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Prediction the Groundwater Level of Bastam Plain (Iran) by Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract Prediction of the groundwater level (GWL) fluctuations is very important in the water resource management. This study investigates the potential of two intelligence models namely, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in the forecasting of the groundwater level of Bastam Plain in Iran. For this purpose, 9 years data-sets including hydrological and hydrogeological parameters like rainfall recharge, irrigation returned flow and also pumping rates from water wells were used as input data to predict groundwater level. The results showed that ANN and ANFIS models can predict GWL accurately. Also, it was found that the ANFIS model (with root-mean-square-error (RMSE) 0.02 m and determination coefficient (R^2) of 0.96) performed better than the ANN model with RMSE=1.06 m and R^2=0.83. Finally, three scenarios were considered to predict the groundwater level in the next 2 years as follows 1- The rainfall recharge and pumping rate of water wells will be constant, 2- The rainfall recharge will be constant, but the pumping rate of water wells will be reduced equal to the water deficit of the aquifer, 3- The pumping rate of water wells will be constant but the rainfall recharge will be reduced 30 %. The prediction with these scenarios showed that the groundwater level has the minimum reduction when the pumping rate of water wells is equal to the water deficit of the aquifer.

Keywords Groundwater level · Bastam plain · Adaptive neuro-fuzzy inference system · Artificial neural network

1 Introduction

Groundwater is one of the major sources of supply for industrial, domestic and agricultural purposes. In some areas, such as arid and semi arid area, it is the only source of supply, while in some other regions it is chosen because of its ready availability (Nayak et al. 2006). In recent years, groundwater supplies have been overused, especially in industry and agriculture and this causes the groundwater level to be declined (Sreekanth et al. 2010). Accurate

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prediction of groundwater level is one of the most important stages in sustainable yield of groundwater resources and it help engineers, planners and water managers to make appropriate decisions to avoid or reduce adverse effects such as loss of pumpage in water wells, aquifer compaction and land surface subsidence (Prinos et al. 2002; Shirmohammadi et al. 2013; Moosavi et al. 2013). Researchers were used different methods such as numerical groundwater models, time series models, and empirical models to predict the groundwater level. The disadvantage of using numerical groundwater models is they require thorough knowledge of the geological characteristics of the rocks delete the citation from the text.and the geometrical characteristics of fractures in karstic aquifers (Trichakis et al. 2011). Recently, new data-driven techniques such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) have been accepted as an efficient alternative tool for modeling of complex hydrologic systems and widely used for prediction (Gail et al. 2002; Sreekanth et al. 2010; Guldal and Tongal 2010).

There are different kinds of ANN structure that many researchers have used them in their studies (Yang et al. 1996, 1997, 2009; Coulibaly et al. 2000, 2001; Daliakopoulos et al. 2005; Bhattacharjya and Datta 2005; Nayak et al. 2006; Nourani et al. 2008; Kentel 2009; Ghose et al. 2010; Mohanty et al. 2010; Emamgholizadeh 2012; Emamgholizadeh et al. 2013a; Akrami et al. 2014).

Trichakis et al. (2011) were used ANN model to simulate karstic groundwater level of Edward’s aquifer in Texas, USA. The results show that the ANN can to predict GWL and it is still a useful way to simulate karstic aquifers that are difficult to be simulated by numerical groundwater models.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is also efficient in modeling nonlinear systems like as ANN. In the fuzzy systems, relationships are represented explicitly in the form of if-then rules (Kurtulus et al. 2010). ANFIS is a branch of fuzzy logic with several layers that adapt fuzzy system parameters to predict the output of system and it has become coordinated according to post distribution algorithm based on gathering input and output data. So many researchers have been used ANFIS model. This model with high abilities can be a suitable for modeling non-linear systems. ANFIS model was used by many researchers of hydrology, hydrogeology and other engineering problems (Ponnambalam et al. 2003; Nayak et al. 2004; Chang and Chang 2006; Kisi 2006; Tutmez et al. 2006; Affandi and Watanabe 2007; Yarar et al. 2009; Esen and Inalli 2010; Kurtulus and Razak 2010; Sreekanth et al. 2010; Sanikhani and Kisi 2012; Emamgholizadeh et al. 2013b). For example Bisht et al. (2009) predicted increasing level of groundwater by using two methods namely: fuzzy logic modeling and ANFIS. Evaluating the efficiency of models, ANFIS has superiority to fuzzy logic models. Also Güldal and Tongal (2009) used return neuro network method (RNN), ANFIS and random methods to predict the water level of Egirdir Lake in Turkey. In their study ANFIS was more efficient than other models. Shirmohammadi et al. (2013) applied several data-driven techniques including system identification, time series, and ANFIS models to predict groundwater level for different forecasting period. They showed that the ANFIS could provide accurate prediction of groundwater level for 1 and 2 months ahead appropriately.

Iran is arid and semi arid country. In this area the groundwater is the main source of supplying for agriculture, drinking and industrial consumptions. So, the prediction of the groundwater level is necessary for planning and managing of the water resource. To the best of our knowledge, no research has been published that use ANN and ANFIS for groundwater level forecasting with different hydrological parameters such as effective rainfall and irrigation returned flow as well as hydrogeological parameters such as pumping rates from water wells. Also due to overexploitation and also changing precipitation types in the study area the aquifer experienced rapidly drop. The objective of this study is to examine the ability of ANN and ANFIS models to capture periodic oscillations in observations as well as the rapidly drop of the GWL data. Finally by selecting the best model base on statistical criteria, three scenarios considered for prediction GWL in the next 2 years.

2 Materials and Methods

2.1 Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) is massively parallel distributed information processing system that has certain performance of characteristics resembling biological neural networks of the human brain (Haykin 1999, 2005; Nayak et al. 2006; Mohanty et al. 2010). ANN models have been widely applied in various fields of science and technology involving time series forecasting, pattern recognition and process control (Nayak et al. 2006).

The neural network is defined by the structure of adjoin between nodes, method of measuring the weight of adjoin and an action function (Mohanty et al. 2010). There are different kinds of neural networks like: Hapfild, Perceptron and etc. Neural networks are categorized according to their learning algorithm. Different kinds of learning algorithms are feed forward back-propagation, radial basis function, gradient descent with momentum and adaptive learning rate back propagation, Levenberg–Marquardt (LM), Bayesian regularization (BR) and etc. (ASCE 2000a, b). The neural network usually is used for hydrological usage is a multilayer progressive neural network with back propagation learning algorithm. In this study, multilayer perceptron layer (MLP) with hidden layer (s) in which was trained with Back Propagation (BP) algorithm is used. Different transfer functions are applied in the hidden layer (s) and a linear function in the output layer. The ANNs with this configuration commonly used and it improved extrapolation ability (ASCE 2000a; Maier and Dandy 2000). The mathematical expression of the MLP is as follows:

$$y_i = f\left(\sum_{i=1}^{N} w_{ji}x_i + b_j\right) \tag{1}$$

Where x_i is the i_{th} nodal value in the previous layer, y_j is the j_{th} nodal value in the present layer, b_j is the bias of the j_{th} node in the present layer, w_{ji} is a weight connecting x_i and y_j, N is the number of nodes in the previous layer, and f is the activation function in the present layer (Yoon et al. 2010).

2.2 Adaptive Neuro-Fuzzy Inference System

Adaptive neuro-fuzzy inference system (ANFIS), first introduced by Jang (1993), is a universal approximation methodology and, as such, is capable of approximating any real continuous function on a compact set to any degree of accuracy. This model has also a good capability in training, producing and categorizing and also it has this superiority that allow us to bring out fuzzy rules form numerical data or knowledge of export and make rule-based adaptively (Jang et al. 1997). Generally, the ANFIS model architecture consists of five layers configured like any multi-layer feed forward neural network and named according to their operative function, such as 'input nodes', 'rule nodes', 'average nodes', 'consequent nodes' and 'output nodes', respectively (Chen et al. 2006).

2.3 Study Area

The study area is located between eastern longitude of 54° 50' and 55° 10' and northern latitude of 36° 27' and 36° 42' in Semnan province of Iran (Fig. 1). This Plain is located in

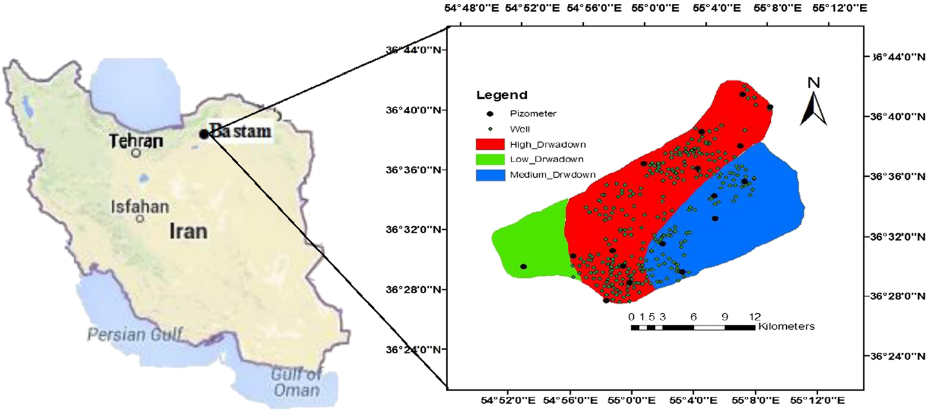

Fig. 1 Location of the of study area in northeastern Iran, the production wells and monitoring piezometers in Bastam Plain aquifer

semi-arid climate, and it is one of the important Plains in Iran from agricultural view point. The local average annual temperature and rainfall in the study area are 12 °C and 163.3 mm, respectively. Agricultural activities are the main source of livelihood in this region.

2.4 Geology and Hydrogeology of Bastam Plain Aquifer

The Bastam Plain is covered by alluvial deposits and its bedrock in central, east and north-west consists of the Mio-Pliocene marlstone and in the north includes carbonate rocks. Bastam Plain alluvial aquifer is one of the 14 aquifers within Shahrood County, partly underlies the city of Bastam. The alluvial aquifer occupies an area of approximately 405 km^2; its storage coefficient, based on geological logs and pumping test data, is 0.04 (Karami et al. 2009). The aquifer in this Plain is an unconfined aquifer (Karami 2010). Soil types include sandy loam to middle coarse sand with no apparent typical homogeneous characteristics. All the withdrawal groundwater is used for farm irrigation with the exception of a few wells which are used for irrigating green areas of the city. The number of production wells varies from year to year because some become dry after a few years of pumping. The groundwater is the only source of water for drinking, farming and industrial usage. There is no permanent river in this Plain but temporary rivers flow during wet season. This Plain includes 400 production wells, 54 springs and 23 Qanats (is one of a series of well-like vertical shafts, connected by gently sloping tunnels. It creates a reliable supply of water for human settlements and irrigation in arid and semi-arid climates).

2.5 Data Description

The artificial intelligence models were tested with data taken from local Shahrood Water Authority, Iran. Water-level data have been recorded in 17 piezometers which have been drilled and are continuously maintained and monitored by the Shahrood Water Authority (see Fig. 1). These piezometers are installed to record groundwater levels only. The groundwater level of Bastam Plain faces a severe problem of depletion. The main reasons are the increasing numbers of wells in the study area and therefore increasing withdrawal of groundwater; reducing entering surface water to the Plain due to diversion it for framing at the upstream of Plain and also using traditional irrigation with low efficiency for agriculture. Fig. 2a illustrates the groundwater level of the Bastam Plain alluvial aquifer. Based on the

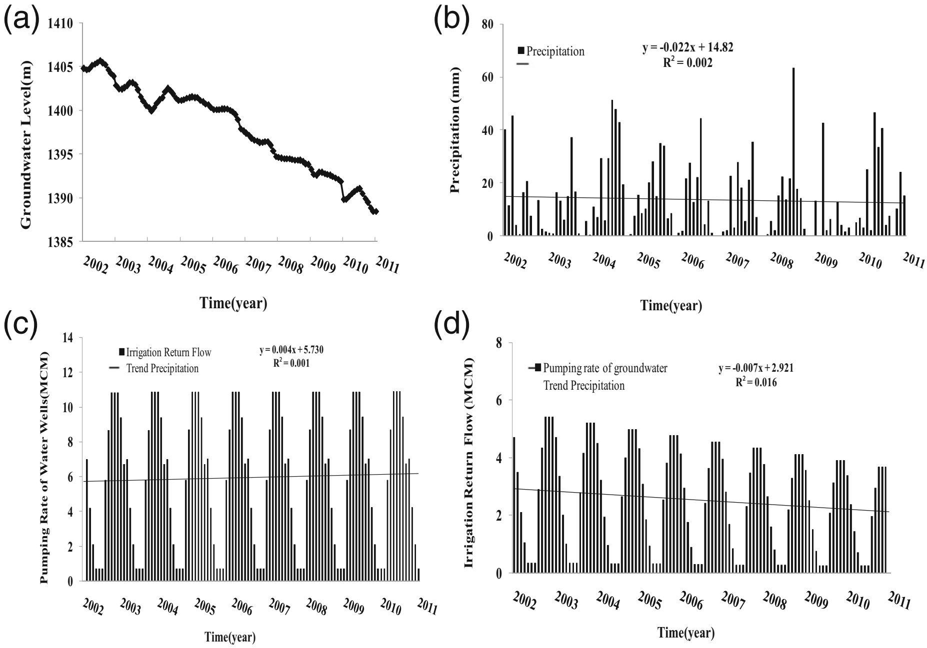

Fig. 2 **a** Groundwater level (m), **b** Precipitation (mm), **c** Pumping rate of water wells (MCM) and **d** Irrigation return flow (MCM) versus time (year) for the past 9 years in the Bastam Plain

groundwater levels drawdown, the study area can be divided to three zones with low, medium and high drawdown (see Fig. 1). The average water level drawdown over 9 years in these three zones is 1.6 m, 3.4 m and 16.4 m, respectively. In overall, the monitoring data show that the groundwater level in Bastam alluvial aquifer continuously declined from 2002 to 2011, falling averagely 8.6 m in 9 years. This constitutes a loss of 139 million m^3 (MCM) from the aquifer's stored groundwater reserve.

The pumping rate of water wells, irrigation returns flow and rainfall recharge (part of precipitation which infiltrated and joined to the groundwater) are used as input data for artificial models to predict groundwater level (GWL). The time series of data are shown in Table 1 and in Figs. 2 and 3.

Figure 2b shows monthly precipitation data at the meteorological station of Bastam Plain. The annual precipitation in the form of snow and rain is 163.3 mm; significantly less than the average annual precipitation of Iran (250 mm).

As the trend line in Fig. 2b shows it can be concluded that the average precipitation at the station has no noticeable changes for the past 9 years (2002– 2011). However, in the study area the contribution of snow from total precipitation has been reduced due to climate change in recent years.

For calculating rainfall recharge different formulas were presented by researchers such as Chaturvedi (1973); Kumar and Seethapathi (2002) and Contor (2004). In this study the formula of Contor (2004) is used as following:

$$\mathrm{R} = K \times P^N \tag{2}$$

Where R is recharge from precipitation (in feet per month), K is a dimensionless empirical slope parameter, P is precipitation (in feet per month), and N is dimensionless empirical

Table 1 Annual average groundwater level of the Bastam plain based on records for 17 piezometers, rainfall recharge, irrigation return flow and pumping rate of water wells

Rainfall Recharge (mm)	Irrigation Return Flow (MCM)	Pumping rate of water wells (MCM)	GWL (m asl)
3.46	2.99	5.98	1404.9
2.03	2.89	5.74	1402.3
6.04	2.77	5.51	1401.3
3.53	2.65	5.27	1401.1
3.08	2.53	5.03	1399.5
2.78	2.41	4.79	1396.3
3.97	2.29	4.55	1394.3
1.69	2.17	4.31	1392.6
4.52	2.05	4.07	1390.0

coefficient. The empirical parameters for three different soil types of lava rock (K=0.69, N=1.2), thin soil (K=0.463, N=1.5), and thick soil (K=0.136, N=2), where the units are in feet per month. The pumping rate of water wells and irrigation return flow are shown in Fig. 2c and d, respectively. The trend line in these figures obviously demonstrate that the average pumping rate of water wells has increased, but the irrigation return flow to Bastam Plain decreased for the past 9 years (2202–2011).

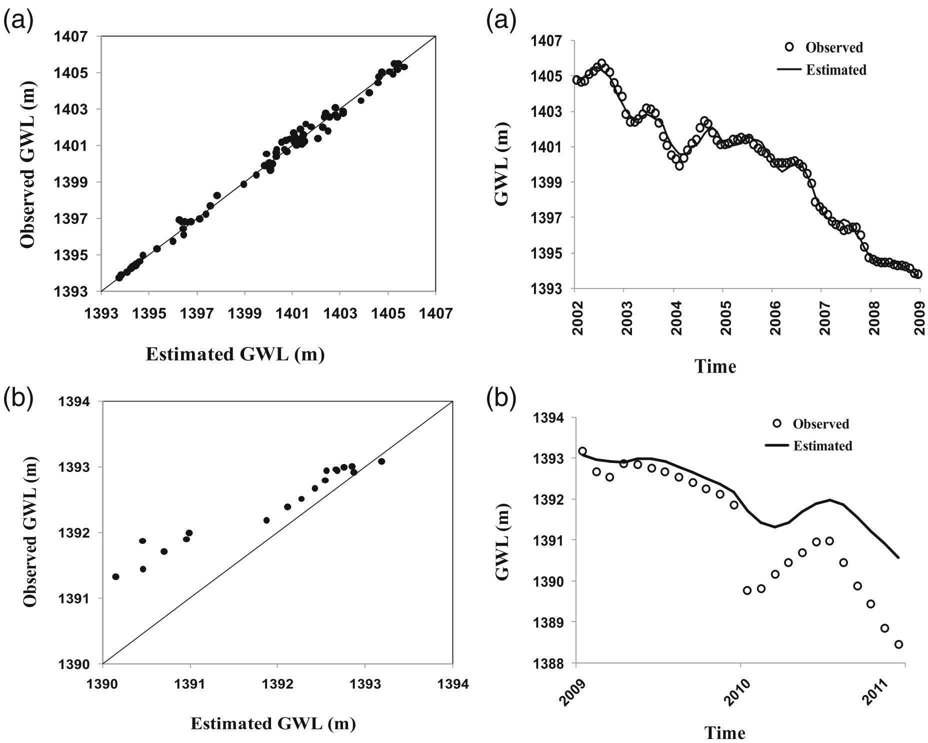

Fig. 3 Observed and estimated groundwater level from ANN model for (**a**) training and (**b**) testing stages

2.6 Methodology

In this study for training and testing of ANN and ANFIS models, monthly data have been used. In the ANN and ANFIS models, one of the most important steps in developing a satisfactory forecasting model is the selection of the input variables. Because, these variables determine the model structures and affect the weighted coefficient and the results of the modeling process. The input layers were the pumping rate of water wells, irrigation return flow and rainfall recharge, and the output layer was groundwater level (GWL). The homogeneity and reliability of the used data were controlled by the authorities before they were released.

The input data at different times t_0, t_{0-1}, t_{0-2}, t_{0-3}, t_{0-4} were used. In order to remove the periodicity present in the data, the standardization of data were done base on Eq.3. So the data are scaled to a limit between 0 and 1.

$$X_N = \frac{X - \overline{X}}{\sigma} \tag{3}$$

Where X_N is the normalized data, X is the value which we want to normalize, $\overline{X}$ is the mean value of the data and σ is the standard deviation of the data.

As the zone of high drawdown with area of 196.24 km^2 contains most area of Bastam Plain and most wells located in this region (see Fig. 1), therefore in this study this region considered for modeling. The average monthly groundwater level (GWL) of Bastam Plain which have been recorded in 17 piezometers for the past 9 years were determined by Thiessen polygon-weighting method. The whole data set includes 9 years (2002–2011) data points, which was divided into two parts of training and testing set with respectively 84 (2002–2009) and 24 (2009–2011) data points. The testing set was not used in the training step, thereby enables us to assess the performance of the models. In order to compare the performance of ANN and ANFIS configurations three statistical parameters were used in this research. These statistical parameters are the root mean square error (RMSE), mean absolute error (MAE) and the coefficient of determination, R^2, of the linear regression line between the predicted values from either the regression, ANN and ANFIS models and the desired output. These parameters are defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - \overline{Y_i}\right)^2}{n}} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n} \left|Y_i - \overline{Y_i}\right|}{n} \tag{5}$$

$$R^2 = 1 - \frac{\sum \left(Y_i - \overline{Y_i}\right)^2}{\sum Y_i^2 - \frac{\sum \overline{Y_i^2}}{n}} \tag{6}$$

Where n is the number of input samples, Y_i and $\overline{Y_i}$ are the predicted and observed (target) groundwater level (GWL), respectively. The R^2 shows the degree which two variables are linearly related. In this study Qnet 2000 and Matlab 7.1. (2005) (Mathworks Inc.) softwares are used in artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) analyses, respectively.

3 Results and Discussion

3.1 ANN Model

In addition to the selecting of input data which affect the performance of ANN model, selecting of the number of hidden nodes and the transfer function between nodes are also important. The number of neurons (nodes) in the input and output layers is generally simple because it is dictated by the number of model inputs and outputs and usually the choice of input data is based on the nature of the problem. Determining the optimum structure of the ANN model, especially selecting the number of layers and neurons (nodes) in the hidden layer (s) is one of the most important and difficult tasks (Baziar and Ghorbani 2011) and they are typically determined by trial-and-error (Eberhart and Dobbins 1990). In this study, the optimal structure was specified by changing the number of hidden nodes from 1 to 8 and picking the ANN structure which leads to the best results. The ANN training was stopped when maximum iterations of 100,000 were reached. A learning rate coefficient of α=0.01 and momentum factor of α=0.1 were used in this study. Also, the ANN model was run with different transfer functions including Sigmoid ($f(x)=1/1+\exp(-x)$), Gaussian ($f(x)=e^{-xx}$), Hyperbolic Tangent ($f(x)=\tanh(x)$) and Hyperbolic Secant ($f(x)=Sech(X)$).

For investigation of the effect of input data on the performance of ANN model, four lag times (t_{0-1}, t_{0-2}, t_{0-3}, t_{0-4}) were considered for data. The results show that the second time delay has the minimum RMSE and MAE values (RMSE=1.69 m and MAE=1.40 m) (see Table 2). Also the ANN model trained with different hidden layers and transfer functions. Comparison of results indicated that the ANN model with one hidden layer and transfer function of hyperbolic tangent gives the best results in training and testing stages (see Table 3). Fig. 3 shows the observed and estimated groundwater level in both training and testing stages. As displayed in this figure it is obvious that during the training stage, the ANN model estimate the GWL better than the testing stage.

As it shown in Fig. 3 the difference between observed and estimated groundwater level in first year (2009–2010) is less than second year (2010–2011). In other word, the ANN model with MAE, RMSE, and R^2 of 0.23 m, 0.25 m, and 0.89 in the first year predict better than

Table 2 Results of modeling from ANFIS model with different lag times

Lag time	Training			Testing		
	R^2	RMSE (m)	MAE (m)	R^2	RMSE (m)	MAE (m)
t	0.91	0.98	0.79	0.76	1.81	1.56
t-1	0.97	0.58	0.49	0.80	1.72	1.41
t-2	0.97	0.55	0.45	0.82	1.69	1.40
t-3	0.92	0.97	0.77	0.78	1.77	1.53
t-4	0.92	0.94	0.75	0.79	1.74	1.48

Table 3 Results of modeling with ANN model with different transfer function

No.	Transfer function	Training			Testing		
		R^2	RMSE (m)	MAE (m)	R^2	RMSE (m)	MAE (m)
1	Sig.	0.97	0.55	0.45	0.82	1.69	1.40
2	Gauss.	0.99	0.35	0.28	0.79	1.77	1.38
3	Tan. H.	0.99	0.36	0.28	0.83	1.06	1.00
4	Sec. H.	0.98	0.42	0.33	0.80	1.56	1.20

second year with MAE, RMSE, and R^2 of 1.47 m, 1.54 m, and 0.80. As the results show that the ANN model cannot to capture rapidly drop of GWL which occurred at the end of year 2009 (testing stage).

3.2 ANFIS Model

Same to ANN model, data with different lag times introduced to ANFIS model. The results indicated that the second lag time has the minimum RMSE and MAE (RMSE= 0.10 m and MAE=0.09 m for testing stage). Also, the performances of the ANFIS model with different input MFs, hybrid and back propagation learning algorithms, and also constant and linear output MFs, show that the best results were achieved when the input MFs were trapezoid by help of minimal aggregation method and the learning algorithm was hybrid, and the output MF was linear (R^2=0.96 and RMSE=0.02 m and MAE=0.01 m in correctness testing level) (see Table 4). Remarkably, the GWL estimates from ANFIS capture oscillations in observations in training stage, but its performance, same to ANN model, is not good in testing stage. This is also confirmed by the scatter plots (left panel) and sample-wise (right panel) in Fig. 4.

As can be seen from the Fig. 4, same to ANN model the prediction of ANFIS model in the first year (2009–2010) with MAE, RMSE, and R^2 of 0.18 m, 0.21 m, and 0.93 is better than second year (2010–2011) with MAE, RMSE, and R^2 of 0.39 m, 0.45 m, and 0.85. The main

Table 4 Results of modeling with ANFIS model with different transfer function

Number	Function	Training			Testing		
		R^2	RMSE (m)	MAE (m)	R^2	RMSE (m)	MAE (m)
1	Tri	0.99	0.01	0.009	0.89	0.10	0.09
2	Trap	0.99	0.01	0.007	0.96	0.02	0.01
3	Gbell	0.99	0.01	0.007	0.81	0.09	0.07
4	Gauss	0.99	0.01	0.007	0.85	0.10	0.08
5	Gauss2	0.99	0.009	0.007	0.47	0.15	0.12
6	Sig	0.99	0.01	0.009	0.81	0.09	0.07
7	Dsig	0.99	0.009	0.007	0.89	0.08	0.06
8	psig	0.99	0.009	0.007	0.89	0.08	0.06
9	Pi	0.99	0.01	0.008	0.9	0.05	0.03
10	S	0.99	0.01	0.008	0.88	0.07	0.05
11	Z	0.99	0.01	0.008	0.81	0.09	0.07

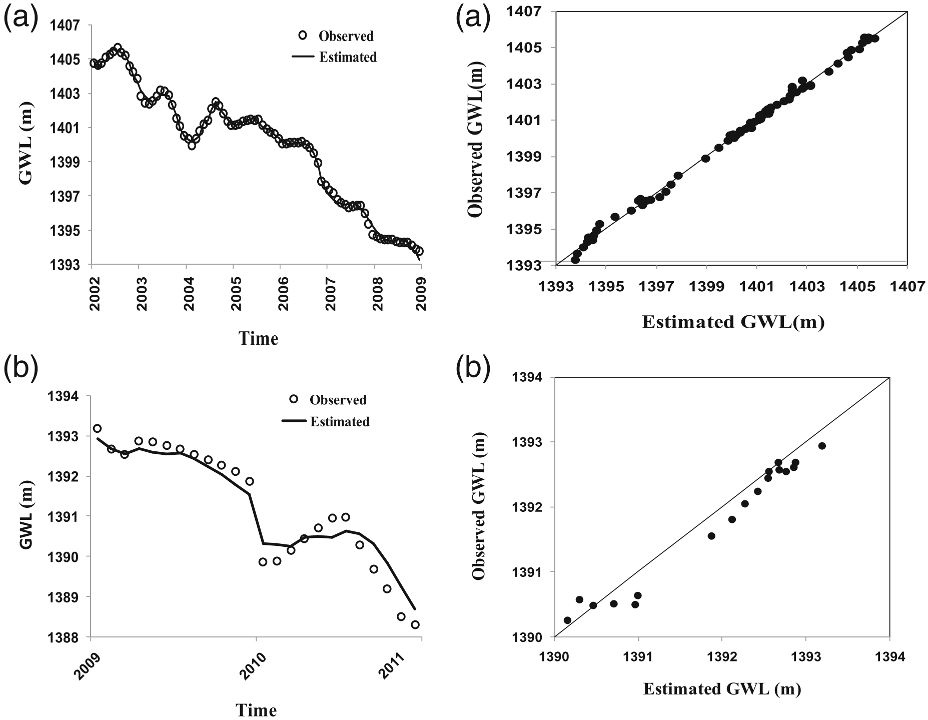

Fig. 4 Observed and estimated groundwater level from ANFIS model for (**a**) training and (**b**) testing stages

reason for that is as it mentioned in section 3.1, in the end of year 2009 the GWL rapidly dropped and therefore the ANFIS model can not to make proper fuzzy rules corresponding to dropping in the data set.

3.3 Comparing ANN and ANFIS

To assess the capability of ANN and ANFIS models in estimating GWL, their results are compared with each other. As the results of Table 3 shows the best ANN model estimated the groundwater level with R^2=0.83, RMSE=1.06 m, MAE=1.00 m in testing stage. Also the best ANFIS model predict the groundwater level with R^2= 0.96, RMSE=0.02 m and MAE=0.001 m (see Table 4). The comparison of results obtained from two models shows that the accuracy of these models decreased in second year (2010–2011) rather than first year (2009–2010). By using ANN and ANFIS models, the MAE (RMSE) reduced by 84.4 % (83.9 %) and 53.4 % (53.2 %) compared to first year. In overall, the comparison between ANN and ANFIS models show that the ANFIS model performs better than the ANN model in testing stage. The main reason is that ANFIS model integrates both neural networks and fuzzy logic principles; therefore it has potential to capture the benefits of both in a single framework. Therefore, the ANFIS model seem to be more adequate than the ANN model for the process of establishing a rating relationship between input data (the pumping rate of water wells, irrigation return flow and rainfall recharge) and GWL.

3.4 Predicting the Groundwater Level

After analyzing and selecting the best structure of ANFIS model, the groundwater level has been predicted for next 2 years. Three scenarios were used to predict the groundwater level as following:

1) The rainfall recharge (R) and pumping rate of water wells (P) will be constant in the next 2 years.
2) The rainfall recharge will be constant, but the pumping rate of water wells will be reduced equal to the water deficit of the aquifer (WD).
3) The pumping rate of water wells will be constant but the rainfall recharge will be reduced 30 %.

In the first scenario, when R and P are constant, the prediction shows that the groundwater level will be 1.8 m.

In the second scenario, the following formula is used to calculate the water deficit of the aquifer (WD):

$$S_y = \frac{\Delta V}{\Delta h.A} \tag{7}$$

Where S_y is the storage coefficient of the Plain (specific yield), ΔV (m^3) (or WD) is the water deficit of the aquifer or the water volume that is withdrawn from the aquifer, Δh (m) is the difference in head of the groundwater and A (m^2) is the area of Plain. Based on Eq.6 and considering specific yield equal to 0.04, the decreased water volume of the aquifer calculated 19 Mm^3/year. To make the minimum or to settle this rate, the pumping rate of water wells should be decreased up to 26 % in next 2 years. Prediction with this scenario (R=constant and P=WD) shows that the groundwater level will decrease 0.73 m.

Finally, in the third scenario, the groundwater level decreasing will be 2 m, respectively (see Fig. 5).

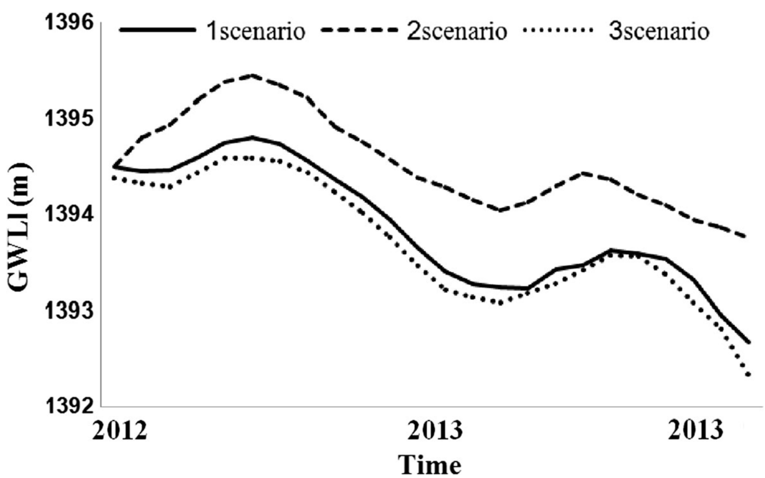

Fig. 5 Predicting the groundwater level with 3 scenarios

4 Conclusions

With respect to the importance of prediction groundwater level (GWL) in the study area (Bastam Plain, Iran), of Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models, based on their advantages, have been used to predict groundwater level (GWL).

Three input variables namely, rainfall recharge, irrigation returned flow, as well as pumping rates from water wells are used in ANN and ANFIS models to estimate GWL. The input data with four lag times introduced to models. Results show that whenever data are used with two lag times, the model has a maximum correlation coefficient and minimum RMSE and MAE. Also, it was found that both models give good results. RMSEs from the ANN and ANFIS models when trained with mentioned dataset were 0.36 m and 0.01 m. But the results of ANFIS better than ANN model. The results show that the applying ANFIS model with different structures has the most accuracy and less error when it used with trapezoidal membership functions and hybrid optimization method. So ANFIS model was used to predict groundwater in next 2 years using three scenarios. The results showed that the groundwater level has the minimum reduction when the pumping rate of water wells is equal to the water deficit of the aquifer.

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