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Application of Several Data-Driven Techniques for Predicting Groundwater Level

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Abstract In this study, several data-driven techniques including system identification, time series, and adaptive neuro-fuzzy inference system (ANFIS) models were applied to predict groundwater level for different forecasting period. The results showed that ANFIS models out-perform both time series and system identification models. ANFIS model in which preprocessed data using fuzzy interface system is used as input for artificial neural network (ANN) can cope with non-linear nature of time series so it can perform better than others. It was also demonstrated that all above mentioned approaches could model groundwater level for 1 and 2 months ahead appropriately but for 3 months ahead the performance of the models was not satisfactory.

Keywords Groundwater level prediction · System identification · Time series · ANFIS

1 Introduction

Groundwater is one of the main sources of water supply in rural, urban areas, in particular, arid and semi-arid regions has many advantages over surface water. Some of the most important advantages are: (I) it is usually reliable even in times of drought; (II) physically

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groundwater is generally clear, colorless with little or no suspended solids and has a relatively constant temperature; (III) it is very pure and free of organic matter. Studies conducted on groundwater levels reveal spatial and temporal information on aquifers and help planners to make appropriate decisions. Groundwater overexploitation is becoming a serious issue globally, especially in developing countries (Konikow and Kendy 2005). Prediction of groundwater level is one of the most important stages in sustainable yield of groundwater resources.

Among variety of techniques employed to predict groundwater level, time series models, system identification and artificial intelligence are very suitable in this field (Ahn 2000; Daliakopoulos et al. 2005; Wong et al. 2007). Time series models have an important place in literature in view of generating new sequence time series having same statistical parameters with observed time series and predicting future time series. The development of time series models consists of three phases: identification, estimation and diagnostic checking. Şen et al. (2000) used simple linear and periodic nonlinear models for modeling deterministic part of lake level time series and a second order Markov model for the remaining stochastic part. Irvine and Eberhardt (1992) developed multiplicative, seasonal ARIMA models for Erie and Ontario lakes using standardized, monthly mean level data for predicting 1, 2, 3 and 6 months ahead levels. But traditional methods such as the ARIMA or Box-Jenkins assume that a given time series is generated form an underlying linear process. Hence they may not always perform well when applied for modeling hydrological time series which are often nonlinear (Tokar and Johnson 1999). Vaziri (1997) used ANN and ARIMA models for predicting water surface levels in the Caspian Sea. The identification phase involves the determination of the differencing requirement for making a non-stationary time series, stationary, and the identification of the temporal structure of the model. Stationarity is a necessary condition for building an ARIMA model. In order to convert non-stationary to stationary, autocorrelation coefficient function (ACF) and Partial ACF (PACF) of the differenced time series are used to identify the temporal structure of the models (Han et al. 2010).

In system theory, the definition of an appropriate mathematical–physical representation of a dynamic system through transfer functions is called system identification (Erdoğan and Gulal 2009). System identification is an iterative process, where models are identified with different structures from data and the models performances are compared. The procedure is started by estimating the parameters of simple model structures. If the model performance is poor, the complexity of the model structure could be increased. Ultimately, the simplest model that describes the dynamics of the system well is chosen. A number of researches have been conducted using these models. Altunkaynak (2007) compared the performance of ANN models with the traditional ARMAX models in forecasting 1 month-ahead lake levels. Talei et al. (2010) tested several ARX models to select the best one in order to model rainfall-runoff process. Celik and Ertugrul (2010) also tested several Fuzzy-ARX to model human operators behavior.

Fuzzy logic is based on the concept of fuzzy sets. A fuzzy set is defined as a set without crisp or clear boundary. Unlike two-value Boolean logic, fuzzy logic is multi-valued and deals with degrees of membership and degrees of truth. Fuzzy logic uses any logical value from the set of real numbers between 0 (completely false) and 1 (completely true) which is known as its membership value and the function that represents such values is called a membership function.

A particular form of neuro-fuzzy systems is ANFIS which has shown significant results in modeling nonlinear functions (Jang et al. 1997). The ANFIS is a universal estimator and is able to approximate any real continuous function on a compact set to any degree of accuracy. The basic structure of the type of fuzzy inference system could be considered as a model that maps input characteristics to input membership functions. Then it maps input membership function to rules and rules to a set of output characteristics. Finally it maps output characteristics to output membership functions, and the output membership function to a single valued output or a decision associated with the output. Several researchers have used ANFIS in groundwater management field (Chu and Chang 2009; Firat et al. 2009). Nayak et al. (2004) proposed the application of ANFIS to hydrological time series modeling and specific application to model river flow of Baitarani River in Orissa state, Indiana. Vafakhah (2012) compared ANN, ANFIS and ARMA for 1 day, 2 day and 3 day-ahead streamflow forecasts in two hydrometry stations of Hajighoshan and Tamar on Gorgan River. The results showed that ANNs were found to be superior to the ANFIS and ARMA for 1 day, 2 day and 3 day ahead streamflow forecasts.

Amabile et al. (2008) fitted Time series models to SWAT simulated data and to historical records and showed that time series fitted to SWAT data for groundwater table depth have a good performance for forecasting this variable. Hasmida (2009) applied ARIMA model (parametric method) and Mann-Kendall test (non-parametric method) to analyze the water quality (NH4, turbidity, color, SS pH, Al, Mn and Fe.) and rainfall-runoff data for Johor River recorded for a long period. Pekarova et al. (2009) explored the long-term trends in water quality parameters of the Danube River at Bratislava, Slovakia (Chl-a, Ca, EC, SO42-, Cl-, O2, BOD5, N-tot, PO4-P, NO3-N, NO2-N, etc.), for the period 1991–2005. They applied Box-Jenkins models (with two regressors—discharge and water temperature) to simulate the extreme monthly water quality parameters.

Faruk (2010) described a hybrid neural network and ARIMA model for water quality prediction. They showed that the hybrid model provides strong modeling framework capable of capturing the nonlinear nature of the complex time series and thus producing more accurate predictions.

Hasebe and Nagayama (2002) compared between reservoir operation using the fuzzy and neural network systems. They showed that the fuzzy system is effective. Chang and Chang (2006) used the adaptive network-based fuzzy inference system (ANFIS) to build a prediction model for reservoir management in the Shihmen reservoir. They showed that the ANFIS could be used profitably and provide high accuracy and reliability for reservoir water level forecasting for future. Several other researchers evaluated the ability of ANNs to be used for reservoir modeling (Raman and Chandramouli 1996; Jain et al. 1999).

Luk et al. (2000) used ANNs to forecast short-term rainfall for an urban catchment. They showed that the ANNs could provide the most accurate predictions when an optimum number of spatial inputs were included into the network. Several other researches also demonstrated that ANNs are an efficient alternative to traditional methods (French et al. 1992; Grimes et al. 2003). Dalcin et al. (2005) used ARX models to appropriately compute the short term flow in rivers. Faruk (2010) applied a hybrid ARIMA and neural network, which consists of an ARIMA methodology and feed-forward, back-propagation network structure with an optimized conjugated training algorithm.

The aim of this study is to evaluate the performances of time series (ARMA, ARIMA, and SARIMA), fuzzy-time series, system identification (ARX, ARMAX), fuzzy-system identification and ANFIS models for 1-month, 2-month and 3-month-ahead ground water forecasts.

2 Materials and Methods

2.1 Study Area and Available Data

The study area is located in Mashhad plain, Khorasan Razavi province, Iran (Fig. 1). The study area extends between 59° 03′ to 59° 26′ E longitude and 36° 15′ to 36° 32′ N latitude and covers 112.32 km^2.

Location of piezometric wells, hydrometric stations, raingauge stations and climatologic stations are also showed in Fig. 1. The annual mean precipitation of Mashhad plain is 253 mm and the annual maximum and minimum temperatures are 35 C (in summer season) and 15 C (in winter season), respectively.

In this study, from the observed data for 15 years (from 1992 to 2007), the first 10 years data were used for training and the second 5 years data were used for validation.

In the first step, monthly total precipitation data were chosen as the input data according to the correlation matrix between monthly total precipitation, average monthly discharge and

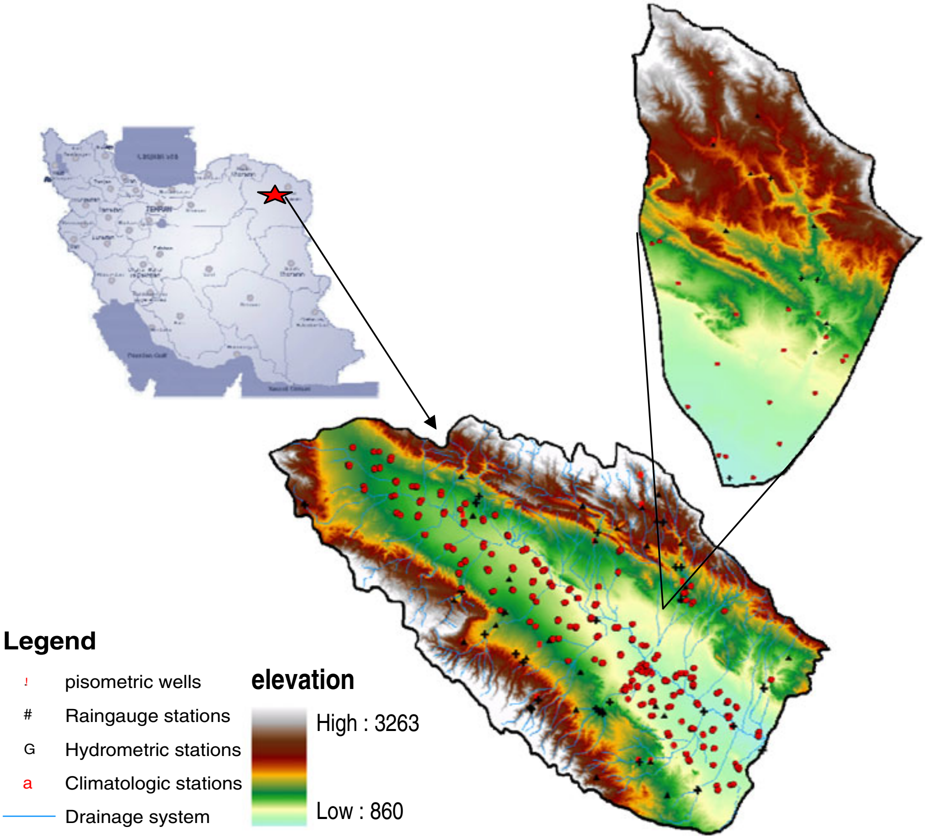

Fig. 1 Location of the study area in the Mashhad plain, Iran

average monthly evaporation. For data pre-processing, the data were normalized between 0 and 1 using Eq. 1.

$$x_n = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x_n is the normalized value of each data, x_i is the actual value of each data, xmin and xmax are the minimum and maximum values of the data set, respectively.

The correlation analysis of the data was employed for selecting appropriate input vectors to the time series, system identification and ANFIS models. The auto-correlation statistics and the corresponding 95 % confidence bands from lag-0 to lag-15 were estimated for the groundwater level time series as shown in Fig. 2. For the groundwater level time series, the partial auto-correlation function (PACF) indicated significant correlation up to lag-2 for this time series within the confidence limits. The rapid decaying pattern of the PACF confirmed the dominance of the autoregressive process relative to the moving average process. The partial auto-correlation coefficients suggested incorporating daily groundwater level data up to 2-

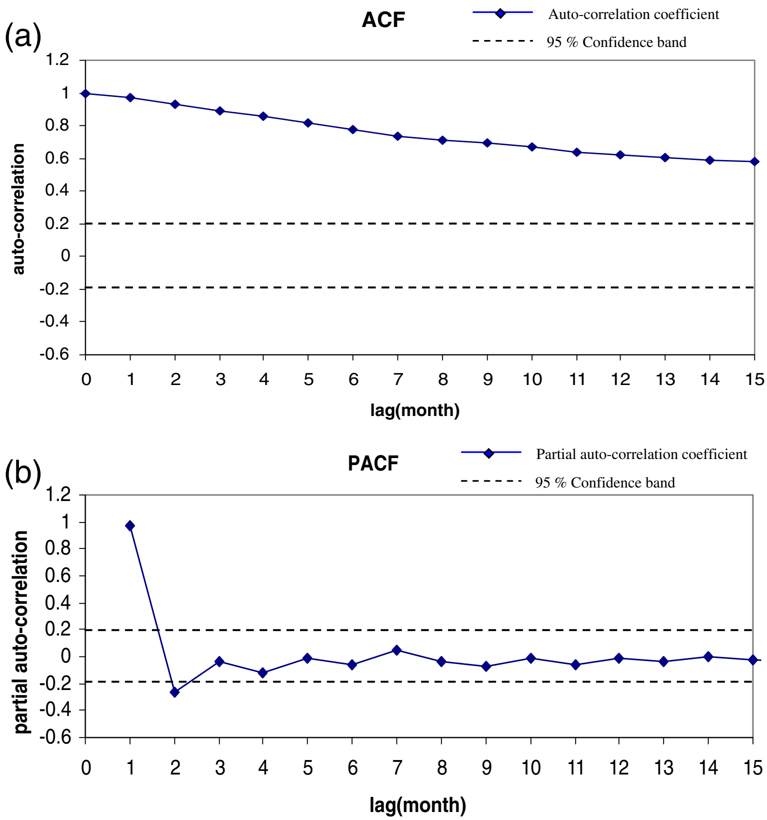

Fig. 2 **a** Auto-correlation and **b** partial auto-correlation functions of the monthly groundwater level time series

month lag in input vector to the time series, system identification and ANFIS models (Kisi 2010).

2.2 System Identification

2.2.1 ARX Model

In the ARX model structure, the output at a specific time is considered to be linear combinations of the previous outputs and inputs and the current input. A discrete-time designation of the ARX model is:

$$\begin{aligned} &y(t) + a_1 y(t-1) + \cdots + a_{n_a} y(t-na) = \\ &b_1 u(t-1) + \cdots + b_{nb} u(t-n_k-n_b+1) + e(t) \end{aligned} \tag{2}$$

where t represents integer time step, e(t) denotes the modeling error, y is the output, u is the input, ai's and bj's are model parameters to be estimated using the data and na, nb and nk are the orders of the output, input and input–output delay, respectively (Celik and Ertugrul 2010). In order to build ARX model, monthly total precipitation data were used as input for 1-month, 2-month and 3-month-ahead groundwater forecasts. In this study, linear parametric model was used as estimation model. Several delay orders were tested using trial and error procedure. The parameters of na, nb and nk vary from 0 to 9 (Talei et al. 2010).

2.2.2 ARMAX Model

All of the modeling steps in ARMAX are similar to ARX but for the delay orders. The ARMAX model is defined as follows:

$$\begin{aligned} &y(t) + a_1 y(t-1) + \cdots + a_{n_a} y(t-na) = \\ &b_1 u(t-nk) + \ldots + b_{n_b} u(t-nk-nb+1) + \\ &\cdots + c_1 e(t-1) + \ldots + c_{n_c} e(t-nc) + e(t) \end{aligned} \tag{3}$$

where y(t) is the output at time t, ai's and bj's are model parameters to be estimated using the data, na is the number poles of the system, nb is the number of the zeros of the system, nc is the number of previous error terms on which the current output depends and nk is the number of input samples that occur before the inputs affect the current output (Celik and Ertugrul 2010). The zeros and the poles are equivalent ways of describing the coefficients of the model. The poles relate to the "output-side" and the zeros relate to the "input-side" of this equation. The number of poles (zeros) is equal to number of sampling intervals between the most and least delayed output (input) (Ljung 1995). Similar to ARX model in order to build ARMAX model, monthly total precipitation data were used as input to 1-month, 2-month and 3-month ahead groundwater level forecasts. Also linear parametric model was employed as estimation model. Several delay orders were tested using a trial and error procedure. The parameters of na, nb, nc and nk vary from 0 to 9 (Talei et al. 2010).

2.3 Time Series Models

2.3.1 ARMA Model

Autoregressive moving average (ARMA) model which is indicated by ARMA (p, q) can be expressed as:

$$y_t = \delta + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \phi_j e_{t-j} + e_t \tag{4}$$

where δ is the constant term of the ARMA model, φi indicates the i^{th} autoregressive coefficient, Φj is the j^{th} moving average coefficient, et shows the error term at time period t, and *yt* refers the value of groundwater level observed or forecasted at time period t (Erdem and Shi 2011). In this study, groundwater level time series were used for 1-month, 2-month and 3-month-ahead forecasts of groundwater level.

2.3.2 ARIMA and SARIMA Models

Autoregressive integrated moving average (ARIMA) models are one of the most important linear models for time series forecasting. ARIMA models have been originated from the combination of autoregressive models (AR) and the moving average models (MA). ARIMA fits a Box-Jenkins ARIMA model to a time series. ARIMA is used to model time series behavior and to generate forecasts. ARIMA modeling uses correlational techniques and can be used to model patterns that may not be visible in plotted data (Box et al. 2008). In ARIMA, the future value of a variable is assumed to be a linear function of several past observations and random errors. An SARIMA model can be explained as ARIMA (p, d, q) (P, D, Q)s, where (p, d, q) is the non-seasonal part of the model and (P, D, Q)s is the seasonal part of the model in which p is the order of non-seasonal auto-regression, d is the number of regular differencing, q is the order of non-seasonal MA, P is the order of seasonal auto-regression, D is the number of seasonal differencing, Q is the order of seasonal MA, and s is the length of season (Faruk 2010).

2.4 Hybrid Models

In this step data were updated using a fuzzy interface system. Zadeh (1965) first introduced the concepts of the fuzzy logic and pioneered its development. The fuzzy concepts and operational algorithms are given in many textbooks such as Kosko (1993) and Ross (1995). Fuzzy logic allows for something to be partly this and partly that, rather than having to be either all this or all that (Kisi 2009). The degree of “belongingness” to a set or category can be described numerically by a membership number between 0 and 1 (Russel and Campbell 1996). So the updated data were used as input for the best mentioned model. A Fuzzy Inference System (FIS) includes four steps: (1) fuzzification of the input variables, (2) evaluation of the output for each rule, (3) aggregation of the rules’ outputs, and (4) defuzzification which can be done by different approaches like the Center of Area (COA) and Mean of Maximums (MOM) (Talei et al. 2010). In this study several membership functions such as Triangular, Gaussian and Bell-shaped were tested and imported to the models as input data.

2.5 ANFIS Model

This model was trained and tested using the same data sets as those were used in system identification models. There is not any basic rule to determine the number of membership functions (MFs) of ANFIS models and they usually determined by trial and error. To select the number of MFs, a modeler should avoid using a large number of membership functions or parameters to save time and calculation effort (Keskin et al. 2004). Four different types of membership function (MF) were tested in this study, i.e. gaussian (MFgauss), bell-shaped (MFgbell), triangular (MFtri), and spline-based (MFpi), or piduetoits shape (Jang 1993). ANFIS models with different types of MF were run with 2, 3, 4, and 5 MFs and with 500, 1,000, 1,500, 2,000, 2,500, 3,000 and 4,000 iterations for each node of input data (Rajaee 2011).

2.6 Performance Evaluation of Models

Coefficient of determination (R^2) and root mean squared error (RMSE) were used to evaluate the performances of models and select the best one.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_o - y_e)^2}{\sum_{i=1}^{N} (y_o - y_o)^2} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_o - y_e)^2}{N}} \tag{6}$$

where y_o, y_e and N, are observed groundwater level, estimated groundwater level and number of data, respectively.

$$AIC(k) = n \ln(MSE) + 2k \tag{7}$$

where N is the number of data points (for calibration), and k is the number of free parameters used in models. MSE stands for mean square error. The Akaike information criteria (AIC) were used for selecting the best time series model (Akaike 1974). In brief, the models' predictions are optimum if R^2, RMSE and AIC are found to be close to 1, 0, and 0, respectively. The higher the R^2 value (with 1 being the maximum value) and he lower the RMSE and ACI values (with 0 being the minimum value) the better is the performance of the model.

Table 1 System identification models

Models	L_{t+1}	L_{t+2}	L_{t+3}
ARX	(9 6 0)	(9 6 0)	(7 9 5)
ARMAX	(4 9 2 6)	(4 9 2 5)	(4 9 2 5)
Fuzzy-ARX	(9 2 6)	(7 9 5)	(7 9 5)
Fuzzy-ARMAX	(4 9 2 5)	(4 9 2 6)	(4 9 2 6)

Table 2 R^2 and RMSE for different system identification models with the best orders for different time step predictions (Verification data set)

Models	Time step prediction					
	L_{t+1}		L_{t+2}		L_{t+3}	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
ARX	0.78	2.556	0.77	2.697	0.75	2.993
ARMAX	0.87	0.927	0.85	1.020	0.80	1.112
Fuzzy- ARX	0.91	0.765	0.89	0.910	0.84	1.021
Fuzzy- ARMAX	0.85	1.021	0.83	1.330	0.79	1.524

2.7 Sensitivity Analysis

The purpose of sensitivity analysis is to analyze the response of the model dynamics to a variation in the values of some parameters (Park et al. 2007). Sensitivity analysis is performed by modifying the parameter values, one across its entire range at a time, while holding all other input values constant (Shu et al. 2007). In this study, it was performed related to the number of observation data points (piezometric wells) and the length of the observation period (15 years) for the best models of each category for the 1 month ahead time step. Then the profile plots, showing the effect of the parameters on the models performance criteria, were constructed decreasing the observation data points and the length of the observation period while all other variables are held constant.

3 Results and Discussion

3.1 System Identification and Fuzzy-System Identification

In this study, several ARX and ARMAX as system identification models and hybrid Fuzzy-system identification models were tested to forecast groundwater level. Table 1 shows the best models of ARX and ARMAX chosen in this research. Table 2 shows R^2 and RMSE for different system identification models with the best orders for different period-ahead forecasts for validation data set. As it is understandable from Table 2 Fuzzy-ARMAX out-performed other models in order to forecast groundwater level. The best Fuzzy-ARMAX model for 1-month ahead forecast was (4-9-2-5). It can be shown that data preprocessing by using a fuzzy interface system can improve the ability of system identification models. ARMAX also out-performs ARX model.

Table 3 Time series models

Models	L_{t+1}
ARMA	(1 1)
ARIMA	(3 1 3)
SARIMA	(3 1 0)(5 0 1)
Fuzzy-ARMA	(1 1)
Fuzzy-ARIMA	(3 1 3)
Fuzzy-SARIMA	(3 1 0)(5 0 1)

Table 4 R^2 RMSE and AIC for different Time series models with the best orders. (Verification data set)

Models	Time step prediction		
	L_{t+1}		
	R^2	RMSE	AIC
ARMA	0.63	2.991	201.3
ARIMA	0.75	2.543	174
SARIMA	0.77	1.843	122.1
Fuzzy-ARMA	0.80	1.448	70.6
Fuzzy-ARIMA	0.86	0.995	5.1
Fuzzy-SARIMA	0.89	0.953	3.3

It is also understandable that all these models can forecast groundwater level for 1 and 2 month ahead better than 3 months ahead. The model performance was decreased dramatically for 3-month-ahead forecasts. The order of system identification models from the aspect of performance is as follow: Fuzzy-ARMAX, Fuzzy-ARX, ARMAX and ARX, respectively.

3.2 Time Series and Fuzzy-Time Series Models

In this study, three models of ARMA, ARIMA and SARIMA were tested as time series models and hybrid fuzzy-time series models. Tables 3 and 4 show the best time series models and R^2, RMSE and AIC for different time series models with the best orders for validation data set, respectively. As it is obvious from these tables, fuzzy-SARIMA model out-performs other models. It is also clear that ARIMA model performs better than ARMA models to forecast groundwater level 1- month-ahead. The order of time series models from the aspect of performance is as follow: Fuzzy-SARIMA, Fuzzy-ARIMA, Fuzzy-ARMA, SARIMA, ARIMA and ARMA, respectively.

3.3 ANFIS Model

Table 5 shows the results obtained from employing ANFIS models with the best number of membership functions (i.e. 5 MFs), for the best iteration (i.e. 4,000), and

Table 5 Results of ANFIS models with the best number of membership functions (5 MF), the best iteration (2000), and different time step predictions (Verification data set)

Membership Function	Time step prediction					
	L_{t+1}		L_{t+2}		L_{t+3}	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
MF_{gauss}	0.94	0.595	0.92	0.621	0.89	0.996
MF_{gbell}	0.95	0.529	0.93	0.633	0.89	0.953
MF_{pi}	0.92	0.570	0.90	0.697	0.86	1.043
MF_{tri}	0.90	0.589	0.90	0.683	0.85	1.173

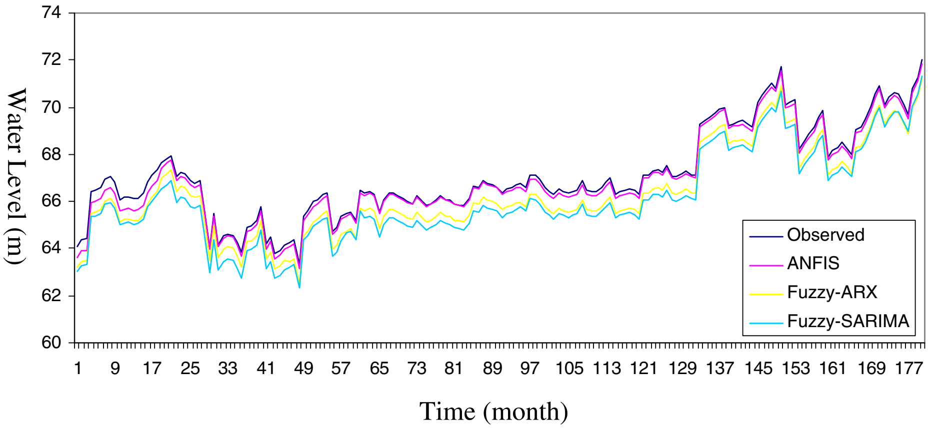

Fig. 3 The best models predictions versus observed data

for the different period ahead forecasts. As shown in this table, the best membership type selected is bell-shaped. Similar to other aforementioned models, ANFIS models forecasted groundwater level for 1-month and 2- month ahead appropriately, but for 3-month-ahead forecast, the efficiency criteria were not satisfactory.

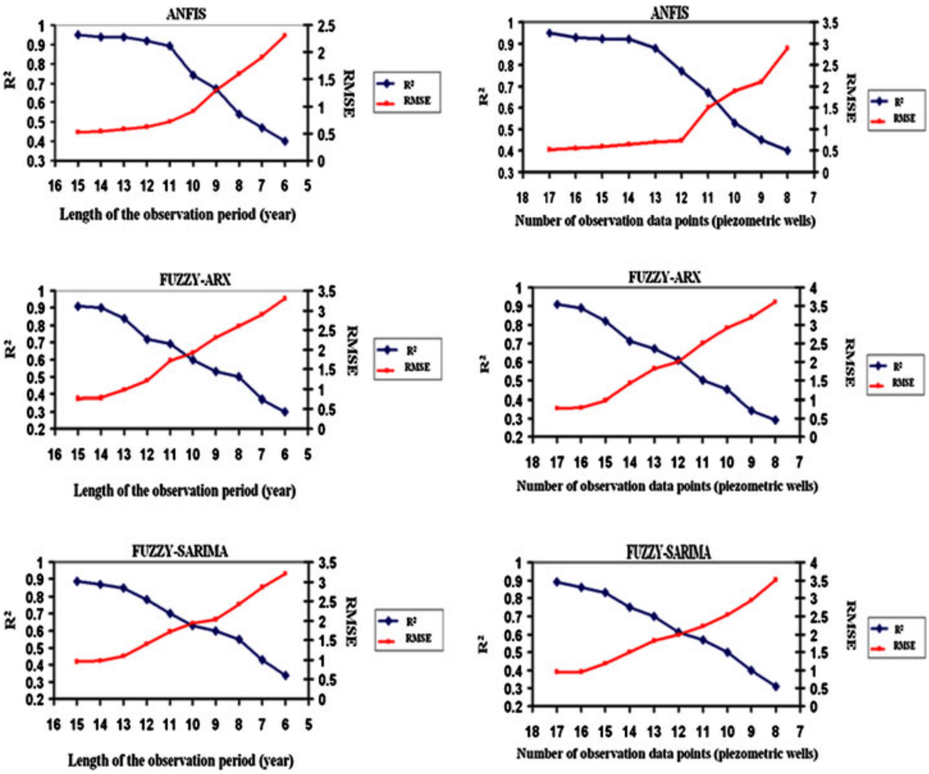

Fig. 4 Sensitivity analysis of the best models related to the number of observation data points and the length of the observation period

In general, ANFIS performs more efficiently than time series and system identification models. The reason for this may be related to the combination of fuzzification of the input through membership functions and artificial neural network. Figure 3 shows the observed groundwater levels versus predicted groundwater levels using the best models. These results are consistent with Talebizadeh and Moridnejad (2011) and Yarar et al. (2009) results.

3.4 Sensitivity Analysis

Figure 4 shows that in each model, the RMSE increases and R^2 decreases by decreasing the observation period. In the ANFIS model, when the observation period decreases to 11 years, the RMSE increases and R^2 decreases sharply. It means that the observation period less than 11 years is not satisfactory for ANFIS model. This value for Fuzzy-ARX is to 12 years. It means that the observation period less than 12 years is not satisfactory for Fuzzy-ARX and Fuzzy-ARIMA models. It can be concluded that Fuzzy-ARX and Fuzzy-ARIMA models are more sensitive than ANFIS model in the case of observation period.

Figure 4 also shows that in each model, the RMSE increases and R^2 decreases by decreasing the number of observation data points (piezometric wells). In the ANFIS model, when the number of observation data points decreases to 13 piezometric wells, the RMSE increases and R^2 decreases very sharply. It means that the number of piezometric wells less than 13 is not acceptable for ANFIS model. This value for Fuzzy-ARX and Fuzzy-ARIMA models is to 15 wells. It means that the number of piezometric wells less than 15 is not agreeable for Fuzzy-ARX and Fuzzy-ARIMA models. It can be also concluded that Fuzzy-ARX and Fuzzy-ARIMA models are significantly more sensitive rather than ANFIS model in the case of the number of observation data points.

4 Conclusions

In this study, several data-driven techniques including time series models, system identification models and ANFIS were tested and evaluated in order to groundwater level forecasting on the basis of performance criteria. It was demonstrated that system identification performed better than time series.

The obtained results also showed that ANFIS outperformed all other models. It may be related to the combined effect of fuzzification of the input through membership functions and the ability of ANNs. Because the data were first fuzzified and then fed to the ANN model and neural network modeling have been performed on the fuzzified data so, the ability of these modeling approach have been improved. The greatest advantage of a neural network is its ability to model complex nonlinear relationship without a priori assumptions of the nature of the relationship like a black box. It develops a fuzzy expert system that is more transparent to the user and also less likely to produce memorization errors than a neural network. Furthermore, ANFIS keeps the advantages of a fuzzy expert system, while removing (or at least reducing) the need for an expert.

Also, it can be mentioned that both time series models may be unable to cope with the non linearity behavior of data because of their non linear nature. An important direction for future work is the use of hybrid wavelet-time series and wavelet-system identification models in order to improve the ability of these methods.

References

Ahn H (2000) Modeling of groundwater heads based on second-order difference time series models. J Hydrol 234(1–2):82–94
Akaike H (1974) A new look at the statistical model identification. Autom Control IEEE Trans 19(6):716–723. doi:10.1109/tac.1974.1100705
Altunkaynak A (2007) Forecasting surface water level fluctuations of lake Van by artificial neural networks. Water Resour Manage 21(2):399–408. doi:10.1007/s11269-006-9022-6
Amabile V, Gabriel G, Bernard AE (2008) Fitting of time series models to forecast streamflow and groundwater using simulated data from SWAT. J Hydrol Eng 13(7):554–562
Box GEP, Jenkins GM, Reinsel GC (2008) Time Series Analysis: Forecasting and Control. Holden Day
Celik O, Ertugrul S (2010) Predictive human operator model to be utilized as a controller using linear, neuro-fuzzy and fuzzy-ARX modeling techniques. Eng Appl Artif Intell 23(4):595–603. doi:10.1016/j.engappai.2009.08.007
Chang FJ, Chang YT (2006) Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. Adv Water Resour 29:1–10
Chu H-J, Chang L-C (2009) Application of optimal control and fuzzy theory for dynamic groundwater remediation design. Water Resour Manage 23(4):647–660. doi:10.1007/s11269-008-9293-1
Dalcin C, Moens WL, Dierickx PH, Bastin G, Zech Y (2005) An integrated approach for real time flood map forecasting on the Belgian Meuse River. Nat Hazard 36:237–256
Daliakopoulos IN, Coulibaly P, Tsanis IK (2005) Groundwater level forecasting using artificial neural networks. J Hydrol 309(1–4):229–240
Erdem E, Shi J (2011) ARMA based approaches for forecasting the tuple of wind speed and direction. Appl Energy 88(4):1405–1414
Erdoğan H, Gulal E (2009) Identification of dynamic systems using Multiple Input–Single Output (MISO) models. Nonlinear Anal: Real World Appl 10(2):1183–1196
Faruk D (2010) A hybrid neural network and ARIMA model for water quality time series prediction. Eng Appl Artif Intel 23(4):586–594
Firat M, Turan ME, Yurdusev MA (2009) Comparative analysis of fuzzy inference systems for water consumption time series prediction. J Hydrol 374(3–4):235–241
French MN, Krajewski WF, Cuykendall RR (1992) Rainfall forecasting in space and time using a neural network. J Hydrol (137):1–31
Grimes DIF, Coppola E, Verdecchia M, Visconti G (2003) A neural network approach to real time rainfall estimation for Africa using Satellite data. J Hydro Meteorol (4): 1119–1133
Han P, Wang PX, Zang SY, De Hai Z (2010) Drought forecasting based on the remote sensing data using ARIMA models. Math Comput Model 51:1398–1403
Hasebe M, Nagayama Y (2002) Reservoir operation using the neural Network and fuzzy systems for dam control and operation support. Adv Eng Softw 33(5):245–260
Hasmida H (2009) Water quality trend at the upper part of johor river in relation to rainfall and runoff pattern. MS thesis, Faculty of Civil Engineeing, Universitiy Teknologi, Malaysia
Irvine KN, Eberhardt AJ (1992) Multiplicative, seasonal ARIMA models for Lake Erieand Lake Ontario water levels. JAWRA J Am Water Resour Assoc 28(2):385–396. doi:10.1111/j.1752-1688.1992.tb04004.x
Jain SK, Das A, Srivastava DK (1999) Application of ANN for Reservoir in flow prediction and operation. J Water Resour Plan Manage 125(5):263–271
Jang JSR (1993) ANFIS: adaptive-network-based fuzzy inference system. Syst Man Cybern IEEE Trans 23(3):665–685. doi:10.1109/21.256541
Jang JSR, Sun CT, Mizutani E (1997) Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence. Prentice-Hall, Eaglewood cliffs. doi:10.1109/tac.1997.633847
Keskin ME, Terzi Ö, Taylan D (2004) Fuzzy logic model approaches to daily pan evaporation estimation in western Turkey/Estimation de l'évaporation journalière du bac dans l'Ouest de la Turquie par des modèles à base de logique floue. Hydrol Sci J 49(6):1001–1010. doi:10.1623/hysj.49.6.1001.55718
Kisi O (2009) Neural networks and wavelet conjunction model for intermittent streamflow forecasting. J Hydrol Eng 14(8):773–782

Kisi O (2010) Wavelet regression model for short-term streamflow forecasting. J Hydrol 389(3–4):344–353
Konikow LF, Kendy E (2005) Groundwater depletion: A global problem. Hydrogeol J 13(1):317–320. doi:10.1007/s10040-004-0411-8
Kosko B (1993) Fuzzy Thinking: The New Science of Fuzzy Logic. Flamingo
Ljung L (1995) System identification toolbox. MathWorks, Inc. pp:274
Luk KC, Ball JE, Sharma A (2000) A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting. J Hydrol 227(1–4):56–65
Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS (2004) A neuro-fuzzy computing technique for modeling hydrological time series. J Hydrol 291(1–2):52–66
Park YS, Rabinovich J, Lek S (2007) Sensitivity analysis and stability patterns of two-species pest models using artificial neural networks. Ecol Model 204:427–438
Pekarova P, Onderka M, Pekar J, Roncak P, Miklane KP (2009) Prediction of water quality in the Danube River under extreme hydrological and temperature condition. J Hydrol Hydromechanics 57(1):3–15
Rajaee T (2011) Wavelet and ANN combination model for prediction of daily suspended sediment load in rivers. Sci Total Environ 409(15):2917–2928
Raman H, Chandramouli V (1996) Deriving a general operating policy for reservoirs using neural network. J Water Resour Plan Manage 122(5):342–347
Ross TJ (1995) Fuzzy Logic with Engineering Applications. Willy
Russel SO, Campbell PF (1996) Reservoir operating rules with fuzzy programming. J Water Resour Plan Manag ASCE 122(3):165–170
Şen Z, Kadioğlu M, Batur E (2000) Stochastic modeling of the Van Lake monthly level fluctuations in Turkey. Theor Appl Climatol 65(1):99–110. doi:10.1007/s007040050007
Shu LC, Wang MM, Liu RG, Chen GH (2007) Sensitivity analysis of parameters in numerical simulation of groundwater. J Hohai Univ (Nat Sci) 35(5):491–495
Talebizadeh M, Moridnejad A (2011) Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models. Expert Syst Appl 38(4):4126–4135
Talei A, Chua LHC, Wong TSW (2010) Evaluation of rainfall and discharge inputs used by Adaptive Network-based Fuzzy Inference System (ANFIS) in rainfall–runoff modeling. J Hydrol 391:248–262
Tokar AS, Johnson PA (1999) Rainfall-runoff modeling using artificial neural networks. J Hydrol Eng ASCE 4(3):232–239
Vafakhah M (2012) Application of artificial neural networks and adaptive neuro-fuzzy inference system models to short-term streamflow forecasting. Can J Civ Eng 39(4):402–414. doi:10.1139/l2012-011
Vaziri M (1997) Predicting Caspian Sea surface water level by ANN and ARIMA models. ASCE J Waterw Port Coast Ocean Eng 123(4):158–162
Wong H, W-c I, Zhang R, Xia J (2007) Non-parametric time series models for hydrological forecasting. J Hydrol 332(3–4):337–347
Yarar A, Onucyıldız M, Copty NK (2009) Modelling level change in lakes using neuro-fuzzy and artificial neural networks. J Hydrol 365(3–4):329–334
Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353