used data sets generated by MOD- FLOWfortrainingoftheANNs.TheresultsindicatedthatANNmodels needed less input data and took less time to run, compared to MOD- FLOW. Nourani et al. (2008) compared six diff erent types ofANNs for

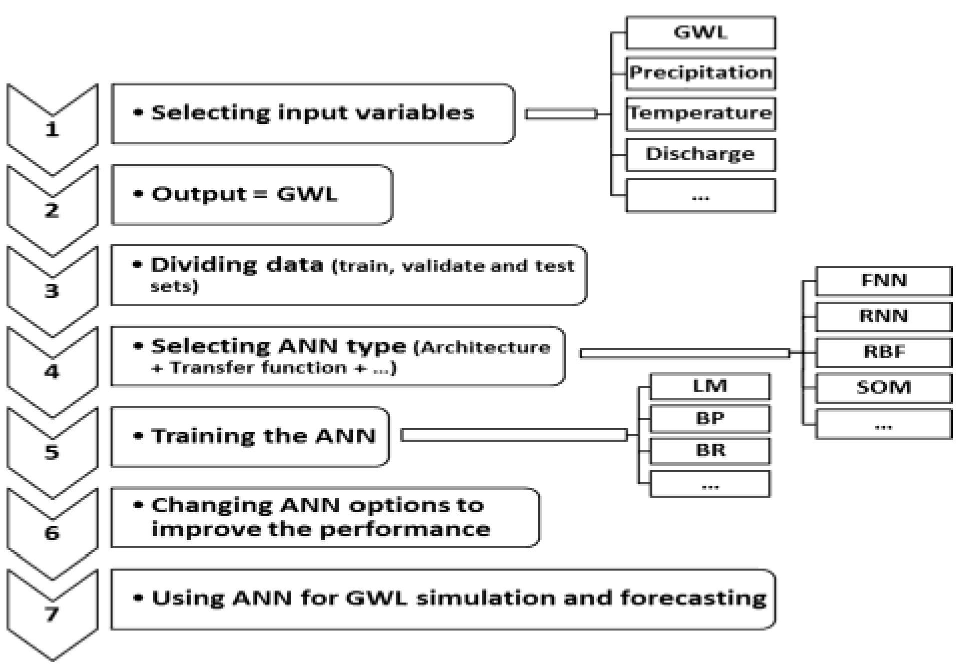


Fig. 2. The stages of using ANNs for GWL forecasting.

spatiotemporal GWL forecasting in Tabriz aquifer, Iran. The monthly GWL in central well, precipitation, mean temperature and average discharge were selected as the inputs. The optimal ANN was a FNN trainedwithLMalgorithm,whichwasthenappliedtoforecastGWLsof selected wells, as the spatialmodel.

Feng et al. (2008) applied FNN to investigate the eff ects of 7 factors i.e.: initial GWL, precipitation, evaporation, water reservoir inflow, population, synthesis irrigation ratio, and irrigation area, on monthly GWLinshiyangriverbasin,China.Sensitivityanalysiswiththemodels demonstrated that groundwater extraction for irrigation is the pre- dominant factor responsible for declining GWL. Tsanis et al. (2014)developed a FNN, trained with the LM algorithm with five input vari- ables,i.e., precipitation, temperature, runoff ,GWLandspecificyieldfor forecasting the monthly GWL in Messara Valley, Crete, Greece. They used a deterministic component, which linked precipitation with the seasonal recharge of the aquifer and projected the seasonal average precipitations. Results showed that the specific yield marginally im- proved the forecasting but the linearly projected precipitation compo- nent drastically increased theforecasting.

Banerjeeetal.(2009)usedFNNmodeltrainedwithLMalgorithmto predict the monthly GWL of four diversified wells in Kurmapally wa- tershed, Hyderabad, India. They have not mentioned the used input variables but forecasted the GWL considering varying recharge and pumping conditions. Yang et al. (2009)applied the BP-ANN and the integratedtimeseries(ITS)modelstoforecastmonthlyaverageGWLin the western Jilin province of China. The input variables were only the past GWLs at diff erent intervals of time. The simulation results in- dicatedthatbothANNandITSmodelswereaccurateinreproducingtheGWLs,butinthetestphase,theANNwassuperiort otheITS.

Mohanty et al. (2010) developed three diff erent training algorithms, viz., LM, BR and GDX algorithms for weekly GWL forecasting in a tropicalhumidregion,easternIndia.Theinputstothemodelsconsisted of precipitation, pan evaporation, river stage, water level in the drain, pumping rate and GWL in the previous week. The BR algorithm was found slightly superior to the two other algorithms. Chen et al. (2010)combined the theory of SOM and RBF. The proposed model could de- cide the number of RBF-ANN hidden units with using the two-dimen- sional feature map which is constructed by SOM. The inputs were the monthly average GWLs of six wells in southern Taiwan, while the outputwasthemonthlyaverageGWLofanindividualwell.Theresults showedthatthefour-siteinputmodelwasmorecompetentcomparedto the single-site model and six-site model. One year later, Chen et al.(2011)combined of the SOM and BP-ANN for the same study area. Here, the model inputs were the monthly average GWLs of ten wells, while the output was the GWL of an individual well. It was found that themulti-siteSOM-BP-ANNmodelprovidedthemostaccuratepredic- tions in comparison to the autoregressive integrated moving average (ARIMA) and single ANNmodels.

Trichakis et al. (2011)simulated daily GWL by MLP at a well lo- cated in the karstic artesian Edward's aquifer in Texas, USA. The input variables were the day number, precipitation, pumping and GWL. The testing data were used to check the ability of the MLP to interpolate or extrapolate in other wells in the region. The results showed that there was a need for exact knowledge of pumping from each well in karstic aquifers as it was difficult to simulate the sudden drops and rises. Sreekanth et al. (2011) compared the FNN trained with LM algorithm andANFISforestimationoftheGWLoftheMaheshwaramwatershed, India. The inputs included the monthly GWL in 22 wells along with rainfall, temperature, evaporation and relative humidity. The results showed that the FNN provided better accuracy compared toANFIS.

Rakhshandehroo et al. (2012) used FNN, RBF, RNN and a general- ized regression neural network for monthly GWL prediction in Shiraz plain, Iran. The precipitation, GWL, temperature, evaporation and runoff wereutilizedastheinputdata.BestperformanceswereachievedbyFNNandRNNnetworks,respectively.Taormi naetal.(2012)appliedFNNforlongperiodsimulationsofhourlyGWLsinacoastalunconfinedaquifersitedintheLagoon ofVenice,Italy.TheFNNwasfirsttrainedto perform one-hour-ahead predictions using past GWL, rainfall and eva- potranspiration data. After the training, simulations were produced by feeding back the computed outputs in place of past observed data. The FNN reconstructed accurate GWL for long periods, at least six months, relying only on the rainfall and evapotranspiration data. Sahoo and Jha(2013) compared MLP trained with LM algorithm and multi linear re- gression (MLR) approach in monthly GWL forecasting considering rainfall, temperature, river stage, GWL and 11 seasonal dummy vari- ables as inputs. The study area was Konan basin, located in Kochi, Japan. They concluded that MLP models have better results; however, considering the practical advantages of the MLR, it was recommended as a cost-eff ective GWL modelingtool.

Ying et al. (2014) compared the RBF-ANN, ARIMA and ITS models forGWL forecasting of two wellsinJilin,China.MonthlyGWLwasthe only variable used to develop the models. They concluded that for forecasting the dynamics of the GWL, the RBF-ANN is preferable, but for analyzing GWL variation, the ITS and ARIMA may be more appro- priate.

Juanetal.(2015)developedtwoFNNmodels,onewiththreeinputs (previous GWL, temperature and precipitation) and another with two inputs (temperature and precipitation only) to forecast the daily var- iations of the supra-permafrost GWL in the Qinghai-Tibet plateau, China. The FNNs were trained with LM algorithm, and the results in- dicated that the three inputs model produced better accuracy perfor- mance. However, if there are no field observations of the GWL, the models developed using only two inputs also have good accuracy. Gholami et al. (2015) used a MLP trained with LM algorithm to simu- lateannual GWL fluctuationsoftwowellslocatedinanalluvialaquifer of the Caspian Sea southern coasts, Iran, for the period from 1912 to 2013. The tree-ring diameter and the precipitation during the growing season weret heinputparametersfortheMLP,andtheGWLduringthegrowingseasonwastheoutput.Theresultsshowedthattheinteg rationofdendrochronologyandANNrendersahighdegreeofaccuracyinthe simulation of annual GWL. Mohanty et al. (2015)applied FNN for si- multaneous forecasting of the weekly GWL in 18 wells located over a river basin in India. The inputs were selected as rainfall, pan evapora- tion, river stage, water level in the surface drain, pumping rates of 18 sites and GWLs of 18 sites in the previous week, which led to 40 input nodesand18outputnodes.ComparisonbetweentheLM,BRandGDX training algorithms showed that the GDX was the most suitable algo- rithm for the studyarea.

Sun et al. (2016)applied an MLP trained with LM algorithm to forecast the daily GWL in a freshwater swamp forest of Singapore. The inputs to the model were the surrounding reservoir levels and rainfall. TheresultsrevealedthatMLPproducedbetterpredictionwithaleading time of 1 day compared toMLR.

Wunsch et al. (2018)used the nonlinear autoregressive with exo- genous inputs neural network (NARX) for GWL forecasting of several wells in southwest Germany. Precipitation and temperature were chosen as input variables. All input and target time series were de- composed using the seasonal trend based on loess algorithm to detect significant time lags and determine input and feedback delays needed for NARX application. The results showed that NARX is suited to per- formGWLpredictionsforuninfluencedobservationwells,eventhough the number of input variables is limited. Ghose et al. (2018) developed theRNN model to forecast monthlyGWLofawellinOdisha,Indiaasa function of rainfall, temperature, humidity, runoff and evapo- transpiration. From the results, evapotranspiration and runoff were the influencing parameters which aff ect the GWL, and inclusion of them improved the modelefficiency.

Lee et al. (2018)applied the FNN to predict hourly GWL of 8 ob- servation wells located in Yangpyeong riverside area, South Korea. They investigate the relative impacts of the input variables, and as a result used the river level and pumping rates from two extraction wells as input variables, while the precipitation was found to be a weak influencing factor, and therefore it was not used as an input variable. Kouziokas et al. (2018)used multiple FNN with various network structures and training algorithms to forecast the daily GWL of a well located in Montgomery County, Pennsylvania, USA. Using the hu- midity, precipitation, and temperature as input variables the FNN with the LM training algorithm was the best model.

Results

AnassessmentofthevariousstudiesonANNmodelingoftheGWL revealed the followingissues:

1) The ANN models can be extended easily from univariate to multi- variate cases compared to the conceptual models, and the model complexity can be varied simply by altering the transfer function, training algorithm or network architecture.Similartotheregression models,theinputvariablescanbeconsideredbasedonanempirical proof or a correlation analysis. The results of the reviewed papers alsoindicatedthatANNscapturethecomplexnon-linearbehaviorof the GWL time series relatively better than the regular regression models such as ARIMA andMLR.

2) The reviews reveal that the LM algorithm is the most popular training algorithm used to train ANNs for GWL modeling. The LM algorithmisamodificationoftheclassicNewtonalgorithmusedfor finding an optimum solution to a minimization problem. The LM algorithm is often characterized as more stable and efficient, and some researchers point out that it is faster and less easily trapped in local minima than other training algorithms (Daliakopoulos et al.,2005). Zounemat-kermani et al. (2013) in a study of comparison the performanceof RBF and LMfeed-forwardANNsforpredictingdaily watershed runoff, concluded that LM algorithm is superior to the RBFinpredictionofonedayaheadbaseandhighflows,buttheRBF algorithm out performed the LMinpredictingfloodevents.TheGWL time series do not possess a characteristic such as flood in runoff time series, therefore it seems that the superiority of LM in GWL modeling correspond to the results of the study of Zounemat-ker- mani et al.(2013).

3) The three layers FNN with the sigmoid transfer function in the hidden layer and linear transfer function in output layer is the most commonstructureofANNforGWLmodeling.Thesigmoidfunction is diff erentiable,

continuous, and monotonically increasing in its domainanditisthemostfrequentlyemployedfunctioninmodeling (Ravansalar and Rajaee, 2015). It should be mentioned that in the majority of reviewed papers the structure of ANN and number of hidden neurons were achieved by a trial-and-errorprocedure.

ADAPTIVE neuro-fuzzy inference system (ANFIS) for GWLmodeling
Introductory

The adaptive neuro-fuzzy inference system is a combination of an adaptive neural network (AN) and a fuzzy inference system (FIS), thus it has potential to capture the benefits of two methods in a single fra- mework. Jang (1993) introduced architecture and a learning procedure for the ANFIS that uses a neural network learning algorithm for con- structing a set of fuzzy if-then rules with appropriate membership functions (MFs) from the specified input-output pairs. The FIS corre- sponds to a set of fuzzy if-then rules that have learning capability to approximate nonlinear functions. There are two approaches for FIS, namely Mamdani and Sugeno. The diff erences between these two ap- proaches arise from the consequent part. Mamdani's approach uses fuzzyMFs,whereasSugeno'sapproachuseslinearorconstantMFs.The ANFISisanAImethodwithflexiblemathematicalconstructionwhichis capable of identifying complex nonlinearity and uncertainties due to randomness and imprecision between variables, without attempting to reach an understanding as to the nature of the phenomena. This ap- proach is capable of approximating any real continuous function on a compact set to any degree of accuracy. Thus, in parameterestimation/forecasting, where the given data are such that the system associates measurable system variables with an internal system parameter, a functional mapping may be constructed by ANFIS that approximates the process of estimation of the internal system parameter. More in- formation on ANFIS can be found in Jang (1993).

BIBLIOGRAPHICreview

In the area of GWL modeling with ANFIS, Kholghi and hosseini(2009) applied the ordinary kriging and ANFIS for spatialinterpolation of GWL in an unconfined aquifer in Qazvin, Iran. They use the GWL data of 95 wells for training and testing the models. The Gaussian MF wasused in the ANFIS models. The results showed that the contourplot of isopieze lines estimated by ANFIS was more efficient than those by kriging.
Jalalkamali et al. (2011)investigated the abilities of ANFIS and ANN with various combinations of monthly temperature, rainfall and GWLs in two neighboring wells as the inputs to predict the GWL of another well, located in Kerman plain, Iran. The results showed that applying the GWLs of the current and one month before ofthewelland the neighboring wells was the best input combination to predict GWL, andtheANFISmodelsusingGaussianMFhadbetterresultscompared to theANNs.

Shirmohammadi et al. (2013)applied system identification, time series, and ANFIS models to predict monthly GWL in Mashhad plain, Iran.Theonlyinputvariableofthemodelswastheprecipitation.Inthe ANFIS models, they tested several MFssuchasTriangular,Gaussianand Bell-shaped functions. The results showed that the Bell-shaped MF had the best performance, and the ANFIS model outperformed both time series and system identificationmodels.

Emamgholizadeh et al. (2014)compared ANN and ANFIS in fore- casting of monthly GWL in Bastam plain, Iran. They considered the rainfall recharge, irrigation returned flow and pumping rates from waterwellsasinputdataandfoundthatANFISoutperformedtheANN. The results showed that applying ANFIS with diff erent structures had the most accuracy when it used withtrapezoidal MF.

Mirzavand et al. (2015) investigated the abilities of ANFIS and SVR in estimating monthly GWL fluctuation in the Kashan plain, Iran, by using the inputs of stream flow, evaporation, spring discharge, aquifer dischargeandrainfall.TheresultsindicatedthattheANFISmodelusing Bell-shaped MF performed better than the SVR. Khaki et al. (2015)applied ANN and ANFIS to simulate monthly average GWL in the Langat Basin, Malaysia. The GWL, rainfall, humidity, evaporation, minimum temperature and maximum temperature were applied as the inputvariablesofthemodels.TheobtainedresultsoftheANFISmodels were superior to those of ANNs, and in the ANFIS models the Bell- shapedMFoutperformedtheGaussianMF.Gongetal.(2015)testedthe validityofANN,SVMandANFISinthepredictionofthemonthlyGWL for two wells near Lake Okeechobee in Florida, United States. The precipitation,temperature,pastGWLsandlakelevelwereusedasinput data. The results showed that the GWL predictions from ANFIS and SVMweremoreaccuratethanthatfromANN.

Results
ThereviewofcitedstudiesonANFISmodelingoftheGWLshowed that:
1) In the cited papers, applying ANFIS as an alternative approach to predict the GWL leads to more accurate

results in comparison with the ANN. Since ANFIS integrates both neural networks and fuzzy logic principles, it is more likely to deal with non-stationary time series moreeff ectively.

2) In three studies (i.e., Shirmohammadi et al., 2013; Mirzavand et al.,2015; Khaki et al., 2015) the Bell-shaped MF was the best in com- parison with other MFs, while in two studies (i.e., Kholghi andhosseini, 2009; Jalalkamali et al., 2011) the Gaussian MF yielded higheraccuracy,andinthestudyofEmamgholizadehetal.(2014) the Trapezoidal MF was the best in comparison of others. In the meanwhile, Gong et al. (2015) have not mentioned anything about the used MF. Generally, there was not any exact method for choosing the MFs in the reviewed papers, and instead, a trial-and- error procedure was used for finding an appropriate MF. So, use of thoseMFswhichdonotcauseoverfittingandgiveleasterrorcanbe recommended.

Genetic PROGRAMMING (GP) for GWLmodeling

Introductory

The GP as a generalization of genetic algorithm (GA) is an evolu- tionary algorithm based on biological evolution inspired by Darwinian theoriesofnaturalselectionandsurvivalofthefittest.TheGPconsiders an initial population of randomly generated equations, which are achieved from the random variables, numbers and functions. The function involves arithmetic operators (+, –, ×, ÷) and other math- ematical functions (e.g., sin, cos, etc.) or user-defined expressions, which should be chosen based on some understanding of the process. The initial population is then applied to an evolutionary process to evaluate the fitness of the evolved programs by defining a fitness function. In forecasting problems the root mean squared error (RMSE) between forecasted and observed data is often used as the fitness function. The programs that best fit the data are then selected to pro- duce better program through two genetic operators: crossover and mutation. The evolution process is repeated and driven towards tofind expressions which describe the data and give the best performance of themodel.

BIBLIOGRAPHICreview

Shirietal.(2013)investigatedtheabilitiesofGP,ANFIS,ANN,SVM and ARIMA techniques for daily GWL forecasting in Korea. The GWL, rainfall and evapotranspiration data were used as the inputs of the models.ForGPmodels,therootrelativesquarederrorwasemployedas the fitness function. The results showed that GP models were superior compared to other models. Fallah-Mehdipour et al. (2013)compared the capability of the GP and ANFIS to predict and simulate monthly GWLs in three wells in the Karaj plain of Iran. The precipitation, eva- poration and GWLs were used as the inputs of the models. They have noted that the fitness function of GP was considered an error criterion, but they have not mentioned the type of it. Results showed that in the GPmodelstheaverageerrorswerelesscomparedtotheANFISmodels.

Results

Originally developed for optimization problems, the GP was ex- tended to solve forecasting problems such as GWL forecasting. In this case, the minimum error (e.g. RMSE) between forecasted and observed GWLs has been applied as the fitness function of the GP. Although, amongother AImethods, theGPmaynotbethebestwaytoforecastthe GWL, in the two aforementioned studies, this model outperformed other models. Similar to the ANN and ANFIS, in the reviewed GP pa- pers, the input parameters were chosen based on a combination of empirical and trial-and-error analysis. The low number of papers on GWLmodelingviaGPdemonstratestheneedtoinvestigatemoreabout application of GP and in GWLmodeling.

Support vector MACHINE (SVM)for GWL modeling

Introductory

The SVM is a statistical machine learning theory. It has not a priori determined structure, but the input vectors supporting the model structure are selected through a model training process (Vapnik, 1998). This machine learning method is based on the extension of the idea of identifying a hyper-plane that separates two classes in classification. A SVM constructs hyper-planes in an infinite dimensional space, which can be used for classification, regression, or other tasks. The mappings used by SVM schemes are designed to ensure that dot products maybe computed easily in terms of the variables in the original space, by de- fining them in terms of a kernel function selected to suit the problem. The SVM can also be used as a regression method. The support vector regression (SVR) method uses the same principles as the SVM for classification, with only a few minor diff erences. The SVRgeneral- izationperformancedependsonagoodsettingofsomeparameters and the kernel function. The SVR parameters represent some constants like regularization constant and kernel function constant, and control the prediction (regression) model complexity. The kernel function changes the dimensionality of the input space to perform the regression task with more confidence. A full mathematical overview of SVM is pre- sented by Vapnik (1998). Originally developed for classification, it was extendedtosolvepredictionproblems,andinthiscapacitywasusedin hydrology relatedtasks.

BIBLIOGRAPHICreview

Yoon et al. (2011) developed ANN and SVM models for predicting GWL fluctuations of two wells at a coastal aquifer in South Korea, consideringasix-hourlytimestep.ThepastGWL,precipitationandtide level were selected as the inputs of the models. It was found that the past GWL was the most eff ective input variable for the study site, and tidelevelwasmoreeff ectivethanprecipitation.Theresultsshowedthat the performance of the SVM was better than the ANN. Yoon et al.(2016)utilized a weighted error function approach to improve the performance of ANN and SVM models for the prediction of dailyGWL in response to rainfall. The input variables were GWL and rainfall data in South Korea. The comparison of the models showed that the re- cursive prediction performance of the SVM was superior theANN.

Huang et al. (2017) used the chaos theory to select the best input lagsof GWL timeseries, anddevelopedtheSVMandBP-ANNmodels. Usingtheparticleswarmoptimizationmethodtoobtaintheparameters of SVM, the models were applied to predict the daily, weekly and monthly GWL in China. The chaotic SVM model had higher accuracy than the linear SVM and chaotic BP-ANN models. Nie et al. (2017)employed precipitation, evaporation, and temperature as the inputs of SVM and RBF-ANN models to forecast monthly GWL in Jilinprovince, China. The SVM model was more accurate and had feweruncertainties causedbyerrorsinthemeasurementsoftheinputsandoutputs.

Mukherjee and Ramachandran (2018) applied the GRACE satellite terrestrial water storage (TWS) data along with meteorological vari- ables precipitation, min and max temperature, humidity and wind to predict GWL with the SVR, ANN and linear regression models. The results showed that TWS is a highly significant variable to modelGWL, and the SVR was the best model. Guzman et al. (2018) compared SVR andNARX-ANNmodelsforGWLpredictionofanirrigationwelllocated in the southeastern USA. They evaluated the best combination from three input variables, i.e., daily GWL, precipitation and evapo- transpiration data for each model. The GWL + precipitation scenario provides the optimal combination for model inputs, and the SVR was superior to the ANN. Tang et al. (2018) concluded that the least square SVM perform better than classical SVM and some other AI models in GWL forecasting. The only input variable was the hourly GWL of four observation wells located in northernUK.

Results

The SVMs/SVRs are powerful machine learning methods that have been developed and applied for many classification/prediction pro- blems over past years. Although the number of published papers con- sideringGWLmodelingviaSVMislow,howeveritshouldbenotedthat SVM has been used for predicting of many time series for a myriad of practical applications in theworld.

In the SVM modeling, the appropriate selection of the kernel func- tion and parameter values is critical. In the five of seven aforemen- tionedpapers,theRBFkernelfunctionwasselected,whereasinthetwo otherones (i.e.,Yoonetal. (2011) andMukherjeeandRamachandran (2018)) the utilized kernel function was not mentioned. Over period of years, the RBF function has become the choice of many researchers as the kernel function for SVR because of its accuracy and reliable per- formance (Suryanarayana et al., 2014).

For selecting the optimum parameters of SVM model, most of the papers have employed a procedure like trial-and-error, except Huanget al. (2017)that have been used the particle swarm optimization method to obtain the optimum parameters of SVM.

Hybrid AI techniques for GWLmodeling

Introductory

Since it has been revealed that the AI models have some limitations withthenonlinearandnon-stationaryprocesses,somehybridmodeling approaches which include certain data-preprocessing and/or combine diff erent AI techniques have been also developed in the recent years to increase the capabilities of the AI methods. Combining diff erent AI methods in diff erent stages of the modeling, and applying efficient methods for input data pre-processing make the developing of these models more eff ective. For example, the GP technique can be used to optimize the AI input variables and/or AI regulation parameters. In another example, the geostatistical techniques such as Kriging can be combined with the AI methods for spatiotemporal GWL modeling. According to the capability of geostatistics tools in spatial estimation, hybrid AI-geostatistic models have been applied in some papers to use their potential for spatiotemporal simulation ofGWL.

The wavelet analysis is an example for the data pre-processing, which has been widely used in GWL modeling. Wavelet analysis is applied for de-noising, compression and decomposition of input data timeseries.Waveletisatime-dependentspectralanalysisthatunravels time series in the time-frequency space to provide a time-scale de- scription of the processes and their relationships (Daubechies, 1990). The Wavelet analysis can be performed continuously or discretely. The continuous wavelet transform (CWT) can operate at every scale; but it requires a lot of computational time, and generates a large amount of data. In many studies the discrete wavelet transform (DWT) was used, where only a subset of scales and positions are chosen to make the calculations. In the wavelet-AI models cited in scientific papers, the decomposed sub-time series were used as the inputs of AI models, in- steadofthemaintimeseries.Theschematicstructureofsomeofhybrid AImodelsforGWLmodelingisshowninFig.3.

BIBLIOGRAPHICreview

AfterwardstheAImethodsweredevelopedforpredictionproblems, the researchers tried to combine diff erent type of them to overcome the shortcomings and increase their accuracy. Almost since 2011, there has been an interest in application of the wavelet analysis in combination with diff erent AI methods. Adamowski and Chan (2011)used a Wa- velet-ANN model for GWL forecasting at two sites in Quebec, Canada. Themonthlytotalprecipitation,averagetemperatureandaverageGWL were decomposed at two levels by wavelets and imposed to the ANN. The model was found to provide more accurate GWL forecasts com- pared to the ANN and ARIMA models. Nourani et al. (2011) presented an ANN-geostatistics methodology for spatiotemporal prediction of GWL in Shabestar plain, which adjoins to Urmieh Lake as a coastal aquifer in Iran. Monthly GWLs data from 11 piezometers, rainfall, and lakewaterlevelsweretheinputs ofANN. TheANNwastrainedforeach piezometer to predict the GWL of the next month. Then Kriging was applied to the outputs from ANN models in order to estimate GWL at any desired point in theplain.

Kisi and Shiri (2012)investigated the ability of a Wavelet-ANFIS model to perform one-, two- and three-day-ahead GWL forecasting oftwowellslocatedinIllinoisState,USA,usingonlypastdailyGWLdata. They found that excluding the detail coefficients from the inputs and using only approximation components significantly increase the accu- racy of ANFIS models. The hybrid model outperformedANFIS,particularly for two- and three-day-ahead forecasts.

Moosavi et al. (2013a) applied a number of diff erent structures for ANN, ANFIS, Wavelet-ANN and Wavelet-ANFIS models to evaluate their performances to forecast GWL with 1, 2, 3 and 4 months ahead undertwocasestudiesinMashhadplain,Iran.Itwasdemonstratedthat wavelet transform can improve the accuracy of forecasting. It has been alsoshownthattheforecastsmadebyWavelet-ANFISmodelsaremore accurate than those by other models. They found that the decomposi- tion level in wavelet transform should be determined according to the periodicity and seasonality of data series. Moosavi et al. (2013b)also investigated the optimum structures of Wavelet-ANN and Wavelet- ANFISmodelsforGWLforecastinginthesamecasestudies.Theyused the optimization Taguchi method to assess diff erent factors aff ecting the performance of models. It was revealed that transfer functions ofANN,membershipfunctiontypesofANFISandthemotherwavelettype are the most important factors. Comparison of optimal models de- monstratedthebetterperformanceofWavelet-ANFIS.MaheswaranandKhosa (2013) showed that wavelet based nonlinear as wavelet-Volterra model performed better than Wavelet-ANN and wavelet-linear regres- sion models for GWL forecasting. The study area was northernSaanich Peninsula, Canada, and the inputs of the models were the level five decomposed monthly average GWL timeseries.

Suryanarayana et al. (2014)predicted monthly GWL of three ob- servation wells in the city of Visakhapatnam, India, using wavelet-SVR modeling. The monthly data of precipitation, maximum temperature, mean temperature and GWL for the period 2001–2012 are used as the input variables. Results indicated that wavelet-SVR model gives better accuracy compared with SVR, ANN and ARIMA models. Heetal.(2014)linkedwaveletandfractaltheorymethodstoANNforGWLforecasting of three sites located in Ganzhou region, northwest China. The fractal dimension was convenient for quantitatively describing theirregularity orrandomnessoftimeseriesdata.Theresultsshowedthatthismodelis suitable for sites at which the fractal dimension of the wavelet de- composition detail components is large. Tapoglou et al. (2014)com- binedANN,fuzzylogicandKriginginordertosimulatethespatialandtemporaldistributionofGWLinanareaacrosstheIs arRiverinBavaria, Germany. The daily data including the GWLs in 64 wells, the surface water elevation at five observation points across the river, temperature andrain fall were used as input variables to the64ANNs.Diff erentANN architectures and variogram models were tested together with the use or not of a fuzzy logic system. The isocontour maps were presented for the hydraulic head. The best results were achieved with the use of the fuzzylogicsystemandbyutilizingthepower-lawvariogram.

Yang et al. (2015) developed a wavelet-ANN and an ITS model to predict GWL of as hallow coastalaquiferinFujianprovince,China. The input was only the monthly GWL time series of two representative wells. The wavelet-ANN models provided more accurate results com- pared to the ITS models. Khalil et al. (2015)compared MLR, ANN, wavelet-MLR, wavelet-ANN, and a wavelet-ensemble ANN model for the forecasting of GWLs as a result of recharge via tailings from an abandoned mine in Quebec, Canada. The wavelet- ensemble ANN consisted of a group of wavelet-ANN members, where each of these members was trained for the same problem, and then combined to produce the output. The daily tailing recharge, total precipitation and mean air temperature were used as inputs, while the output was GWL for lead times of 1-day, 1-week and 1-month. The wavelet-ensemble ANN model performed best for each of the three lead times. Nouraniet al. (2015) proposed a wavelet-entropy data pre-processing approach for ANN-based GWL modeling. They used the SOM-based clustering technique to identify spatially homogeneous clusters of GWL data and the wavelet transform to extract the non-stationary GWL, runoff and rainfall time series. The results indicated that the SOM method de- creased the dimensionality of the input variables and the wavelet analysis increased the performance of the ANN model. Jha and Sahoo(2015)developed five hybrid ANN-GA models for simulating spatio-

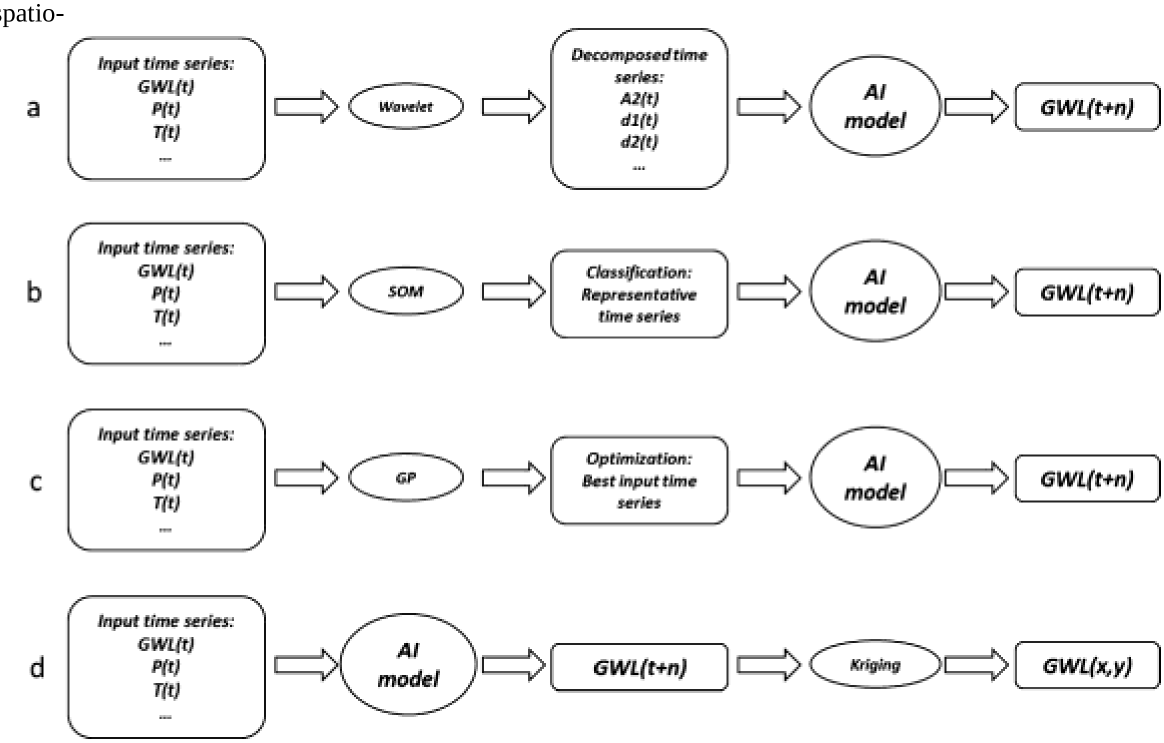


Fig. 3. Schematic structure of some hybrid AI models for GWL modeling. a) Wavelet-AI model b) SOM-AI model c) GP-AI model d) AI-Kriging model.

as rainfall, max and min temperature, river stage and GWL have been considered to simulate GWL at 17 sites. The inputs and parameters of theANNwereoptimizedusingGAoptimizationtechnique.TheGAwas superior to the commonly used trial-and-error method for determining optimal ANN architecture andinputs.

Chang et al. (2016)combined the SOM, the Nonlinear Auto- regressive with Exogenous Inputs (NARX) network and the kriging for predicting monthly GWL in Zhuoshui River basin, Taiwan, based onhydrologic data such as rainfall, stream flow and GWL. The SOM was used to classify thes patiotemporalpatternsofregionalGWL,theNARXwasusedtopredictthemeanofregionalGWL,andthekrigingwasuse dtointerpolatethepredictionsintofinergridsoflocations.Consequently the prediction of a GWL map was obtained. Han et al. (2016) coupled SOM and a statistical method to predict spatiotemporal monthly GWL in an arid irrigation district in the western Hexi Corridor, northwest China. The SOM was applied to identifys patiallyhomogeneousclusters ofwells, and the GWLf ore castingwasperformedthroughdevelopinga stepwise cluster multisite inference model with various predictors in- cluding climate conditions, well extractions, surface runoff s, reservoir operations and GWL measurements at previous steps. Hosseini et al.(2016) combined ANN and ant colony optimization (ACO) to simulate the GWL in Shabestar plain, Iran. The back-propagation ANN was uti- lized to reproduce GWL variations using the input variables including: rainfall, averagedis charge, temperature,evaporation,andsomeannual timeseries. Then,ACOwasusedtooptimizeandfindinitialconnection weights and biases of a BP algorithm during the training phase. They foundthatthehy brid model could reduceovertraining.

Nourani and Mousavi (2016) presented a hybrid Wavelet-AI-mesh- less model for spatiotemporal GWL modeling in Miandoab plain, Iran. InthiswayfirstlymonthlyGWLindiff erentwellswerede-noisedusing threshold-basedwaveletmethodandtheimpactofde-noisedandnoisy data was compared in temporal GWL modeling by ANN and ANFIS. Then,bothANNandANFISmodelswerecalibratedusingGWLdataof each well, rainfall and runoff to predict the GWL at one month ahead. Finally, the simulated GWLs were considered as interior conditions for the multi-quadric RBF based solve of governing partialdiff erential equation of groundwaterflowtoestimateGWLatanydesiredpointwithin the plain. The results showed that the wavelet de-noising ap- proach can enhance the performance of the modeling.

Ebrahimi and Rajaee (2017)investigated the eff ect of wavelet analysis on the training of the ANN, MLR and SVR approaches in si- mulating GWL. The only input variable was the monthly GWL data of twowellsintheQomplain,Iran.Theresultsshowedthatforbothwells, the Meyer wavelet produced better results compared to the other wa- velets,andthewavelet-MLRandwavelet-SVRwerethebestmodelsfor the wells 1 and 2 respectively. Barzegar et al. (2017) combined wavelet with ANN and group method of data handling (GMDH) models for forecasting the monthly GWL in Azarbijan, Iran. The GWL time series were decomposed with diff erent wavelets at two levels, and the step- wise selection was used to select appropriate lag times as the inputs of the models. To combine the advantages of diff erent wavelets, a least squares boosting algorithm was applied. The boosting multi-wavelet- ANNmodelsprovidedthebestperformances.Wenetal.(2017)applied wavelet-ANN with three diff erent input combinations, i.e., (1) GWL only, (2) climatic data, and (3) GWL and climatic data to forecast the monthly GWL of two wells in Zhangye basin, China. The model with only GWL as its input yielded the best performance for one-month forecasts. However for two- and three-monthly forecasts, the model withGWLandclimaticdataasinputswassuperior.

Rakhshandehroo et al. (2018)used wavelet-ANN trained with im- proved harmony search algorithm to forecast the long term daily GWL of two wells in southeast USA. The only input variable was the daily GWL,andtheone-year-aheadpredictionwiththeproposedmodelwas acceptable. Yu et al. (2018)compared the wavelet-ANN and wavelet- SVR models in forecasting of monthly GWL of 3 wells in northwest China.Fourwaveletdecompositionlevelswereemployedtodecompose input time series discharge, evapotranspiration and GWL. The results showedthatthewavelet-SVRperformedbetterthanwavelet-ANN.ZareandKoch(2018)usedwavelet-ANFISmodelwithseveralcombinations ofGWLandprecipitationastheinputstosimulatemonthlyGWLinthe Miandarband plain, Iran. The results indicated that using the Symlet mother wavelet with two decomposition levels outperformed other models.

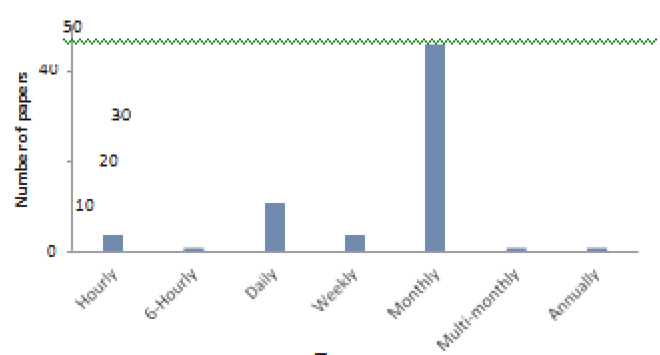


Fig. 4. Number of times various time steps have been used for GWL modeling.

Results

In the last years, development of hybrid modeling approaches is seen, and in particular, there has been an increasing interest in wave- lets-AI approaches for GWL modeling. These studies have shown that the hybrid/coupling models performed better than the regularmodels. As a downside, however, these models have also been criticized on various aspects and, in particular, the risk posed by overtraining of the model and the difficulties of parameter estimation using heuristic methods (Maheswaran and Khosa, 2013). A review of the various stu- dies on hybrid AI modeling of the GWL revealed the followingissues:

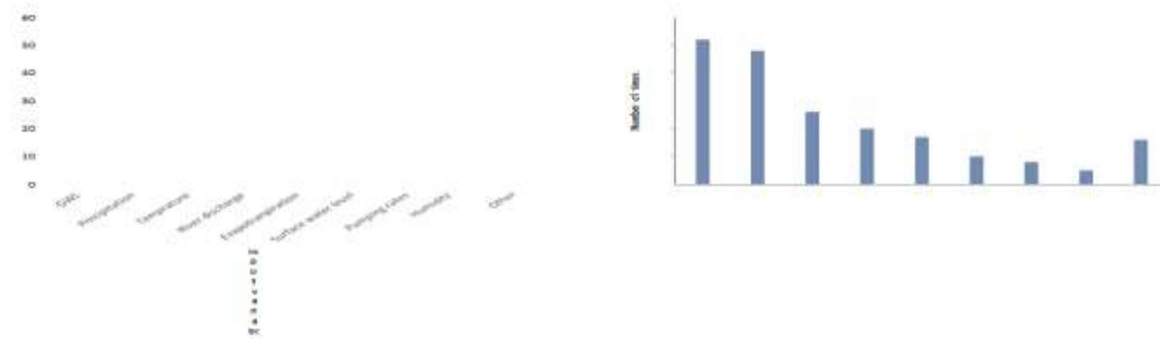
1) By using the hybrid models and in particular wavelet analysis to extract the input time series, a greater understanding and ability to simulateGWLcanbeachieved.Theresultsofthestudiesexploredin this section have revealed a higher degree of efficiency of hybrid modelscomparedwithsinglemodelsinaccuratelyforecastingGWL.
2) In the all reviewed wavelet-AI papers, the DWT has been appliedto decompose time series rather than CWT. In addition to the simpli- city of using DWT, this can partly be due to the nature of GWLtime series, because they are recorded discretely. Furthermore, the GWL islinkedwithseveralhydrologicalphenomena; Thus,useofDWTat specific levels which likely refers to hourly, daily or monthly eff ects appearstobemoreusefulthanapplicationofCWTwhichgenerates much more redundantinformation.
3) The more frequently mother wavelets used for GWLdecomposition are db2 and db4, which have been considered as the appropriate mother wavelets. According to the Nourani et al. (2014), similarity inshapebetweenthemotherwaveletandthetime-seriesisoftenthe best guideline in choosing a reliable mother wavelet. Therefore, it can be an indication of a relative similarity between the general shapeof GWLtimeseriesandDaubechiesfamilywavelets.
4) AccordingtothestudyofMaheswaranandKhosa(2012)inthefield of hydrological forecasting, some mother wavelet forms that have a compact support showed better performance in the case of time series that have a short memory with transient features. In contrast, mother wavelets with a wider support yielded better forecasting efficiencies with regard to the time series that have long-term fea- tures. Therefore, in the case of GWL time series, it does not seem that compact wavelets to be suitable for decomposition, because the GWL time series have long-term features rather than transient fea- tures, and therefore the wavelets with a wider support are more compatible with the timeseries.
5) In the aforementioned wavelet-based papers, five papers (Adamowski and Chan, 2011; Moosavi et al., 2013a,b; Nourani et al., 2015; Ebrahimi and Rajaee, 2017) have used the decom- position level 2, two papers (Suryanarayana et al., 2014; Wen et al., 2017) have used the decomposition level 4 and one paper (Maheswaran and Khosa, 2013) has used the decomposition level 5 as the optimum decomposition levels. In the meanwhile, in KisiandShiri(2012),Yangetal.(2015)andRakhshandehrooetal.(2018)

In this section, some general results derived from the 67 reviewed papers such as the results related to the considering time steps, input variables, data set size, data division, study areas and type of aquifers, etc. have been mentioned and discussed.

Time stepselection

Inthecaseofutilizedtimesteps,themajorityofAImodelsreviewed in this study have been considered the monthly time steps for GWL modeling. The distribution of the utilized time steps is given in Fig. 4. As can be seen, the monthly time step was used in 46 of the 67 papers reviewed, followed by daily (11 papers), daily (4 papers) and weekly(4 papers) time steps. A number of diff erent time steps (i.e., 6-hourly, multi-monthlyandannually)wereusedinsomeofthepapersreviewed as well. The high use of the monthly time steps can be related to the highavailabilityofmonthlyrecordedGWLdatacomparedtoothertime steps. In the most parts of the world, the GWLs do not have often sig- nificanthourly,dailyorevenweeklyvariations;howeverinsomeareas like coastal aquifers (Yoon et al., 2011; Taormina et al., 2012) or areas near the lake of dams (Lee et al., 2018), the GWLs are under influence oftidal/lakeeff ects,andmayhavehourlyordailyvariations.

Fig.5showstheinputvariablesthathavebeenemployedinAIGWLmodelingaccordingtothereviewedpapers. FromFig.5,itcanbefound that the past steps of the GWL time series is the most frequently used input variable for AI models to forecast the GWL. Among 67 papers,52 papers have been employed the GWL as an input variable. Even 12 papers have been considered the GWL as a single auto-correlatedinput variable without any other exogenous input variable. As well as the GWL, the precipitation has been frequently used (48 times) as an input variable. Furthermore, some hydrological time series such as tem- perature, river discharge (surface runoff), evapotranspiration, surface water (lake) level, pumping rates (extraction from wells) andhumidity



Input variables

Fig. 5. The input variables that have been employed for AI-GWL modeling.

havebeenalsousedastheinputvariablesinthereviewedpapers.Other employed input variables such as irrigation patterns, population, day number, seasonal dummy variables, tree-rings, etc. have been used toa lesser extent in the reviewed papers, and it seems that some of them cannot be easily accommodated at the stage of input consideration. Although in the stage of input consideration some of the hydrological time series have been used more than the others, however it should be noted that the input data selection has been mostly based on data availability in the study area rather than a physical analysis for the required data. In the meanwhile, this cannot be considered as aweakness of these studies because in many regions data is limited, and also it is the nature of AI models that they can work with any data. However it is better that a statistical analysis and in particular a correlationanalysisbedonewithdifferentdatabeforeemployingthemformodelinginordertoobtainsuitableinputpattern forAImodels.

DATA setsize

According to the Table 1, the number of total sample data sets ap- plied for GWL modeling varies from 23 sets (Banerjee et al., 2009) to 23,850 sets (Taormina et al., 2012). Generally the more samples especially for training can ensure better performance of model giving a better chance for locating global minimum of the error function, pro- vided that an overtraining does not happen during training. However there are some cases that we may not be able to even collect 40samples for training the model like the data of annual tree-rings in Gholamiet al., (2015). The quality of the available data and the relevance of the input data with the desired output are also important since a large amount of irrelevant data can hinder the model performance by con- fusing the training process (Tsanis et al., 2014). There therefore has to be a balance between the quantity of data and the relevancy to the output.

In the all 67 reviewed papers there was not any fixed rule that say how to get an optimum data set size required for AI modeling. Itseems that considering the available data, experimental or perhaps trial-and-errortoolswereusedhere.FromTable1itcanbeseenthatthemajority of studies have been applied a data set size between 100 and 200 sets, and perhaps this can be considered as a suitable data set size. In the meanwhile it can be found that AI models are capable to deal with different size of data set, but there was not any certain comment in the reviewed papers about that in each sample size (i.e. big or small) what should we do for optimizing the model performance (e.g. which training algorithm is better for small sample size in ANN?). It seems trial-and-error procedures have been usedhere.

DATAdivision

Inthecaseofdatadivisionfortraining,validationandtestingtasks, there was not a specific rule in the reviewed papers which explain how to consider an optimum amount for each sub-data set. In some of the reviewed papers, the total data set were divided into three parts and in some others into two parts (Fig. 6). In the three part data division, the first part was used as a training or calibration set; the second part as a validationsettoascertainthatthemodelisgeneralizingandtostopthe training before overfitting, and the third part for a testing of the model in the prediction stage. The names of these three parts, i.e., training, validation and test parts, of course, may be different in some papers. For example in Wunsch et al. (2018), the word "validation" has been used for "testing" set and vice versa. But according to the reviewed papers, two parts data division i.e., using only the training and testing sets is also acceptable in the modeling of GWL time series, considering the fact that some researchers do not mention the validation step. As canbeseenfrom

Fig.6mostofpapershaveusedtwopartsdatadivision (training and testing sets), while some papers have included the vali- dationset,too.Among46papersthathaveusedtwopartsdatadivision, the training-testing sets respectively vary from 56% to 44% (Juan etal.,2015) to 90%–10% (Maheswaran and Khosa, 2013; Khalil et al., 2015) of the total data with an average of approximately 70%–30%. In the remaining 20 papers that have added the validation set, the training, validation and testing sets are averagely 60%, 18% and 22% of total data, respectively. It should be noted that in Banerjee et al., (2009)there was not any explanation about the validation or testing sets, and the performance criteria has been only mentioned for the trainingdata.

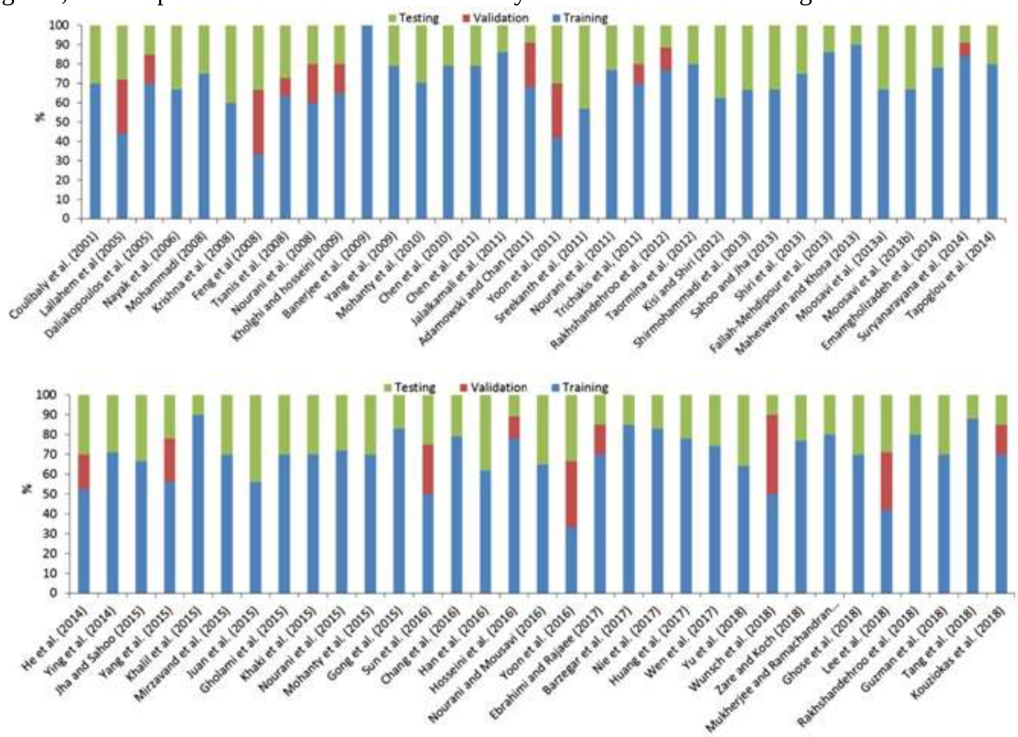


Fig. 6. Percentage of the training, validation and testing sets used in the studies related to AI-GWL modeling.

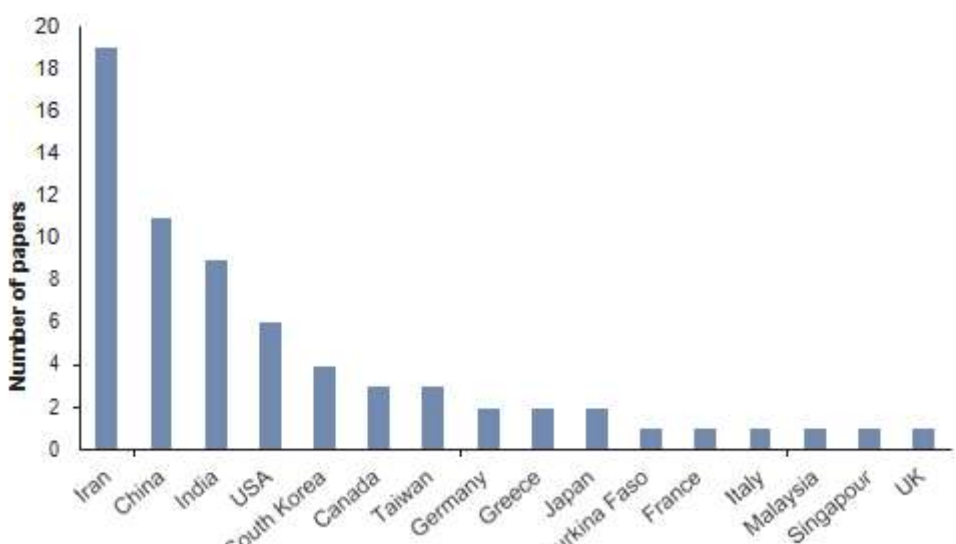


Fig. 7. Number of published papers with respect to the countries where the study areas are located.

Fig. 7shows the number of reviewed papers with respect to the countries where the study areas are located. A large number of the study areas are located in Iran (19 out of 67 cases). This point maybe shows the interest of Iranian researchers in this field, but it can also be duetothearidity/semiaridityofregionslikeIran,suchthatthesurface water resources are low and the groundwater is the most available waterresource,andthereforetheGWLdataaremoreavailablethanthe surface water data. China with 11 and India with 9 case studies are placed in the next categories. In this regard, rest of the world can also be seen from the Fig. 7. It should be noted that the types of aquifers under study, i.e., whether they were confined, unconfined, karstic, sandy, etc. were briefly explained in the most papers. According to the descriptions about the study areas in the reviewed papers, the most of aquifers were unconfined with alluvial materials like sand, silt, clay, gravel, etc. and only a few of them were semi-confined or karstic, chalky, coastal, etc. It is known that the black-box AI techniques are useful for prediction and forecasting, but they are not built using in- sights on the physical processes involved. In this type of modeling, the knowledge about the underlying mechanisms is not necessary and the main purpose is obtaining accurateforecasts.

Used SOFTWAREPROGRAMS

Morethanhalfofthepapersreviewedinthisstudyhavementioned the software programs used for AI modeling, while the rest have pre- ferred not to mention the used software program. Fig. 8 shows number of times that diff erent software programs were used to develop ANN, ANFIS, GP andSVMmodelsforGWLforecasting.Itshouldbenotedthat in Fig. 8, the hybrid models are also considered. As can be seen, the MATLAB is the most used software program. The MATLAB software program has diff erent AI toolboxes that allow the user to easily apply them for the desired purpose with the least needs for coding. Other software programs have been also used. For example the NeuroSolu- tions (Mohammadi, 2008; Jha and Sahoo (2015); Gholami et al., 2015), Qnet (Emamgholizadeh et al., 2014) and R (Mukherjee andRamachandran, 2018) software programs have been used in somecases for developing the ANN. Even the programming languages such as Vi- sual Basic (Tapoglou et al., 2014) and C (Yoon et al., 2011; Shiri et al.,2013) have been used in several papers. The GeneXpro is a software program in the field of GP and evolutionary computation that has been used by Shiri et al. (2013). Details regarding these software programs can be found on the web, and we do not discuss about them here. Al- though many papers have not mentioned the used software, it seems thattheMATLABsoftwareprogramisagoodchoicefordevelopmentof the AImodels.

IncorrectdevelopmentofAImodelsforGWLFORECASTING

TheincorrectdevelopmentofAImodelsforGWLforecastingcan be occurred in diff erent stages of the modeling. It may be occurred during the input data consideration. If the data are insufficient, incorrect or irrelevant, we should not expect the model to have correct forecasts. When importing the inputs to the model, it is also important whether the inputs are average or related to a specific time. For example, in the monthly time steps, it is important to know whether the input data are relatedtothemonthlyaverageortoaspecificday

whether they are recorded in the same day of each month or not (i.e., whether the record period is 30 days or longer or shorter). Use of too many inputs is also caused by input redundancy, where they may provideredundantinformation,andcauseoverfitting,andthereforethe real-world forecasted GWL to be incorrect. The incorrect development canalsobeduringthedatadivisionintraining,validationandtesting sub-sets, when the data have not been appropriately divided. The training,validationandtestingsub-setsshouldhavethesamestatistical properties in order to develop the best possible model (Maier et al.,2010). A number of best ways for considering the input data, and input datadivisioncanbefoundinMaieretal.(2010).
One of the most common mistakes occurs when developing hybrid

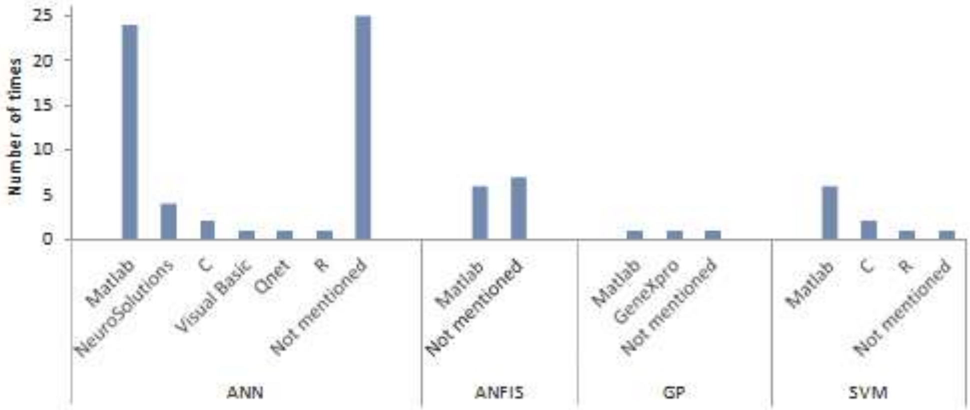


Fig. 8. Number of times diff erent software programs have been used to develop ANN, ANFIS, GP and SVM models for GWL forecasting.

waveletAlmodels.Somerecentwaveletbasedhydrological(includingGWL)forecastingmodelshavebeenincorrectlydeelopedandcannotproperlybeusedforrealworldforecastingproblems(QuiltyandAdamowski,2018).AccordingtotheQuiltyandAdamowski(2018),theincorrectdevelopmentofwaveletbasedforecastingmodelsoccursduringwaveletdecompositionandasaresultimportserrorintothemodelinputs.Theoriginofthiserrorisduetotheboundaryconditionthatislinkedto the waveletdecompositioninthreemainissues,i.e.,usingfuturedata,inappropriatelyselectingdecompositionlevelsandwaveletfilters,andnotproperlypartitioningtraining,validationandtestingdata.Thefuturedataissueoccurswhenagivenwaveletrequiresdatafromthefutureofthetimeseriestocalculateawaveletorscalingcoeffi cientinthepresent.Forsolvingthisproblem,thecausalwaveletalgorithmssuchasAtrousandmaximaloverlapDWTshouldbeusedsincetheydonotusefuturedata.Inaditiontothenotusingthefuturedata,thecausalalgorithmsreducethenumberofwaveletandscalingcoeffi cientsaff ectedbytheboundarycondition,whichmustberemovedfromtheinputsubtimeseriestohavearealworldforecastingmodel.Thepartitioningissueisalsosolvedwhenusingcausalwaveletalgorithms,butthewaveletmustbeappliedtothetesting/predictingsetonerecordatatime,andthentheforecastmustbecalculatedthroughthemodelforeachtesting/predictingrecordandsoon(QuiltyandAdamowski,2018).

In the current review study several AI methods for GWL modeling were investigated by surveying the recent published researches in this field. Here, one of the important issues is exploring which AI method worksbetterandcanbestsimulatetheGWL.Itseemsthattheanswerto this question can be diff erent in diff erent studies. According to the Table 1, among 67 papers, the ANN, ANFIS, GP, and SVM were re- spectively declared as the most appropriate models by 28, 6, 2, and 7 papers; while 17 papers used hybrid wavelet-AI models and 7 papers appliedotherhybridAImodels,andreportedthathybridmodelsledto better modeling. It appears that in the last few years more attentionhas beenpaidtoapplyhybridmodels,sothatapplicationofhybridmodels leadstobetterresultsincomparisonwithsingleAImodels.Inparticular the pre-processing of input data by common tools such as wavelet analysis has frequently been used in this area to achieve better mod- elingperformance.

III. Conclusions andrecommendations

The AI methods have been used for GWL modeling as well asother hydrological and environmental modeling. In this study, 67 papers dealingwithAImethodsinGWLmodelingwhichwerepublishedin29 international journals from 2001 to 2018 were reviewed. From these papers it was found that AI methods can successfully be used to simu- late and predict the GWL time series in diff erent aquifers. This kind of modeling is based on an AI eff ort to find natural relationshipsbetween

GWL and diff erent hydrological variables without the need for con- structinganyconceptualmodel.TheAImodelscanbeusefulwhenitis difficult to build an adequate knowledge driven simulation model due to the lack of the ability to satisfactorily construct a mathematical/ physical model of the underlying processes. These models haveseveral key stages including input data consideration, input data division, regulation of the model features, training, testing, etc. which if all the stagescarefully bedeveloped,itisexpectedthatthemodelperformance to be good. However, it should be noted that there was not a fixed rule for these stages, such that diff erent studies performed each stage based on an empirical manner and/or trial-and-error procedure considering available data and existing conditions. The obtained results from this review study that were embedded in two separated parts (i.e., the re- sults of each AI method and the general results and discussion) can providemanyguidelinesforresearcherstoperformsimilarworksinthe related field, develop innovative methods and improve the quality of modeling .Forthispurpose, thefollowingrecommendationscanalsobe suggested:

1) The AI methods can be linked to conceptual-numerical modelssuch asMODFLOW to developintegratedmodularmodelssuchthateach method covers the weak points of the other method. For example, if anAImodelgeneratesaccurateGWLforecastsinaspecialaquifer, it can be used to prepare and complete GWL data required for MODFLOWastheinput.AccordingtoMohammadi(2008)theANNs needed less input data and took less time to run, compared to MODFLOW, therefore using ANNs (and other AI methods) can de- crease the computations of MODFLOW which are very time-con- suming. In another example the GWL data sets estimated by MOD- FLOW can be used to train AI models, if there was not enough real data.

2) Moreattentionshouldbegiveninthestageofinputconsideration in order to select appropriate input variables and lag times. In the re- viewedpapers,theinputvariableswereoftenselectedbasedondata availability or using simple user-defined relationships. More analy- tical methods or model-based approaches can be applied to de- termine input significance, as suggested by Wu et al. (2014). In particular, utilizing the GWLtimeseriesasthemostwidelyusedand most important input variable for AI GWL forecasting, should bemore investigated. The GWL fluctuations provide a direct measure of the impact of groundwater development, and important in- formation about the aquifer dynamics is embedded in GWL time series, so it can be said that the future of GWL is predictable form the past GWL. Furthermore, in the stage of input consideration, the non-causal wavelets such as A trous and maximal overlap DWT can be explored to unravel the component features of diff erent input variables in order to determine the lags, correlation and interaction between the hydrological variables andGWL.

3) Regarding diff erent AI methods to simulate the GWL, it can be said that it is not practically possible to recommend one particular type of AI model for a given problem. However it is clear that a hybrid/ coupled model likely perform better than a single AI model. Diff erent types of AI techniques can be tested at the diff erent stages of the GWL modeling to select the best AI method in each stage and thencombinethemtohaveanoptimummodelingperformance.

4) In the wavelet decomposition of the GWL, border eff ects as well asthe caution of causality which occurs in the beginning and end of the decomposed sub-time series, is an area that has received a little attentioninthemostpaperswhichhaveusedwavelet-AImodelsfor GWL modeling, so this topic can be raised for the new researches. The decomposition of the total data set at once or each sub-data set (i.e., training, validation and testing sets) separately, and the ways to prepare the decomposed sub-time series for applying them asthe modelinputisaninterestingsubjectdeservingfurtherinvestigation.

5) According to the Quilty and Adamowski (2018), some wavelet- basedhydrological models have beenincorrectlydeveloped,andthe solution is the use of non-causal wavelet algorithms such as Atrous andmaximaloverlapDWTalgorithms.Sincethishasnotbeendone so far in GWL forecasting, the use of these wavelet algorithms should be addressed in a newstudy.

References

[1]. Adamowski, J., Chan, F.H., 2011. A wavelet neural network conjunction model forgroundwater level forecasting. J. Hydrol. 407, 28–40.

[2]. Barzegar, R., Fijani, E., Asghari Moghaddam, A., Tziritis, E., 2017. Forecasting ofgroundwater level fluctuations using ensemble hybrid multi-wavelet neural network-based models. Sci. Total Environ. 599–600, 20–31.

[3]. Banerjee, P., Prasad, R.K., Singh, V.S., 2009. Forecasting of groundwater level in hardrock region using artificial neural network. Environ. Geol. 58 (6), 1239–1246.

[4]. Beale, M.H., Hagan, M.T., Demuth, H.B., 2010. Neural Network Toolbox 7 User's Guide.

[5]. The Mathworks Inc., Natick, Massachusetts, USA.

[6]. Butler,J.J.,Stotler,R.L.,Whittemore,D.O.,Reboulet,E.C.,2013.Interpretationof waterlevel changes in the high plains aquifer in western Kansas. Groundwater 51 (2),180–190.

[7]. Chang, F.J., Chang, L.C., Huang,C.W.,Kao,I.F.,2016.Predictionofmonthlyregionalgroundwater levels through hybrid soft-computing techniques. J. Hydrol. 541,965–976.

[8]. Chen,L.H.,Chen,C.T.,Pan,Y.G.,2010.GroundwaterlevelpredictionusingSOM-RBFNmultisitemodel.J.Hydrol.Eng.15(8),624–631.

[9]. Chen, L.H., Chen, C.T., Lin, D.W., 2011. Application of integrated back-propagationnetwork and self-organizing map for groundwater level forecasting. J. Water Res.Plan. Man. 137 (4), 352–365.

[10]. Coulibaly, P., Anctil, F., Aravena, R., Bobee, B., 2001. Artificial neural network modelingofwatertabledepthfluctuations.WaterResour.Res.37(4),885–896.

[11]. Daliakopoulos,I.N.,Coulibaly,P.,Tsanis,I.K.,2005.Ground water level for ecasting using artificial neural networks. J. Hydrol.309,229–240.

[12]. Daubechies, I., 1990. The wavelet transform, time–frequency localization and signalanalysis. IEEE Trans. Inf. Theory 36 (5).
[13]. Ebrahimi, H., Rajaee, T., 2017. Simulation of groundwater level variations using waveletcombined with neural network, linear regression and support vector machine. GlobalPlanet. Change 148, 181–191.
[14]. Emamgholizadeh, S., Moslemi, K., Karami, G., 2014. Prediction the groundwater level ofbastam plain (Iran) by artificial neural network (ANN) and adaptive neuro-fuzzyinference system (ANFIS). Water Resour. Manag. 28 (15), 5433–5446.
[15]. Feng, S., Kang, S., Huo, Z., Chen, S., Mao, X., 2008. Neural networks to simulate regionalgroundwater levels affected by human activities. Groundwater 46 (1), 80–90.
[16]. Fallah-Mehdipour,E.,BozorgHaddad,O.,Marino,M.A.,2013.Prediction and simulation of monthly ground water levels by genetic programming. J. Hydro-Environ. Res. 7(4),1–8.
[17]. Gholami, V., Chau, K.W., Fadaee, F., Torkaman, J., Ghaffari, A., 2015. Modeling ofgroundwater level fluctuations using dendrochronology in alluvial aquifers. J.Hydrol. 529, 1060–1069.
[18]. Gong, Y., Zhang, Y., Lan, S., Wang, H., 2015. 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. Manag.https://doi.org/10.1007/s11269-015-1167-8.
[19]. Ghose,D.,Das,U.,Roy,P.,2018.Modelingresponseofrunoffandevapotranspirationfor predicting water table depth in arid region using dynamic recurrentneural network. Ground water for.Sustain.Dev.6,263–269.https://doi.org/10.1016/j.gsd.2018.01.007.
[20]. Guzman, S.M., Paz, J.O., Tagert, M.L.M., Mercer, A.E., 2018. Evaluation of seasonally classified inputs for the prediction of daily groundwater levels: NARX networks vs support vector machines. Environ. Model. Assess. https://doi.org/10.1007/s10666-018-9639-x182.a SOM-aided stepwise cluster inference model. J. Environ. Manage. 182, 308–321.
[21]. He, Z., Zhang, Y., Guo, Q., Zhao, X., 2014. Comparative study of artificial neural networksand wavelet artificial neural networks for groundwater depth data forecasting withvarious curve fractal dimensions. Water Resour. Manag. 28, 5297–5317.
[22]. Hosseini, Z., Gharechelou, S., Nakhaei, M., Gharechelou, S., 2016. Optimal design of BP algorithm by ACOR model for groundwater level forecasting: a case study on Shabestar plain. Iran. Arab. J. Geosci. 9 (6). https://doi.org/10.1007/s12517-016-2454-2.
[23]. Huang, F., Huang, J., Jiang, S., Shou, C., 2017. Prediction of groundwater levels usingevidence of chaos and support vector machine. J. Hydroinform. 19 (4), 586–606.
[24]. Jalalkamali,A.,Sedghi,H.,Manshouri,M.,2011.Monthlygroundwaterlevelpredictionusing ANN and neuro-fuzzy models: a case study on Kerman plain. Iran. J.Hydroinform. 13 (4),867–876.
[25]. Jang, J.S.R., 1993. Adaptive-network-based fuzzy inference system. IEEE, Man,Cybernetics. 23 (3), 665–685.
[26]. Jha, M.K., Sahoo, S., 2015. Efficacy of neural network and genetic algorithm techniquesin simulating spatio-temporal fluctuations of groundwater. Hydrol. Process. 29 (5),671–691.
[27]. Juan, C., Genxu, W., Tianxu, M., 2015. Simulation and prediction of supra permafrost ground waterlevelvariationinresponsetoclimatechangeusinganeuralnetworkmodel. J. Hydrol. 529,1211–1220.
[28]. Khaki, M., Yusoff, I., Islami, N., 2015. Simulation of groundwater level through artificialintelligence system. Environ. Earth Sci. 73 (12), 8357–8367.
[29]. Khalil,B.,Broda,S.,Adamowski,J.,OzgaZielinski,B.,Donohoe,A.,2015.Shorttermforecastingofgroundwaterlevelsunderco nditionsofminetailingsrechargeusingwaveletensembleneuralnetworkmodels.Hydrogeol.J.23,121–141.
[30]. Kholghi, M., Hosseini, S.M., 2009. Comparison of groundwater level estimation usingneuro-fuzzy and ordinary kriging. Environ. Model. Assess. 14 (6), 729–737.
[31]. Kisi,O.,Shiri,J.,2012.Waveletandneuro-fuzzyconjunctionmodelforpredictingwatertabledepthfluctuations.Hydrol.Res.43(3),286–300.
[32]. Krishna, B., Satyaji Rao, Y.R., Vijaya, T., 2008. Modelling groundwater levels in an urbancoastal aquifer using artificail neural networks. Hydrol. Process. 22,1180–1188.
[33]. Kouziokas, G.N., Chatzigeorgiou, A., Perakis, K., 2018. Multilayer feed forward models in groundwaterlevelforecastingusingmeteorologicaldatainpublicmanagement.
[34]. Water Resour. Manag. 1–12. https://doi.org/10.1007/s11269-018-2126-y.
[35]. Lallahem, S., Mania, J., Hani, A., Najjar, Y., 2005. On the use of neural networks toevaluate groundwater levels in fractured media. J. Hydrol. 307, 92–111.
[36]. Lee, S., Lee, K., Yoon, H., 2018. Using artificial neural network models for groundwater level forecasting and assessment of the relative impacts of influencing factors.
[37]. Hydrogeol. J. https://doi.org/10.1007/s10040-018-1866-3.
[38]. Maheswaran, R., Khosa, R., 2012. Comparative study of different wavelets for hydrologicforecasting. Comput. Geosci. 46, 284–295.
[39]. Maheswaran, R., Khosa, R., 2013. Long term forecasting of groundwater levels withevidence of non-stationary and nonlinear characteristics. Comput. Geosci. 52,422–436.
[40]. Maier, H.R., Jain, A., Dandy, G.C., Sudheer, K.P., 2010. Methods used for the develop-ment of neural networks for the prediction of water resource variables in river sys-tems: current status and future directions. Environ. Modell. Softw. 25, 891–909.
[41]. Mirzavand, M., Khoshnevisan, B., Shamshirband, S., Kisi, O., Ahmad, R., Akib, S., 2015. Evaluating groundwater level fluctuation by support vector regression and neuro- fuzzy methods: a comparative study. Nat. Hazards. https://doi.org/10.1007/s11069-015-1602-4.
[42]. Mohammadi, K., 2008. Groundwater table estimation using MODFLOW and artificialneural networks. In: Abrahart, R.J., See, L.M., Solomatine, D.P. (Eds.), PracticalHydroinformatics. Water Science and Technology Library, pp. 127–138.
[43]. Mohanty, S., Jha, M.K., Kumar, A., Sudheer, K.P., 2010. Artificial neural network mod-eling for groundwater level forecasting in a river Island of eastern India. WaterResour. Manag. 24, 1845–1865.
[44]. Mohanty, S., Jha, M.K., Raul, S.K., Panda, R.K., Sudheer, K.P., 2015. Using artificialneural network approach for

simultaneous forecasting of weekly groundwater levelsat multiple sites. Water Resour. Manag. 29 (15),5521–5532.

[45]. Moosavi, V., Vafakhah, M., Shirmohammadi, B., Behnia, N., 2013a. A wavelet-ANFIShybrid model for groundwater level forecasting for different prediction periods.Water Resour. Manag. 27, 1301–1321.

[46]. Moosavi, V., Vafakhah, M., Shirmohammadi, B., Ranjbar, M., 2013b. Optimization ofwavelet-ANFIS and wavelet-ANN hybrid models by Taguchi method for groundwaterlevel forecasting. Arab. J. Sci. Eng. 39 (3), 1785–1796.

[47]. Mukherjee,A.,Ramachandran,P.,2018.PredictionofGWLwiththehelpofGRACETWSforunevenlyspacedtimeseriesdatainIndia:analysisofcomparativeperformancesofSVR,ANNandLRM.J.Hydrol.558,647658.

[48]. Nayak, P.C., Satyaji Rao, Y.R., Sudheer, K.P., 2006. Groundwater level forecasting in ashallow aquifer using artificial neural network approach. Water Resour. Manag. 20,77–90.

[49]. Nie, S., Bian, J., Wan, H., Sun, X., Zhang, B., 2017. Simulation and uncertainty analysisforgroundwaterlevelsusingradialbasisfunctionneuralnetworkandsupportvectormachinemodels.J.WaterSupplyRes.T.66(1),15–24.

[50]. Nourani, V., Asghari Mogaddam, A., Nadiri, A.O., 2008. An ANN-based model for spa-tiotemporal groundwater level forecasting. Hydrol. Process. 22, 5054–5066.

[51]. Nourani, V., Ejlali, R.G., Alami, M.T., 2011. Spatiotemporal groundwater level forecastingin coastal aquifers by hybrid artificial neural network-geostatistics Model: a casestudy. Environ. Eng. Sci. 28 (3), 217–228.

[52]. Nourani,V.,HosseiniBaghanam,A.,Adamowski,J.,Kisi,O.,2014.Applicationsofhybridwavelet – artificial Intelligence models in hydrology: a review. J. Hydrol. 514,358–377.

[53]. Nourani,V.,Alami,M.T.,Daneshvar Vousoughi,F.,2015.Wavelet-entropy data pre-processing approach for ANN-based ground water level modeling. J.Hydrol.524,255–269.

[54]. Nourani,V.,Mousavi,S.,2016.Spatiotemporalground water level modeling using hybrid artificial intelligence- mesh less method. J. Hydrol. 536, 10–25.

[55]. Quilty, J., Adamowski, J., 2018. Addressing the incorrect usage of wavelet-based hy-drological and waterresourcesforecastingmodelsforrealworldapplicationswithbestpracticesandanewforecastingframework.J.Hydrol.563, 336–353.

[56]. Rajaee, T., 2011. Wavelet and ANN combination model for prediction of daily suspendedsediment load in rivers. Sci. Total Environ. 409, 2917–2928.

[57]. Rajaee, T., Boroumand, A., 2015. Forecasting of chlorophyll-a concentrations in SouthSanFranciscoBayusingfivedifferentmodels.Appl.OceanRes.53,208–217.

[58]. Rakhshandehroo,G.R.,Vaghefi,M.,AsadiAghbolaghi,M.,2012.Forecastingground-water level in Shiraz plain using artificial neural networks. Arab. J. Sci. Eng. 37,1871–1883.

[59]. Rakhshandehroo, G., Akbari, H., Afshari Igder, M., Ostadzadeh, E., 2018. Long-term groundwaterlevelforecastinginshallowanddeepwellsusingwaveletneuralnet- works trained by an improved harmony search algorithm. J. Hydrol. Eng. 23 (2).https://doi.org/10.1061/(ASCE)HE.1943-5584.0001591.

[60]. Ravansalar, M., Rajaee, T., 2015. Evaluation of wavelet performance via an ANN-based electrical conductivity prediction model. Environ. Monit. Assess. https://doi.org/10.1007/s10661-015-4590-7.

[61]. Sahoo,S.,Jha,M.K.,2013.Groundwater-levelpredictionusingmultiplelinearregressionandartificialneuralnetworktechniques:acomparativeassessment.Hydrogeol.J. 21,1865–1887.

[62]. Shiri, J., Kisi, O., Yoon, H., Lee, K.K., Nazemi, A.H., 2013. Predicting groundwater levelfluctuations with meteorological effect implications – a comparative study amongsoft computing techniques. Comput. Geosci.56, 32–44.

[63]. Shirmohammadi, B., Vafakhah, M., Moosavi, V., Moghaddamnia, A., 2013. Application ofseveral data-driven techniques for predicting groundwater level. Water Resour.

[64]. Manag. 27 (2), 419–432.

[65]. Solomatine, D.P., 2005. Data-driven modeling and computational intelligence methods inhydrology. In: Anderson, M. (Ed.), Encyclopedia of Hydrological Sciences. Wiley,New York.

[66]. Sreekanth, P.D., Sreedevi, P.D., Ahmed, S., Geethanjali, N., 2011. Comparison of FFNNand ANFIS models for estimating groundwater level. Environ. Earth Sci. 62,1301–1310.

[67]. Sun, Y., Wendi, D., Kim, D.E., Liong, S.Y., 2016. Technical note: application of artificialneural networks in groundwater table forecasting – a case study in a Singaporeswamp forest. Hydrol. Earth Syst. Sci. 20, 1405–1412.

[68]. Suryanarayana, C., Sudheer, C., Mahammood, V., Panigrahi, B.K., 2014. An integratedwavelet-support vector machine for groundwater level prediction in Visakhapatnam,India. Neurocomputing 145, 324–335.

[69]. Tang,Y.,Zang,C.,Wei,Y.,Jiang,M.,2018.Data-drivenmodelingofgroundwaterlevel with least-square support vector machine and spatial–temporal analysis. Geotech. Geol. Eng.https://doi.org/10.1007/s10706-018-0713-6.

[70]. Taormina, R., Chau, K., Sethi, R., 2012. Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. Eng. Appl. Artif.Intel. 25, 1670–1676.

[71]. Tapoglou, E., Karatzas, G.P., Trichakis, I.C., Varouchakis, E.A., 2014. A spatio-temporalhybrid neural network-Kriging model for groundwater level simulation. J. Hydrol.519, 3193–3203.

[72]. Trichakis, I.C., Nikolos, I.K., Karatzas, G.P., 2011. Artificial Neural Network (ANN) Basedmodeling for karstic groundwater level simulation. Water Resour. Manag. 25,1143–1152.

[73]. Tsanis,I.K.,Coulibaly,P.,Daliakopoulos,I.N.,2014.Improvinggroundwaterlevelfore-casting with a feed-forward neural network and linearly regressed projected pre-cipitation. J. Hydroinform. 10 (4),317–330.

[74]. Vapnik, V.N., 1998. Statistical Learning Theory. Wiley, New York, USA, pp. 736.

[75]. Wen, X., Feng, Q., Deo, R.C., Wu, M., Si, J., 2017. Wavelet analysis–artificial neuralnetwork conjunction models for multi-scale monthly groundwater level predicting inan arid inland river basin, northwestern China. Hydrol. Res. 48 (6), 1710–1729.

[76]. Wu, W., Dandy, G.C., Maier, H.R., 2014. Protocol for developing ANN models and itsapplication to the assessment of the quality of the ANN model development process indrinking water quality modelling. Environ. Modell. Softw. 54, 108–127.

[77]. Wunsch, A., Liesch, T., Broda, S., 2018. Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (NARX). J. Hydrol. https://doi.org/10.1016/j.jhydrol.2018.01.045.

[78]. Yang, Z.P., Lu, W.X., Lonf, Y.Q., Li, P., 2009. Application and comparison of two pre-diction models for groundwater levels: a case study in Western Jilin Province. China.
[79]. J. Arid Environ. 73, 487–492.
[80]. Yang,Q.,Hou,Z.,Wang,Y.,Zhao,Y.,Delgado,J.,2015.Acomparativestudyofshallowgroundwaterlevelsimulationwith WA–ANNandITSmodelinacoastalislandofsouth China. Arab. J. Geosci. 8 (9), 6583–6593.
[81]. Ying, Z., Wenxi, L., Haibo, C., Jiannan, L., 2014. Comparison of three forecasting modelsfor groundwater levels: a case study in the semiarid area of west Jilin Province. China. J. Water Supply Res. T. 8, 671–683.
[82]. Yoon,H.,Jun,S.C.,Hyun,Y.,Bae,G.O.,Lee,K.K.,2011.Acomparativestudyofartificialneuralnetworksandsupportvectormac hinesforpredictinggroundwaterlevelsinacoastalaquifer.J.Hydrol.396(1),128–138.
[83]. Yoon, H., Hyun, Y., Ha, K., Lee, K.K., Kim, G.B., 2016. A method to improve the stabilityand accuracy of ANN- and SVM-based time series models for long-term groundwaterlevel predictions. Comput. Geosci. 90, 144–155.
[84]. Yu, H., Wen, X., Feng, Q., Deo, R.C., Si, J., Wu, M., 2018. Comparative study of hybrid-wavelet artificial intelligence models for monthly groundwater depth forecasting inextreme arid regions, northwest China. Water Resour. Manag. 32 (1), 301–323.
[85]. Zare,M.,Koch,M.,2018.GroundwaterlevelfluctuationssimulationandpredictionbyANFIS-andhy brid Wavelet-ANFIS/FuzzyC-Means(FCM)clustering models: appli-cation to the Miandar band plain. J.Hydro-Environ.Res.18,63–76.
[86]. Zounemat-kermani, M., Kisi, O., Rajaee, T., 2013. Performance of radial basis and LM-feed forward artificial neural networks for predicting daily watershed runoff. Appl.Soft Comput. 13, 4633–4644.