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Application of Multi-Layer Artificial Neural Networks for Forecasting Groundwater Level (Case study: Yolo County, California)

Esmail Salami Shahid[a], Majid Ehteshami[b], Marjan Salari[*c]

a. Department of Civil Engineering, Shiraz University, Shiraz, Iran.
b. Department of Civil Engineering, K N Toosi University of Technology, Tehran, Iran.
c[*].Department of Civil Engineering, Sirjan University of Technology, Kerman, Iran.
[*]E-mail Address: salari.marjan@gmail.com

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Abstract

Groundwater resources are one of the primary sources of water supply. In recent years, the natural balance between fresh, and saline water due to over-exploitation has deteriorated and groundwater levels (GWLs) in parts of the world aquifers have turned negative. Today, mathematical and unique models used to predict and evaluate groundwater levels. In this study, two separate artificial feed-forward neural networks (ANN) employing backpropagation algorithms have been developed using two sets of groundwater level (GWL) data, to simulate groundwater level fluctuations. The recorded daily GWL data from 1992 to 2014, to be fed as training input to the ANN models. The model inputs are the number of months and the number of years (a logarithmic expression), and monthly GWLs are the model's outputs. Two of the selected models were trained with data from 4/1992 to 12/2012, and then data from 1/2013 to 9/2014 were used for the verification process. The model's mean absolute errors were calculated as 0.51 and 0.66 (ft.), respectively and the prediction rate R for both models was calculated as 0.95. A significant advantage of the current study is its capability to predict the GWL, independent of parameters such as temperature or precipitation rate.

Keywords
Groundwater Level; Modeling; Artificial Neural Network; Yolo County; Simulation

1. Introduction

Groundwater is one of the most critical sources of potable, agricultural and industrial water [1-3]. Improper exploitation of groundwater resources in recent years disturbs its natural balance and groundwater level has been negative in aquifers in parts of the world. To be aware of the status of these resources and their optimal management, it is necessary accurate prediction of groundwater level fluctuations. Evaluation and forecasting of groundwater levels through models with proof capabilities of intelligent models in time series, in particular, helps to predict groundwater resources modeling. In recent years, the application of these models in modeling groundwater has intensified [4]. Two critical characteristics of groundwater are the quality parameters and groundwater level (GWL). Therefore, scientists are challenged to search for approaches to investigate both quality and quantity of GW [4-8]. In evaluating the groundwater system, using short-term and long-term groundwater data and the primary source of information on the potential of hydrological stress is important [9-11]. Most hydrological time series, such as groundwater level changes, always involve unfamiliar and complex processes that cannot be well described and modeled using conventional and classical linear models. Therefore, to model these hydrological phenomena, it is necessary to use nonlinear models [12]. In any simulation process, especially groundwater resource management strategy, a complex model can study the actions and reactions, and in many different aspects, choosing a good model is very important. The most common subject that all researchers are to investigate is to predicting and forecast the depth and quality of groundwater. Gao et al., 2020, researched the impact of shallow groundwater on crops [13]. The effect of groundwater discharge from adjacent aquifers is investigated by Mo et al., 2021 and Burnett et al., 2006 [6,14]. According to the presented experimental results, the observed GWL data show cycle patterns, including annual rotation [15]. Many factors such as global climate events, temperature, evaporations, precipitation, soil texture and permeability can affect GWL changes [16]. Furthermore, pumping rates, tidal fluctuations and GWL itself can affect its evaluations [17]. Yan et al., 2018 demonstrate that the influencing factors on the groundwater level can be in the order of 1- precipitation, 2- river stage and 3- evaporation [18]. There are many studies try to find the relation between groundwater (level and quality) and effective parameters. In some studies, researchers propose model(s) or present equation(s) to show the relation(s) between parameters. Table 1 shows a summary of research that has investigated methods to find an optimal algorithm to forecast and simulate GWL. In some research articles author(s) have tried to predict and simulate the GW quality (Table 1).

Table 1 Groundwater studies performed worldwide

Ref	Author(s)	Study Area	Parameter(s) that are used as input data	Target of the study	Result(s)
[19]	Kamińska et al.	Sosnowica, West Polesie	GWL data points as surface generation 2011	GWL(mm)	Compares Radial Basis Functions (RBF) and Inverse Distance Weighting (IDW) for forecasting the GWL and shows that RBF method is more accurate
[20]	Ahn	Collier County, Florida	daily GWL (m) 1985-1990	GWL(m)	Showed that the second-order difference model in some cases produces lower interpolation error than that of the first-order difference model
[21]	Nurul Islam et al.	Godagari Upazill Bangladesh	annual rainfall (in) 1986-2014	annual GW recharges (in)	Using non-linear regression technique to estimate GW recharges
[22]	Sun	three states of US	GRACE (3) satellite and withdrawal (in 106 g/d) data 2005	GWL changes	Used input data to train a Multilayer Perceptron (MLP) neural network for estimating GWL changes
[23]	Chang et al.	As-contaminated area in Taiwan	Alk, Ca2+, pH 1992-2005	As(mg/lit)	Developed a systematical dynamic-neural model (SDM) to estimate the As concentration
[24]	Abbasi Maedeh et al.	Tehran, Iran	SO_4, Na, Cl, Th, Mg, Ca, K, SAR, $HCo_3$2002-2011	TDS (mg/lit)	Training 5 ANN models, for each model assuming some of the input data as model input for estimate TDS and find best model between them
[25]	Taormina et al.	Venice, Italy	rainfall, evapotranspiration (mm) 2005-2008	hourly GWL(mm)	Made an ANN model to forecast GWL due to rainfall and evaporation from GW
[26]	Jalalkamali et al.	Kerman, Iran	monthly air temperature, rainfall, GWL in neighboring wells 1988-2009	GWL(mm)	Comparing between results of ANN model and neuro fuzzy model and find the NF method to has better performance
[27]	Adamowski et al.	two sites in Quebec, Canada	monthly total precipitation (mm), average temperature (°C) 2002-2009	average monthly GWL (mm)	Representing 3 models: ANN, ARIMA,WA-ANN, and comparing between the results showed that WA-ANN is the best model
[28]	Shiri et al.	Canada	Temperature (C), precipitation (mm), GWL (mm) 1974-2005	Wavelet coherence charts between GWL and T, P, and large-scale climatic patterns	Analyzed the impacts of 4 large-scale climatic patterns such as El Niño on the T,P,GWL by applying the wavelet transform on data
[29]	Seyam, and Mogheir	Gaza, Palestine	Initial chloride (mg/l), recharge rate (mm/m2/month), abstraction (m3/hour), life time (y) and aquifer thickness (m) 1997-2004	GW salinity (mg/l)	Made a Multilayer Perceptron NN (MLP) with four layers for predicting the GW salinity
[30]	Sethi et al.	Orissa, India	monthly rainfall, potential evapotranspiration (PET), water table depth, influencing wells data 2005-2008	one month ahead water table depth (m)	Tested 10 ANN models all with 3 hidden layer but different numbers of neurons in layers then compare their precisions

[31]	Joorabchi et al.	5 coastal areas of Australia	GWL, tide elevation, beach slope and hydraulic conductivity	GW elevation(m)	Trained a feed forward NN with two hidden layers and back propagation algorithm to predict GW elevation then illustrated by sensitivity analysis that variation in tide evaluations is the most important effective parameter.
[32]	Yang et al.	Jilin, China	six antecedent values of GWL (mm) 1986-2000	GWL (mm)	Produced two models, Integrated Time Series (ITS) and ANN and showed that ANN model works slightly better
[33]	Affandi et al.	Jakarta, Indonesia	GWL fluctuation	GWL fluctuation	Used multi-layer back-propagation to predict GWL fluctuation
[34]	Gundogdu et al.	Marmara region, Turkey	monthly GWL (mm) 2002	monthly GWL (mm)	Determined which of 10 empirical semi-variogram models (e.g. Gaussian, exponential, rational quadratic) will be best matched with GWL and resulted that the last one is the best.
[35]	Giustol et al.	Salento Peninsula in Apulia, Italy	monthly rainfall (cm) and GWL (m) 1953-1996	GWL (m)	Presented an initial multi-objective strategy for the optimal design of ANNs and found the selection of the best network structure

There are various methods such as probability properties, time series methods, multiple regression, artificial data generation and artificial intelligence networks with different algorithms for analyzing groundwater level fluctuations [15]. GWL depends on several parameters; therefore, it is hard to estimate [36]. An artificial neural network (ANN) for developing a model to forecast GWL can solve this complexity. ANN algorithms can predict accurate results and are appropriate tools for monitoring and managing GWL fluctuations. This method can also perform as a means to solve engineering and environmental problems [37]. In this study, it is assumed the oscillation factors that discussed above exist as a feature of GWL. Moreover, the probable presence of variables such as global climate events, temperature, precipitation, evaporations, soil texture and permeability, pumping and tidal fluctuations may affect GWL. However, as an assumption, it can't be affected by an unpredicted event such as big earthquakes. To account for effects of pumping, we assume that the pumping from the aquifer can change GWL. In order to increase efficiency in verification and simulation results, ANN models can be adapted to drastic changes of variables through learning algorithm process. The current study shows that a reliable forecasting model can be developed without the need for any detailed analysis of each influential variable on GWL. The presented models use only one influential parameter such as seasonal variations in GWL fluctuations and simulation analyses.

2. Method and materials

Local GWL models are valuable tools for monitoring and assessment. The effective parameters such as geographical site location, spatial distribution of soil characteristics, and impact of probabilistic hydrogeological parameters have a natural of uncertainty. To develop GWL simulation models, there is an essential necessity to have GWL time series data. In this study two wells in Yolo County have been chosen to show how effectively and accurately local ANN models can simulate and predict the GWL. Information on the location of observation wells used in the groundwater model is shown in Table 2.

Table 2 Information on the location of observation wells of the study sites in Yolo County

	Depth(ft)	Station ID	Latitude	Longitude
well #1	80-90	09N03E08C001M	38-38-46.405 N	121-40-3.009 W
well #2	140-150	09N03E08C002M	38-38-46.405 N	121-40-3.009 W

Figure 1 shows the data sets which are used for the modeling. They have been recorded since 4/1/1992, by Department of Water Resources of California that are published and exhibited on their site at www.water.ca.gov/waterdatalibrary/docs/Hydstra/index.cfm. These data are the daily mean of GWL (Figure 1). In first step, daily data transformed to monthly data sets (Figure 2). For well #1 and #2 we have a negligible number of missed data (27 and 28 days respectively). These data are assumed to be equal to the mean GWL of the day before.

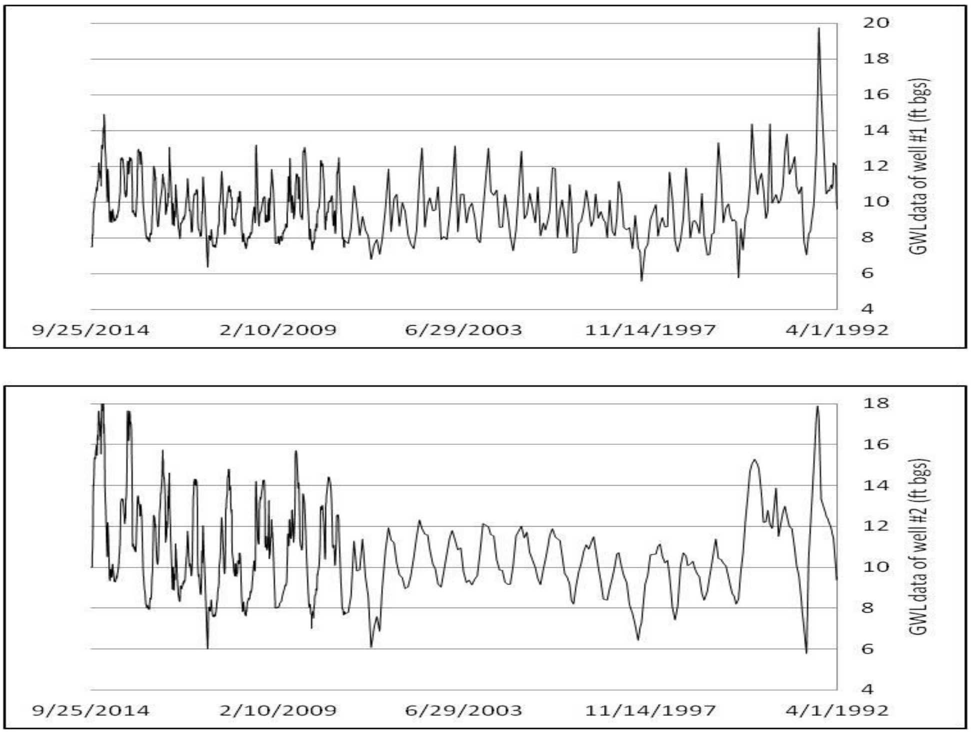


Figure 1. Daily GWL data of well #1 and #2

Number of months and number of years (Table 3) are the model's inputs and monthly GWL (Figure 2) is the model's the target. To reduce the impact of year as a changing variable, in comparison with the number of months the following transformation is used:

$$input.year.data = \log(10 + year - 1991) \quad (1)$$

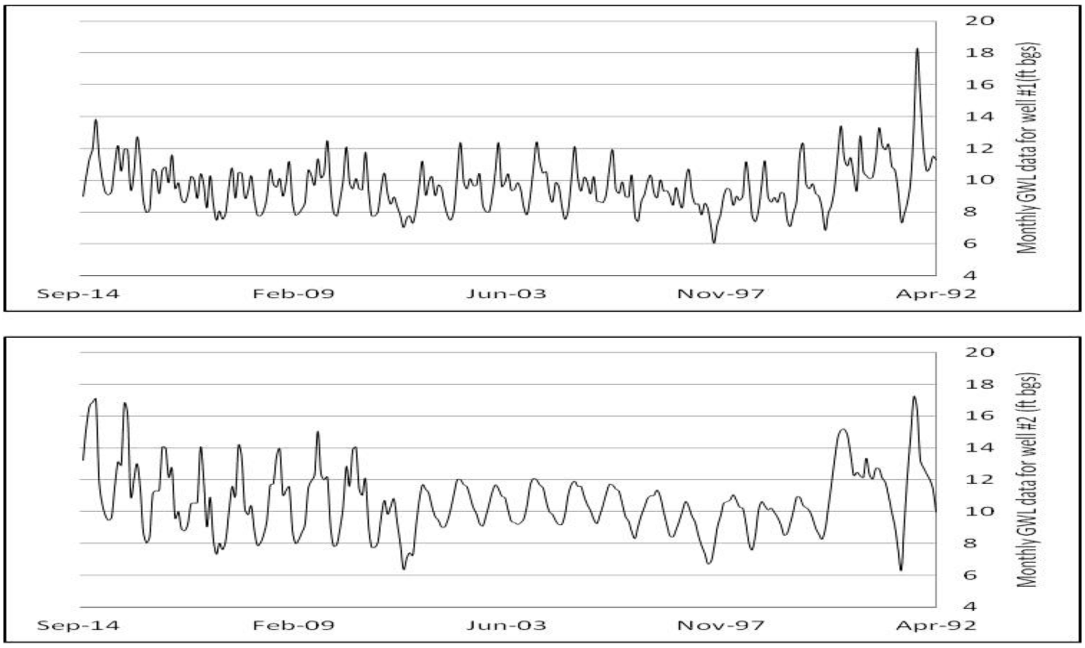


Figure 2. Monthly GWL data of well #1 and #2

Table 3 Input data

Row number	Month	Year	year in logarithmic expression
1	4	1992	1.041393
2	5	1992	1.041393
3	6	1992	1.041393
4	7	1992	1.041393
5	8	1992	1.041393
6	9	1992	1.041393
7	10	1992	1.041393
8	11	1992	1.041393
9	12	1992	1.041393
10	1	1993	1.079181
11	2	1993	1.079181
12	3	1993	1.079181
13	4	1993	1.079181
14	5	1993	1.079181
15	6	1993	1.079181
.	.	.	.
.	.	.	.
.	.	.	.
59	10	2013	1.50515
260	11	2013	1.50515
261	12	2013	1.50515
262	1	2014	1.518514
263	2	2014	1.518514
264	3	2014	1.518514
265	4	2014	1.518514
266	5	2014	1.518514
267	6	2014	1.518514
268	7	2014	1.518514
269	8	2014	1.518514
270	9	2014	1.518514

To evaluate the model's accuracy, data of years 2012 – 2014 are not used in the training step. In order to verify the developed model after the training process, the dates of years 2012-2014 are used as inputs of the models, and GWL is simulated and predicted. Then the simulated GWL data are compared with real data of 2012-2014.

2.1. Modeling

Because of the complexity of the problem, a Multi-layer ANN is a proper way of modeling and simulating the GWL variations [35]. Moreover, for long term GWL predictions; there are many similar ANN studies such as [24, 39].

2.2. Structure of networks

The basis of the artificial neural network algorithm is inspired by the imitation of human learning [40]. The three main layers of ANN architecture include input, hidden, and output layers (Figure 3: Two-layer network). In an intelligent network such as an artificial neural network, the modeling is forward and the signal flows from the input units to the output [41]. According to Figure (3), parameters "a" and "p" are the output of neurons and inputs, respectively, and the hidden layers are composed of several neurons. Also the parameters "w" and "p" are weight and bias, respectively, where all parameters are represented by a matrix. And can be expressed as follows:

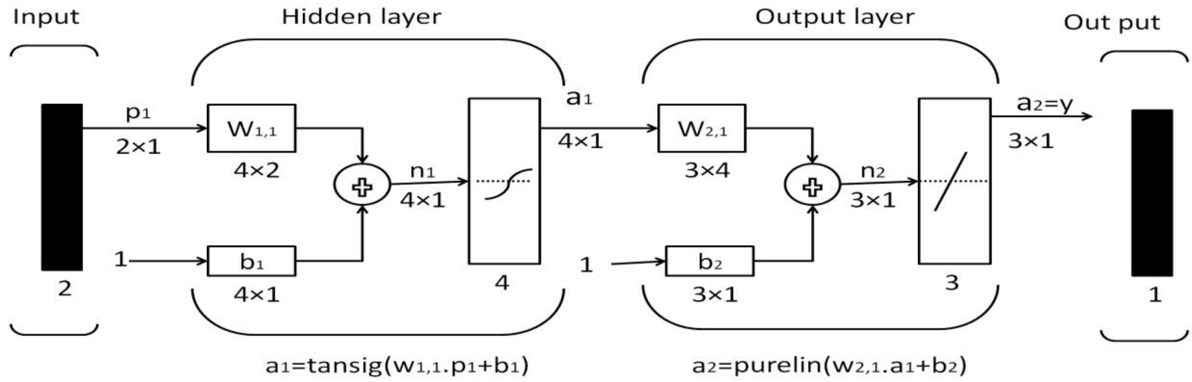


Figure 3. A two layer feed-forward network [42-47]

$$a = f(net) = f(n) = f(w^T.p+b) = f(\sum_{i=1}^{R} w_R{}^T.p_R + b) \quad (2)$$

$$p = \left[p_1, p_2, ..., p_R\right], w = \left[w_1, w_2, ..., w_R\right] \quad (3)$$

The most common "f" functions are shown in Figure 4 as transfer functions. The transfer functions change the output of each layer to a more straightforward /readily applicable expression for calibrating the w_i and b_i(s) in the next layer/step.

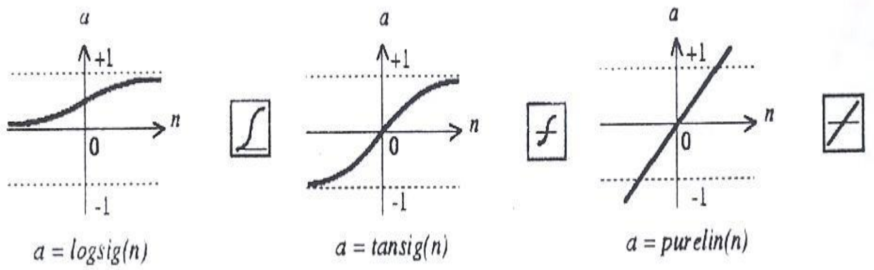


Figure 4. Transfer functions [42-47]

For the training to be performed correctly, the process of trial and error will be continued for calibrating and optimizing the w_i,b_i(s). The evaluation criterion in ANN is to minimize and optimize the mean squared error (MSE) and this process will continue until the necessary accuracy is achieved. Weights and biases change each time the process is repeated [48,49]. According to Equations 4-7, two feed-through networks with a learning rule are used to develop models in the MATLAB environment.

$$w_{i,j}^{(l+1)} = w_{i,j}^{(l)} - \alpha \frac{\partial e(w,b)}{\partial w_{i,j}^{(l)}} \quad (4)$$

$$b_{i,j}^{(l+1)} = b_{i,j}^{(l)} - \alpha \frac{\partial e(w,b)}{\partial b_{i,j}^{(l)}} \quad (5)$$

$$\frac{\partial e(w,b)}{\partial w_{i,j}^{(l)}} = \left[\frac{1}{m} \sum_{i=1}^{m} \frac{\partial}{\partial w_{i,j}^{(l)}} e(w,b;x^{(i)},y^{(i)}) \right] + \alpha\, w_{i,j}^{(l)} \quad (6)$$

$$\frac{\partial e(w,b)}{\partial b_{i,j}^{(l)}} = \left[\frac{1}{m} \sum_{i=1}^{m} \frac{\partial}{\partial b_{i,j}^{(l)}} e(w,b;x^{(i)},y^{(i)}) \right] + \alpha\, b_{i,j}^{(l)} \quad (7)$$

Where α denotes the learning rate.
In the network structure according to Figure 3, the outputs of the previous layers will be the inputs of the neurons of the next layer and the results of the output layer will be compared with the target values. In this study, the mean squares of the MSE error (ft2) are the criteria for comparing the outputs as follows:

$$mse = \frac{1}{m} \sum_{i=1}^{m} e^2 = \frac{1}{m} \sum_{i=1} (t_i - a_i)^2 \quad (8)$$

In this equation, ti is the data of the target value (real) and ai is the output of the network.

3. Results

The ANN models for groundwater level forecasting were developed using the MATLAB R2015b software program. The main aim of this study is to develop two local ANN models to show how simply ANN models can be used for forecasting GWL in upcoming seasons. One of the important advantages of ANN models is their flexibility and excellent adaptation capability to time-varying data sets. In other words, by the passage of time, and acquisition of additional new data sets, the model can adapt itself with them. As a result of this self-adapting ability, the synchronized models will be more accurate and up to date as well. Design parameters of the networks have been represented in Tables 4 and 5. Table 5 shows the mean absolute error MAE (ft) and rate of accuracy R (dimensionless) for the models as it is explained in the following equations:

$$E_i = D_i - M_i \quad (9)$$

E_i = i'th error (ft)

D_i= i'th real data (ft bgs), M_i= i'th estimated data (ft bgs).

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |E_i| \quad (10)$$

$$R = \frac{1}{n} \sum_{i=1}^{n} \left(1 - \frac{|E_i|}{D_i}\right) \quad (11)$$

Table 4 Training parameters

α_0	0.001		**Network type**	feed-forward back propagation
α decrees	0.1		**Training function**	Trainlm (Levenberg-Marquardt)
α increase	10		**Adapting learning function**	Train GDM
maximum α	1E+10		**Performance function**	MSE
min grad	1.00E-10		**Transfer function**	tansign(x)

Table 5 Properties of the models

	Number of hidden layers	**Number of Neurons in Layers**	**MAE(ft)**	**R^2**

Model for well #1	2	10-6 respectively	0.51	0.95
Model for well #2	1	10	0.66	0.95

There are specific window options that user could justifie the parameters of network and network algorithm, the basis of (proper) type of network, learning/training algorithms,transformation function most related to the natural of problem (for example predicting time series data need different type/justifications from those used for produce a pattern/image processor ANN), (best value for) number of (hidden) layers (note that firs/input and last/output layers are obliged) and the number of their neurons related to the complexity of problem and number of parameters (of inputs and outputs), respectively. Training and testing parameters must be chosen concerning, the required precision. There is no special rule for choosing the right/best justifications for parameters of network, and with trial and error best possible condtions could be found.

In this study the models are trained with monthly GWL data from 4/1992 to 12/2012 (249 months, 70% for training, 15% for testing, 15% for verification in training processes). Number of these data was not proper for modeling (insufcient data) so we removed them from training data (more details about these insufcient data comes further) After making models and For testing the model precision, two models are used to simulate and forecast monthly GWL from 1/2013 to 9/2014 (21 months,these data never introduced to the model before). Table 5 indicates an acceptable level of reliability for these two models in simulating GWL's. Therefore, based on this verification analysis, the proposed ANN models are successfully applied as a tool to simulate and predict seasonal GWL variations by using year and month as input data. Figure 5 shows the model results in comparison with the real data values.

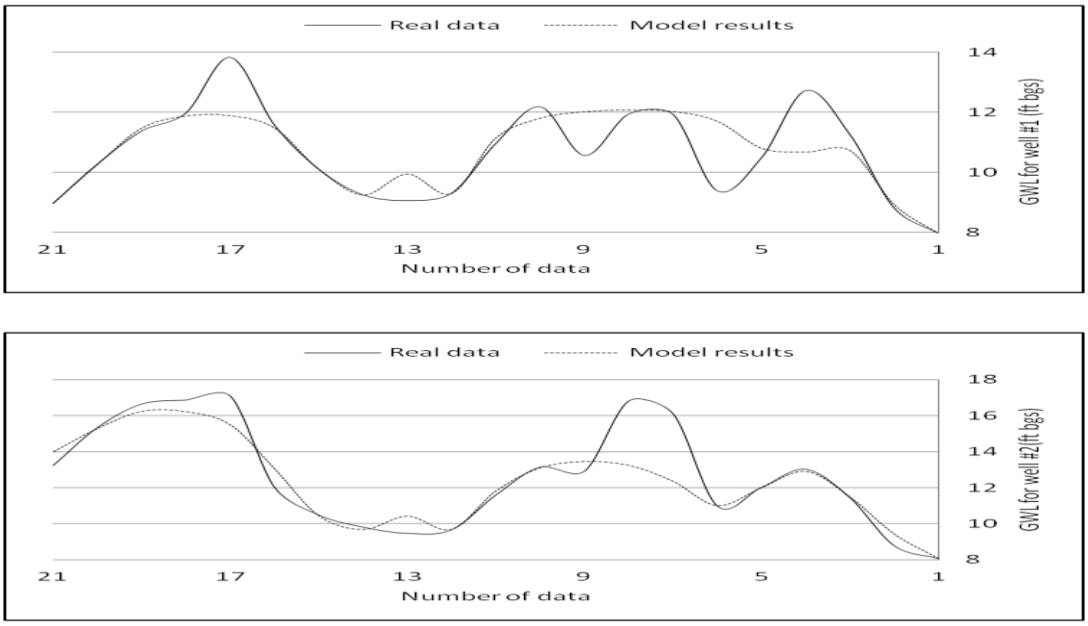
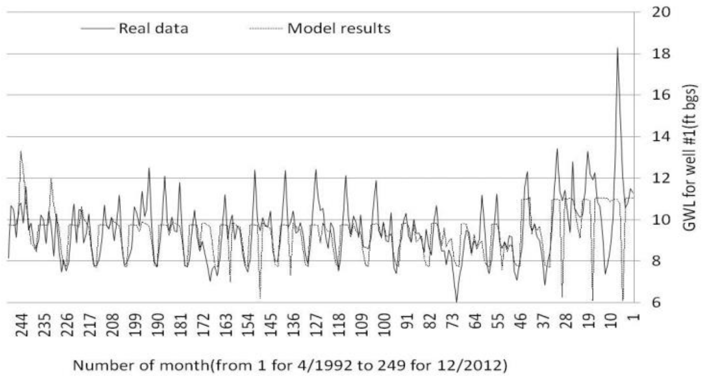


Figure 5. Comparisonbetween the model results and real data values these data never introduced to the models before

Figure 6 shows the models predictions against real data, all of these data used for training process (including: training, testing and verification steps).



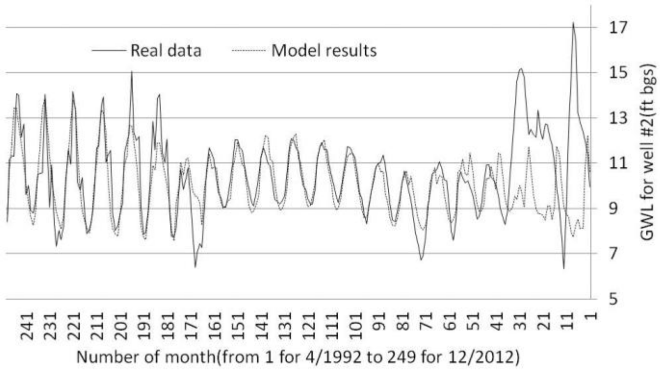


Figure 6. Comparison between real data and model results for data that used for training models (249 months that mentioned before)

In figure 6, MAE is 0.9 and 1 and R is 0.91 and 0.9 for well #1 and #2, respectively. As seen in figure 6 in first 20 months of well #1 (Fig.6) and 40 first months of well#2 (Fig.6) signficant anomalies (could be made by human or natural phenomena) confuses models and lowered the average accuracy of models. Without removing these (insufcient) data from training data, models couldn't get to acceptable results so these data removed from training data and donot introduced to model and after making models these data (first 20 months of well#1 and 40 first months of well# 2) estimated by models.

4. Conclusions

The critical highlight of this study is to develop two state-of-the-art ANN algorithms that are easy to use for predicting seasonal GWL. The main feature of the presented model compared to the similar previous studies is its dedicated vision to simulate GWL directly. In the studies conducted by others, they almost need to know the other parameters such as precipitation and temperature to simulate the GWL. However, the variables such as precipitation and temperature themselves are hydrologically complex and probabilistic parameters to be estimated. Therefore, the previous studies can’t be used easily for forecasting the GWL data. While, the presented models simply can simulate and predict the GWL, without requirement of any extra geo-hydrological parameters. These models also can be used for regenerating the missing data. Main highlights that distinguish this study from other/similar works are [42-47]:

1- Presented models simulate monthly GWL directly, using only date (year, month) as input(s).
2- The models can be employed for regenerating missed data or/and calibration of measurement instruments and controlling operators.
3- Predictions of the model (s) can be used in any related fields (such as water resources

management, scientific studies, and as a replacement for traditional/existed GWL measuring methods)

4- The self-learning and self-adapting abilities of this evolutionary method make it an efficient tool in predicting long term GWL changes.
5- The most important achievement of this study is the method of modeling, which describes how to use only date/time as input data.
6- The proposed modeling method can be employed for modeling in any other similar problems such as yearly and/or daily GWL, sea level data, temperature data, contamination data etc.
7- This study also doesn’t assume any particular circumstance that may impose any limitations on simulation results such as neglecting the effect of pumping such as [2], etc.

for those who interested to works in this (or similar) field will be helpful to know the limitations of this type of modeling :

- these types of models (like most of other hydrological models) are completely localized and couldn't be employed for/in other regions. New models should be made for other locations. The method used for modeling in this study is simply applicable for the other (similar/time series) problems.

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References

[1] Siebert, S., Burke, J., Faures, J.M., Frenken, K., Hoogeveen, J., Döll, P. and Portmann, F.T., 2010. Groundwater use for irrigation–a global inventory. Hydrology and earth system sciences, **14**(10), pp.1863-1880.

[2] Tremblay, L., Larocque, M., Anctil, F. and Rivard, C., 2011. Teleconnections and interannual variability in Canadian groundwater levels. Journal of Hydrology, **410**(3-4), pp.178-188.

[3] Kumar, D.P., 2014. Ground Water Prediction Using Bacterial Foraging Optimization Technique. American Journal of Computing Research Repository, **2**(3), pp.44-48.

[4] Mohamad, A. and Mehdi, M., 2011. Time series analysis of ground water table fluctuations due to temperature and rainfall change in Shiraz plain. International Journal of Water Resources and Environmental Engineering, **3**(9), pp.176-188.

[5] Kim, J.H., Lee, J., Cheong, T.J., Kim, R.H., Koh, D.C., Ryu, J.S. and Chang, H.W., 2005. Use of time series analysis for the identification of tidal effect on groundwater in the coastal area of Kimje, Korea. Journal of Hydrology, **300**(1-4), pp.188-198.

[6] Burnett, W.C., Aggarwal, P.K., Aureli, A., Bokuniewicz, H., Cable, J.E., Charette, M.A., Kontar, E., Krupa, S., Kulkarni, K.M., Loveless, A. and Moore, W.S., 2006. Quantifying submarine groundwater discharge in the coastal zone via multiple methods. Science of the total Environment, **367**(2-3), pp.498-543.

[7] Winkel, L., Berg, M., Amini, M., Hug, S.J. and Annette Johnson, C., 2008. Predicting groundwater arsenic contamination in Southeast Asia from surface parameters. Nature Geoscience, **1**(8), pp.536-542.

[8] Obiefuna, G.I. and Orazulike, D., 2010. Physicochemical characteristics of groundwater quality from Yola Area, Northeastern Nigeria. Journal of Applied Sciences and Environmental Management, 14(1).

[9] Winter, T.C., Mallory, S.E., Allen, T.R. and Rosenberry, D.O., 2000. The use of principal component analysis for interpreting ground water hydrographs. Groundwater, **38**(2), pp.234-246.

[10] Moon, S.K., Woo, N.C. and Lee, K.S., 2004. Statistical analysis of hydrographs and water-table fluctuation to estimate groundwater recharge. Journal of Hydrology, **292**(1-4), pp.198-209.

[11] Ahmadi, S.H. and Sedghamiz, A., 2007. Geostatistical analysis of spatial and temporal variations of groundwater level. Environmental monitoring and assessment, **129**(1), pp.277-294.

[12] Ehteshami, M., Peralta, R.C., Eisele, H., Deer, H.M. and Tindall, T., 1991. Assessing pesticide contamination to groundwater: a rapid approach. Journal of Ground Water, **29**(6), p.939.

[13] Gao, X., Qu, Z., Huo, Z., Tang, P. and Qiao, S., 2020. Understanding the Role of Shallow Groundwater in Improving Field Water

Productivity in Arid Areas. Water, **12**(12), p.3519.

[14] Mo, Y., Jin, G., Zhang, C., Xu, J., Tang, H., Shen, C., Scheuermann, A. and Li, L., 2021. Combined effect of inland groundwater input and tides on flow and salinization in the coastal reservoir and adjacent aquifer. Journal of Hydrology, **600,** p.126575.

[15] Adhikary, S.K., Rahman, M. and Gupta, A.D., 2012. A stochastic modelling technique for predicting groundwater table fluctuations with time series analysis. International journal of applied science and engineering research, **1**(2), pp.238-249.

[16] Erwin, K.L., 2009. Wetlands and global climate change: the role of wetland restoration in a changing world. Wetlands Ecology and management, **17**(1), pp.71-84.

[17] Ataie-Ashtiani, B., Volker, R.E. and Lockington, D.A., 2001. Tidal effects on groundwater dynamics in unconfined aquifers. Hydrological Processes, **15**(4), pp.655-669.

[18] Yan, S.F., Yu, S.E., Wu, Y.B., Pan, D.F. and Dong, J.G., 2018. Understanding groundwater table using a statistical model. Water Science and Engineering, **11**(1), pp.1-7.

[19] Kamińska, A. and Grzywna, A., 2014. Comparison of deteministic interpolation methods for the estimation of groundwater level. Journal of Ecological Engineering, **15**(4), pp.55-60.

[20] Ahn, H., 2000. Modeling of groundwater heads based on second-order difference time series models. Journal of Hydrology, **234**(1-2), pp.82-94.

[21] Islam, M.N., Chowdhury, A., Islam, K.M. and Rahaman, M.Z., 2014. Development of rainfall recharge model for natural groundwater recharge estimation in Godagari Upazila of Rajshahi District, Bangladesh. American Journal of Civil Engineering, **2**(2), pp.48-52.

[22] Sun, A.Y., 2013. Predicting groundwater level changes using GRACE data. Water resources research, **49**(9), pp.5900-5912.

[23] Chang, F.J., Chen, P.A., Liu, C.W., Liao, V.H.C. and Liao, C.M., 2013. Regional estimation of groundwater arsenic concentrations through systematical dynamic-neural modeling. Journal of Hydrology, **499,** pp.265-274.

[24] Maedeh, P.A., Mehrdadi, N., Bidhendi, G.N. and Abyaneh, H.Z., 2013. Application of artificial neural network to predict total dissolved solids variations in groundwater of Tehran Plain, Iran. Int J Environ Sustain, **2**(1), pp.10-20.

[25] Taormina, R., Chau, K.W. and Sethi, R., 2012. Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. Engineering Applications of Artificial Intelligence, **25**(8), pp.1670-1676.

[26] Jalalkamali, A., Sedghi, H. and Manshouri, M., 2011. Monthly groundwater level prediction using ANN and neuro-fuzzy models: a case study on Kerman plain, Iran. Journal of hydroinformatics, **13**(4), pp.867-876.

[27] Adamowski, J. and Chan, H.F., 2011. A wavelet neural network conjunction model for groundwater level forecasting. Journal of Hydrology, **407**(1-4), pp.28-40.

[28] Shiri, J. and Kişi, Ö., 2011. Comparison of genetic programming with neuro-fuzzy systems for predicting short-term water table depth fluctuations. Computers & Geosciences, **37**(10), pp.1692-1701.

[29] Seyam, M. and Mogheir, Y., 2011. Application of artificial neural networks model as analytical tool for groundwater salinity. Journal of Environmental Protection, **2**(01), p.56.

[30] Ranu, R.S., 2010. Prediction of water table depth in a hard rock basin by using artificial neural network. International journal of water resources and environmental engineering, **4**(2), pp.95-102.

[31] Joorabchi, A., Zhang, H. and Blumenstein, M., 2009. Application of artificial neural networks to groundwater dynamics in coastal aquifers. Journal of coastal research, pp.966-970.

[32] Yang, Z.P., Lu, W.X., Long, Y.Q. and Li, P., 2009. Application and comparison of two prediction models for groundwater levels: a case study in Western Jilin Province, China. Journal of Arid Environments, **73**(4-5), pp.487-492.. (www.water.ca.gov/waterdatalibrary/docs /Hydstra/index.cfm).

[33] Affandi, A.K., Watanabe, K. and Tirtomihardjo, H., 2008. Use of Back-propagation Artificial Neural Networks for Groundwater Level Simulation. Asian Journal of Water, Environment and Pollution, 5(1), pp.57-65.

[34] Gundogdu, K.S. and Guney, I., 2007. Spatial analyses of groundwater levels using universal kriging. Journal of earth system science, **116**(1), pp.49-55.

[35] Giustolisi, O. and Simeone, V., 2006. Optimal design of artificial neural networks by a

multi-objective strategy: groundwater level predictions. Hydrological Sciences Journal, **51**(3), pp.502-523.

[36] Vazquez-Amábile, G.G. and Engel, B.A., 2005. Use of SWAT to compute groundwater table depth and streamflow in the Muscatatuck River watershed. Transactions of the ASAE, **48**(3), pp.991-1003.

[37] Weesakul, Uruya, Kunio Watanabe, and Natkritta Sukasem. 2010. "Application of soft computing techniques for analysis of groundwater table fluctuation in Bangkok area and its vicinity." International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies 1, no. **1:** 53-65.

[38] Anctil, F., Filion, M. and Tournebize, J., 2009. A neural network experiment on the simulation of daily nitrate-nitrogen and suspended sediment fluxes from a small agricultural catchment. Ecological Modelling, **220**(6), pp.879-887.

[39] Koncsos, T., 2010. The application of neural networks for solving complex optimization problems in modeling. In Conference of Junior Researchers in Civil Engineering (pp. 97-102).

[40] Samani, N., Gohari-Moghadam, M. and Safavi, A.A., 2007. A simple neural network model for the determination of aquifer parameters. Journal of Hydrology, **340**(1-2), pp.1-11.

[41] Abraham, A., 2005. Artificial neural networks. Handbook of measuring system design.

[42] Salami, E.S., Salari, M., Ehteshami, M., Bidokhti, N.T. and Ghadimi, H., 2016. Application of artificial neural networks and mathematical modeling for the prediction of water quality variables (case study: southwest of Iran). Desalination and Water Treatment, **57**(56), pp.27073-27084.

[43] Salami, ES., Salari, M., Rastegar, M., Nikbakht, S., Sheibania, ME. 2021. Artificial neural network and mathematical approach for estimation of surface water quality parameters (case study: California, USA). Desalination Water Treatment. **100**, p.2.

[44] Shahid, E.S., Salari, M., Ehteshami, M. and Sheibani, S.N., 2020. Artificial neural network (ANN) modeling of cavitation mechanism by ultrasonic irradiation for cyanobacteria growth inhibition. J. Environ. Treat. Tech., **8,** pp.625-633.

[45] Salari, M., HosseiniKheirabad, M., Ehteshami, M., Niloufar, S. and Moaddeli, E.T., 2020. Modeling of groundwater quality for drinking and agricultural purpose: a case study in Kahorestan plain. Journal of Environmental Treatment Techniques, **8**(1), pp.346-352.

[46] Salami, E., Salari, M., Sheibani, S.N., HosseiniKheirabad, M. and Teymouri, E., 2020. Dataset on the assessments the rate of changing of dissolved oxygen and temperature of surface water, case study: California, USA. Journal of Environmental Treatment Techniques, **7**(3), pp.843-852.

[47] Salari, M., Shahid, E.S., Afzali, S.H., Ehteshami, M., Conti, G.O., Derakhshan, Z. and Sheibani, S.N., 2018. Quality assessment and artificial neural networks modeling for characterization of chemical and physical parameters of potable water. Food and Chemical Toxicology, **118**, pp.212-219.

[48] Svozil, D., Kvasnicka, V., Pospichal, J. 1997. Introduction to multi-layer feed-forward neural networks. Chemometrics and Intelligent Laboratory Systems. **39**, 43-62.

[49] Parapari, H.F. and Menhaj, M.B., 2016, January. Solving nonlinear ordinary differential equations using neural networks. In 2016 4th International Conference on Control, Instrumentation, and Automation (ICCIA) (pp. 351-355). IEEE.