

## Comparison study of artificial intelligence method for short term groundwater level prediction in the northeast Gachsaran unconfined aquifer

Akbar Khedri, Nasrollah Kalantari and Meysam Vadiati

### ABSTRACT

Accurate and reliable groundwater level prediction is an important issue in groundwater resource management. The objective of this research is to compare groundwater level prediction of several data-driven models for different prediction periods. Five different data-driven methods are compared to evaluate their performances to predict groundwater levels with 1-, 2- and 3-month lead times. The four quantitative standard statistical performance evaluation measures showed that while all models could provide acceptable predictions of groundwater level, the least square support vector machine (LSSVM) model was the most accurate. We developed a set of input combinations based on different levels of groundwater, total precipitation, average temperature and total evapotranspiration at monthly intervals. For each model, the antecedent inputs that included  $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ,  $T_t$ ,  $ET_t$ ,  $P_t$ ,  $P_{t-1}$  produced the best-fit model for 1-month lead time. The coefficient of determination ( $R^2$ ) and the root mean square error (RMSE) were calculated as 0.99%, 1.05 meters for the train data set, and 95%, 2.3 meters for the test data set, respectively. It was also demonstrated that many combinations the above-mentioned approaches could model groundwater levels for 1 and 2 months ahead appropriately, but for 3 months ahead the performance of the models was not satisfactory.

**Key words** | data-driven methods, fuzzy logic, groundwater level prediction, group method of data handling, support vector machine

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### INTRODUCTION

The nature of groundwater level variation is highly non-linear and depends on the interaction of variable factors such as precipitation, evapotranspiration, soil characteristics and watershed topography (Suryanarayana *et al.* 2014). The existence of these factors has complicated the task of groundwater level prediction. A review of the literature shows that there are two main approaches used in groundwater level prediction, namely data-driven models and numerical models. Classical numerical models such as MODFLOW, FEFLOW and GMS (groundwater modeling system) require costly hydrogeological, meteorological, geomorphological and geophysical input data, which may not

always be available (Movahedian *et al.* 2016). One of the advantages of data-based models over classical numerical models is that they require fewer assumptions about the underlying and usually complex mechanisms used in the formula of numerical models (Yoon *et al.* 2011). Furthermore, classical numerical methods tend to have greater uncertainty due to data inaccuracy, high data requirements and costs, and limited hydrogeological parameters used in groundwater simulation and geological heterogeneity within a model grid (Mohanty *et al.* 2015). Recent studies have indicated that data-driven models could be useful in evaluating the uncertainty, vagueness, variability and

complexities inherent in water resources and environmental management problems.

Over the past few decades, artificial intelligence (AI) methods have been widely used in a variety of applications in water resources studies. Many studies also applied a combination of different AI methods including artificial neural network (ANN), fuzzy logic (FL), adaptive neuro fuzzy inference system (ANFIS), group method of data handling (GMDH) and least squares support vector machine (LSSVM) for groundwater level prediction (Shirmohammadi et al. 2013; Suryanarayana et al. 2014; Mirzavand et al. 2015; Mohanty et al. 2015). For example, ANN models have been used in groundwater level prediction (Coulibaly et al. 2001) and ANFIS has attracted significant interest among engineers in groundwater level modeling (Shirmohammadi et al. 2013; Emamgholizadeh et al. 2014; Nourani & Mousavi 2016). There are only a few applications of GMDH for modeling environmental systems (Samsudin et al. 2010). Several researchers have also reported the successful application of the LSSVM approach for groundwater level prediction (Yoon et al. 2011; Mirzavand et al. 2015).

Using historical hydrometeorological data (e.g. groundwater level, rainfall, river stage and temperature data), Coulibaly et al. (2001) compared the performance of three

different ANN models in order to predict groundwater level. Similarly, Daliakopoulos et al. (2005) evaluated the performance of several types of ANNs and training algorithms in predicting monthly groundwater level fluctuations in an aquifer in the Messara Valley, Crete. Nourani & Mousavi (2016) presented a hybrid artificial intelligence-meshless model for spatiotemporal groundwater level modeling. Using this model, the time series of groundwater levels observed in different piezometers were first de-noised using a threshold-based wavelet method, and the effect of de-noised and noisy data was compared in temporal groundwater level modeling using ANN and ANFIS. It was found that the accuracy of the ANFIS radial basis function (RBF) model was more reliable than that of the ANN-RBF model in both calibration and validation steps. The applications of AI models to predict groundwater levels are categorized in Table 1.

Comparing the performance of different AI models in groundwater level studies is also an active area of research. Gill et al. (2007) compared the performance of ANN with support vector machine (SVM) in groundwater-level prediction under missing data or incomplete data conditions. In general, the potential of the SVM model was superior to the ANN model for input combinations. Moreover, Yoon et al. (2011) developed two nonlinear time-series models for

**Table 1** | Past applications of AI models to predict groundwater level

References	Models					Input variables	Lead time	Time interval
	ANN based	FL	ANFIS	GMDH	LSSVM			
Coulibaly et al. (2001)	✓					H, P, Q, T	$H_{t+1}, H_{t+2}, H_{t+3}$	Monthly
Daliakopoulos et al. (2005)	✓					H, P, Q, T	$H_{t+1}$	Monthly
Gill et al. (2007)	✓				✓	H, P, D	$H_{t+1}, H_{t+2}, H_{t+3}, H_{t+4}$	Weekly
Yoon et al. (2011)	✓				✓	H, P, TL	$H_{t+1}, H_{t+2}, H_{t+4}, H_{t+6}, H_{t+8}$	Hourly
Shiri et al. (2013)	✓		✓		✓	H, P, ET	$H_{t+1}, H_{t+2} \dots H_{t+8}$	Daily
Shirmohammadi et al. (2013)	✓	✓	✓			H, P, E, D	$H_{t+1}, H_{t+2}, H_{t+3}$	Monthly
Emamgholizadeh et al. (2014)	✓		✓			P, D, IR	$H_{t+1}$	Monthly
Mirzavand et al. (2015)	✓		✓			P, D, E, Q, S	H	Monthly
Mohanty et al. (2015)	✓					H, P, ET, Q, D	$H_{t+1}, H_{t+2}, H_{t+3}, H_{t+4}$	Weekly
Nourani & Mousavi (2016)	✓		✓			H, P, Q	$H_{t+1}$	Monthly
Current study	✓	✓	✓	✓	✓	H, T, ET, P	$H_{t+1}, H_{t+2}, H_{t+3}$	Monthly

Models: ANN, Artificial Neural Network; FL, Fuzzy Logic; ANFIS, Adaptive Neuro Fuzzy Inference System; GMDH, Group Method of Data Handling; LSSVM, Least Square Support Vector Machines.

Input variables: H, Groundwater Level; P, Precipitation; E, Evaporation; EP, Effective Precipitation; ET, Evapotranspiration; Q, River Flow; T, Temperature; D, Exploitation Well Discharge; L, Lake Level; TL, Tide Level; IR, Irrigation Return Flow; S, Spring Discharge.

predicting the groundwater level fluctuations using ANNs and SVMs and showed that SVM was better than ANN during both model training and testing phases. Similarly, Emamgholizadeh *et al.* (2014) employed ANN and ANFIS to predict the groundwater level of Bastam Plain in Iran and found that both models could predict groundwater level accurately.

Many recent studies also compared the predictive capacity of several AI techniques in forecasting groundwater level. Shiri *et al.* (2013) compared the abilities of Gene Expression Programming (GEP), ANFIS, ANN and SVM methods in groundwater level forecasting for up to 7-day prediction intervals, and demonstrated that the GEP models were better in forecasting water table level fluctuations up to 7 days beyond data records. Shirmohammadi *et al.* (2013) employed several data-driven techniques, such as system identification, time series and ANFIS models in order to predict groundwater levels for various forecasting periods. The results indicated that ANFIS provided accurate predictions of groundwater levels for 1- and 2-month lead times.

Notwithstanding the notable increase in hydrologic research employing AI data-driven models in researches on rainfall (Nastos *et al.* 2014; Lian *et al.* 2019), streamflow (Shu & Ouarda 2008; Samsudin *et al.* 2010; Sanikhani & Kisi 2012; Humphrey *et al.* 2016; Tiu *et al.* 2018) and drought (Soh *et al.* 2018; Fung *et al.* 2019), few studies have compared the widely accepted models (e.g. ANN, FL, ANFIS, and LSSVM) for groundwater level prediction in the literature (Shiri *et al.* 2013; Emamgholizadeh *et al.* 2014). Based on Table 1, ANN was the most applied model followed by ANFIS. To the best of the authors' knowledge, no study has been carried out to predict groundwater levels using GMDH. Therefore, comparing the performance of widely accepted AI models (ANN, FL, ANFIS and LSSVM) alongside GMDH for groundwater level prediction is the objective of this research.

The present study provides a comparison of different soft-computing AI models for short-term groundwater level prediction. This study made an effort to: (1) assess the effect of different components of the hydrologic cycle – including monthly groundwater level (H), monthly total precipitation (P), average monthly temperature (T), monthly total evapotranspiration (ET) – on the accuracy of

groundwater level modeling; and (2) assess the efficiency of ANN, FL, ANFIS, GMDH and LSSVM in predicting short-term groundwater levels for 1-, 2- and 3-month lead times.

## METHODS

### Artificial neural network

ANN models are powerful non-linear modeling approaches that work by imitating the human brain functions. ANN is able to create a complex network mapping between input and output variables that has the ability to estimate non-linear functions. This study employed one of the most widely used ANNs; that is, the multilayer perceptron (MLP).

A number of studies have found that one hidden layer is sufficient for the ANN model to estimate complex non-linear functions for hydrological data (e.g. Coulibaly *et al.* 2001). Determining the size of the hidden nodes is an important part of the MLP ANN. In many cases, this is done by a trial and error approach. In this study, the optimal size of hidden nodes was specified based on a trial and error approach. There are different types of learning algorithms for training the ANN models. The Levenberg–Marquardt (LM), one of the most efficient and fast algorithms for training in ANNs, was used in this study (Burney *et al.* 2004). MATLAB<sup>®</sup> (Mathworks 2014) was used to build the AI models. The general structure of AI models is depicted in Figure 1. Unlike process-based approaches like numerical models, the AI methods are data-driven approaches. The general structure of AI models is a black-box approach in which tuning AI models is based on the calibration and verification of the input-output data patterns.

### Fuzzy logic

Fuzzy set theory is used to address various types of uncertainty in mathematical form (Zadeh 1965). Fuzzy sets are defined as a membership function that has a domain of interest of 0 to 1. FL is well-suited for modeling complex phenomena that may not yet be fully understood because it can handle imprecise and uncertain data or ambiguous relationships among data sets. Fuzzy inference systems (FIS) are able to transfer the qualitative aspects of expert

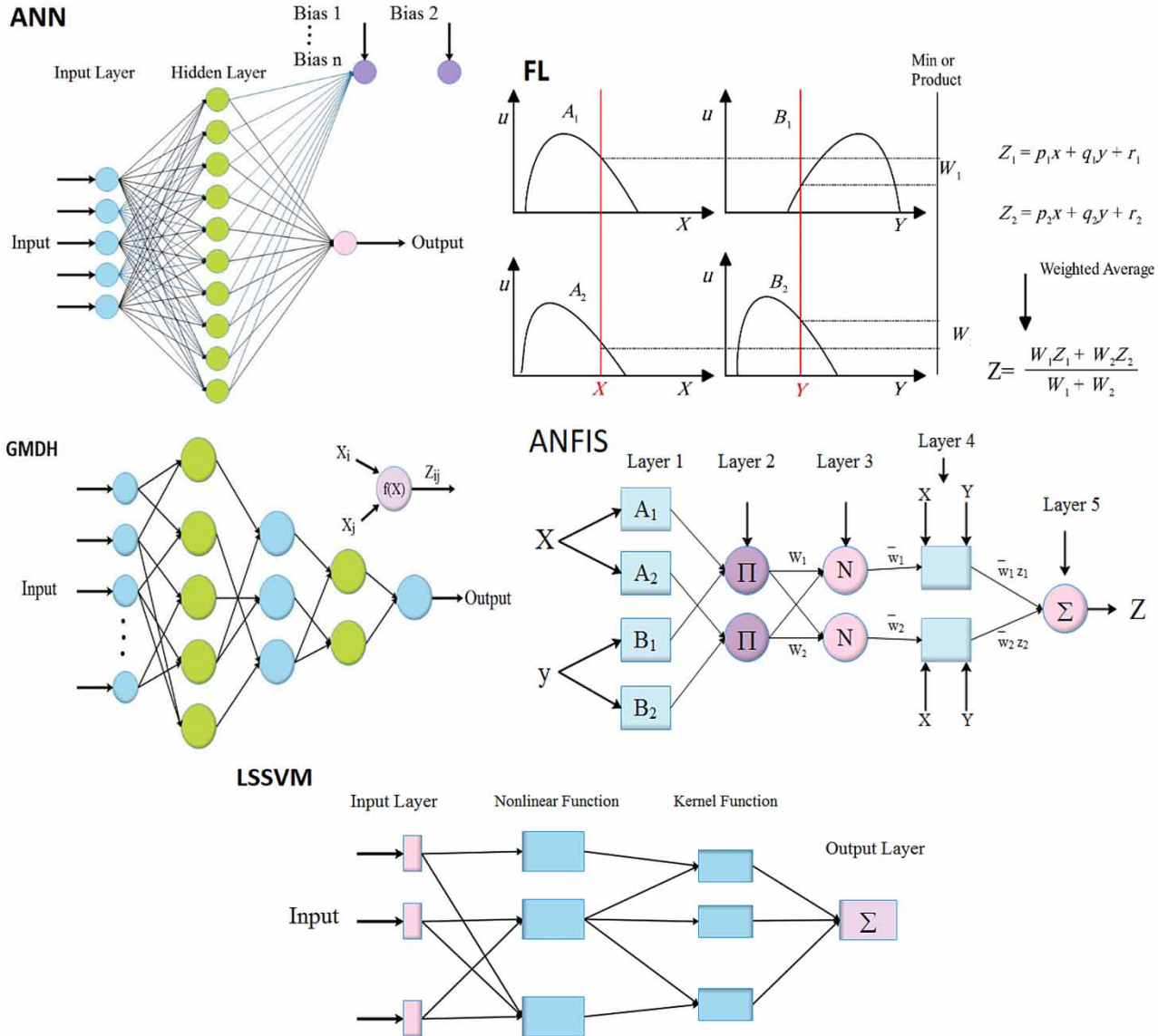


Figure 1 | The general structure of AI models.

knowledge and reasoning processes through fuzzy if-then rules (Zadeh 1965). The Mamdani, Sugeno and Tsukamoto FISs have often been used in the field of water resources and their differences can be seen in the aggregation and defuzzification processes. The FIS model was developed based on the assumption that when a cluster estimation method computed on a series of input and output data is able to produce cluster centres, each can be considered as a prototypical data point illustrating the characteristics of the system in question.

**Adaptive neuro fuzzy inference system**

ANFIS is a supervised model that combines the advantages of ANNs’ learning and the ability of FIS to estimate any real continuous functions in a compact manner (Jang et al. 1997). This is done by applying an ANN learning algorithm and fuzzy reasoning to project the input predictor variables onto an output-predicted space.

The neuro-fuzzy model used in this study implemented Sugeno’s fuzzy approach. For a given input–output data set,

various Sugeno models may be developed using grid partitioning, subtractive clustering and C-mean clustering methods. In this study, the commonly used subtractive clustering method was applied to construct the neuro-fuzzy models. The ANFIS subtractive clustering (ANFIS-SC) model was obtained by combining ANFIS and subtractive clustering. When employing ANFIS-SC, the number of effective 'grid points' to be evaluated equals the number of data points, which is independent of the dimension of the problem. With ANFIS-SC, the need to specify a grid resolution is eliminated but consideration of the tradeoffs between accuracy and computational complexity must be taken into account. The subtractive clustering method also extends the criterion of the mountain method for accepting and rejecting cluster centers. The defining radius is a crucial factor in determining the number of clusters. It is therefore important to select a suitable influential radius to best cluster the data space. Once the radius has been chosen, the number of fuzzy rules and premises of a fuzzy MF are determined. Finally, the linear least squares estimate is used to determine the consequent in the MF as an output, which then allows one to produce a valid FIS.

### Group method of data handling

GMDH is an example of a self-organizing neural network model. Self-organizing neural network models are successfully used in a wide range of science and engineering disciplines, although application in the field of hydrology is still in its infancy (Samsudin et al. 2010).

The GMDH was introduced by Ivakhnenko (1968) as a heuristic method to obtain predictive models of complex systems; it is based on regression and derives complex, high order polynomial models. Initially, the GMDH was proposed as a method for dealing with higher-order regression polynomials, more specifically for solving modeling and classification problems (Samsudin et al. 2010). The main concept behind GMDH is to build an analytical function in a feedforward network based on a quadratic node transfer function whose coefficients are calculated using a regression technique. The main function of GMDH is relatively similar to the principles used in classical neural nets where every layer consists of simple nodes, each of which performs its own polynomial transfer function and passes

its output to nodes of the subsequent layer. More details on GMDH can be found in papers such as Nariman-Zadeh et al. (2002).

### Least square support vector machine

Support vector machines (SVM) are formulated based on statistical learning theory and are derived from the hypothesis of structural risk minimization (Raghavendra & Deka 2014). The purpose of an SVM is to minimize both empirical risk and the confidence interval of the learning machine in order to obtain a good generalization capability (Raghavendra & Deka 2014).

Several algorithms to solve the dual optimization problem of SVMs have been proposed. Conventional quadratic programming algorithms need a very large memory to execute the kernel matrix computation and, therefore, are not ideal for large computations. The sequential minimal optimization (SMO) algorithm (Platt 1999), an analytical solution of a subset that can be obtained without the need to perform a quadratic optimizer, was used in this study. When using the radial basis function kernel (RBF-kernel), the kernel function of LSSVM, the kernel width parameter,  $\gamma$ , has to be chosen carefully. If the value of  $\gamma$  is too large, it may lead to under-fitting the results because input patterns would appear too similar. In contrast, if the value of  $\gamma$  is too small, over-fitting may result because input patterns will appear to be very different (Chang & Lin 2011). The factor,  $C$ , represents the trade-off between the training error and model complexity (the size of model weights) (Basak et al. 2007). The value of  $C$  is specified by the user: if the value of  $C$  is too small, the model will not fit the learning data; if the value of  $C$  is too large, over-fitting will occur for the data and the noise (Lendasse et al. 2005). The optimal values for  $C$  and  $\gamma$  are often specified by trial and error. All of the LSSVM processes in this study were computed using the programming codes of Library for Support Vector Machines (LIBSVM) software developed by Chang & Lin (2011).

### Study area

Gachsaran Plain in the south of Kohgiluyeh and Boyer-Ahmad province in the center of Iran was selected.

Gachsaran Plain is a sub-basin of Zohre watershed. Many deep wells have been drilled in the area to meet increasing water demands, which used to be adequately supplied by rivers, springs, qanats and shallow wells. This has caused a decline in groundwater levels within the Plain.

The map of the study area is depicted in Figure 2. Elevation ranges from a maximum of 2,400 m on Khami Mountain to a minimum of 600 m Above Mean Sea Level (AMSL). The average annual precipitation in Gachsaran city is approximately 320 mm. The average annual

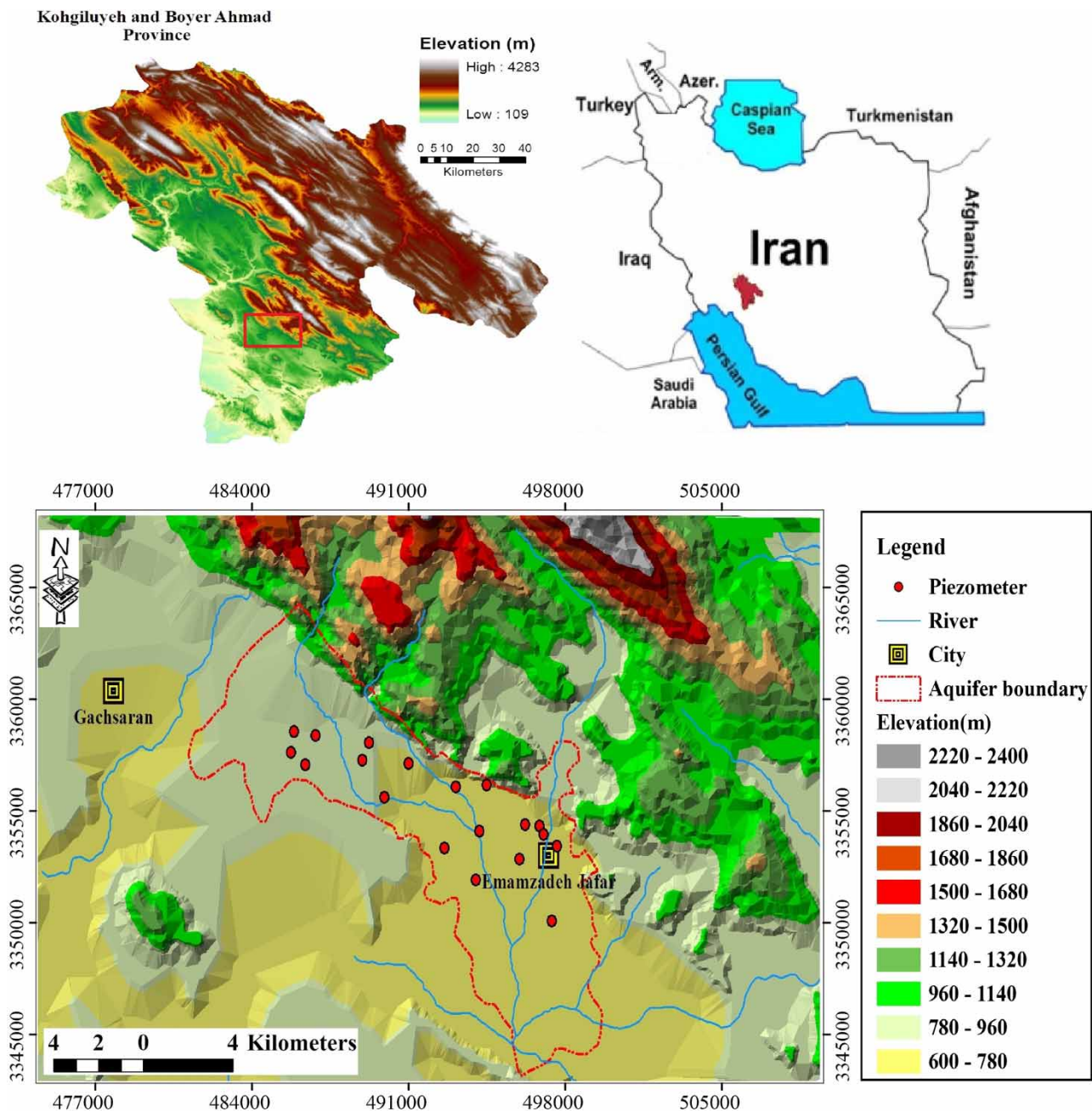


Figure 2 | Location map of the study area.

temperature is 23 °C for the study area. The study area has a dominantly semiarid climate in light of the Domarton classification technique.

### Model development

This paper considers groundwater predictions for lead times of 1, 2 and 3 months using ANN, FL, ANFIS, GMDH and LSSVM. Groundwater level data of the aquifer system was collected from a well that has the overall hydrogeological characteristics of the aquifer system in order to illustrate the performance of the different AI models. The groundwater levels were monitored by the Kohgiluyeh and Boyer Ahmad Regional Water Authority on a monthly basis from March 2002 to May 2016. A monthly time scale has been considered the most suitable scale for modeling groundwater (Nourani et al. 2014). The first 120 monthly data values were used for training and the remaining data were reserved for testing. The data consisted of monthly groundwater level (H in AMSL), monthly precipitation (P in cm), average monthly temperature (T in Celsius), and the monthly evapotranspiration (ET in mm).

### Model implementation

The input and output variables for ANN-based modeling are usually normalized in order to ensure that all variables receive equal attention during the training steps. Choosing appropriate input variables for groundwater level prediction using AI models is an important requirement. Fluctuation of groundwater level in Gachsaran Plain depends on surface water and hydro-meteorological conditions and, therefore, components of the groundwater budget selected as input variables for the AI models are precipitation, temperature, evapotranspiration and groundwater level data.

Several combinations of input variables were tested to predict groundwater level in the observation well. Assuming that  $H_t$  denotes the groundwater level at time  $t$ , inputs include the previous H ( $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ), present T ( $T_t$ ), present and previous P ( $P_t$ ,  $P_{t-1}$ ), present ET ( $ET_t$ ), and the output corresponding to the groundwater level H ( $H_{t+1}$ ,  $H_{t+2}$ ,  $H_{t+3}$ ). The following combinations of input

data for groundwater level predictions were selected based on the correlations among the inputs and groundwater level:

- (1)  $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ;
- (2)  $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ,  $T_t$ ,  $ET_t$ ,  $P_t$ ;
- (3)  $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ,  $T_t$ ,  $ET_t$ ,  $P_t$ ,  $P_{t-1}$ .

### Efficiency criteria

In order to evaluate the performance of the training and testing periods of the developed model, four statistical criteria were used to assess accuracy and precision: mean absolute error (MAE), root mean squared error (RMSE), Correlation Coefficient (R) and Nash–Sutcliffe efficiency (NSE). The best fit between the observed and simulated groundwater levels under ideal conditions would yield MAE and RMSE equal to zero and R and NSE equal to one.

## RESULTS AND DISCUSSION

### Results of the ANN model

The ANN models, with up to three combinations of input data for training and testing, were evaluated based on their outputs of  $H_{t+1}$ ,  $H_{t+2}$  and  $H_{t+3}$  (Table 2). The ANN model with Combination 3 as input and  $H_{t+1}$  as output shows the smallest values of RMSE and MAE and values of R and NSE closest to one in both the training and testing periods. Therefore, this model input combination was selected as the best-fit model for groundwater level prediction. The number of nodes in the hidden layer was determined by a trial and error approach following previous studies. Initial results of our study also indicated that one hidden layer was adequate to approximate the relationship between groundwater level and the different components of the hydrologic cycle. The optimal size of the hidden nodes was determined by systematically increasing the number of nodes until the network performance reached a plateau where significant improvement was no longer observed. For example, the optimal number

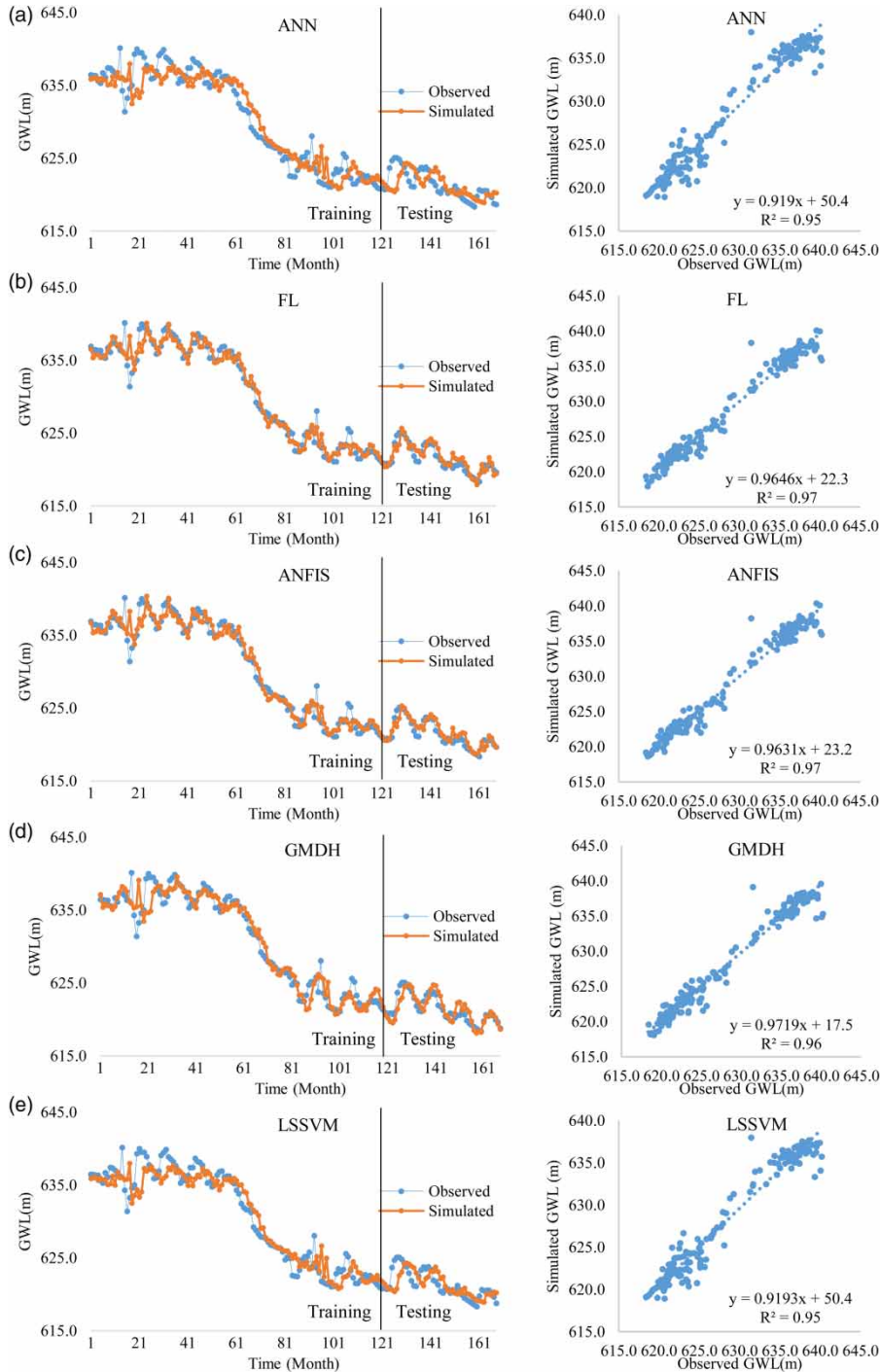
**Table 2** | The performance results of the different combinations using the AI models for the observation well in the  $H_{t+1}$ ,  $H_{t+2}$ ,  $H_{t+3}$  lead months

Model	Input	Structure	Step	$H_{t+1}$				$H_{t+2}$				$H_{t+3}$			
				R	RMSE	MAE	NSE	R	RMSE	MAE	NSE	R	RMSE	MAE	NSE
ANN	Combination 1	2	Train	0.94	1.98	1.55	0.84	0.93	1.84	1.38	0.86	0.90	2.23	1.68	0.81
			Test	0.77	1.16	0.95	0.55	0.58	1.56	1.20	0.22	0.42	1.84	1.44	0.04
	Combination 2	5	Train	0.96	1.32	0.95	0.93	0.95	1.51	0.97	0.91	0.93	1.89	1.22	0.86
			Test	0.84	0.99	0.77	0.67	0.68	1.38	1.15	0.39	0.67	1.69	1.37	0.12
	Combination 3	5	Train	0.94	1.69	1.14	0.88	0.96	1.39	1.05	0.92	0.97	1.33	1.06	0.93
			Test	0.77	1.24	0.95	0.48	0.72	1.64	1.30	0.14	0.62	1.59	1.33	0.22
FL	Combination 1	0.5	Train	0.97	1.51	1.10	0.95	0.96	1.85	1.42	0.92	0.95	2.08	1.66	0.90
			Test	0.82	1.55	1.35	0.32	0.71	1.80	1.57	0.07	0.60	2.22	1.97	0.52
	Combination 2	0.9	Train	0.98	1.26	0.87	0.96	0.98	1.32	1.03	0.96	0.98	1.39	1.11	0.96
			Test	0.90	0.89	0.68	0.78	0.82	1.38	1.08	0.45	0.77	1.71	1.42	0.11
	Combination 3	0.9	Train	0.98	1.25	0.87	0.96	0.98	1.29	1.00	0.96	0.98	1.32	1.04	0.96
			Test	0.88	0.95	0.78	0.75	0.82	1.32	1.03	0.49	0.67	1.95	1.55	0.16
ANFIS	Combination 1	0.5	Train	0.97	1.57	1.15	0.94	0.96	1.85	1.42	0.92	0.95	2.07	1.66	0.90
			Test	0.82	1.31	1.12	0.52	0.71	1.79	1.57	0.07	0.60	2.22	1.97	-0.51
	Combination 2	0.9	Train	0.98	1.26	0.87	0.96	0.98	1.32	1.03	0.96	0.98	1.39	1.10	0.96
			Test	0.90	0.89	0.67	0.78	0.82	1.38	1.07	0.45	0.77	1.71	1.41	0.11
	Combination 3	0.9	Train	0.98	1.25	0.87	0.96	0.98	1.29	1.00	0.96	0.98	1.31	1.04	0.96
			Test	0.88	0.95	0.78	0.75	0.82	1.32	1.03	0.50	0.67	1.95	1.54	-0.16
GMDH	Combination 1	2,1	Train	0.97	1.57	1.14	0.95	0.97	1.81	1.46	0.93	0.95	2.31	1.85	0.89
			Test	0.98	1.36	1.01	0.96	0.96	2.07	1.45	0.91	0.96	1.87	1.53	0.93
	Combination 2	12,15,15,1	Train	0.98	1.36	0.96	0.96	0.98	1.32	0.92	0.97	0.97	1.73	1.27	0.94
			Test	0.96	2.01	1.24	0.92	0.97	1.72	1.34	0.93	0.99	1.31	1.02	0.97
	Combination 3	15,15,15,1	Train	0.99	1.05	0.70	0.98	0.98	1.38	1.02	0.96	0.98	1.51	1.14	0.95
			Test	0.95	2.30	1.17	0.89	0.98	1.44	1.09	0.95	0.98	1.55	1.16	0.96
LSSVM	Combination 1	2, 0.5	Train	0.95	1.97	1.55	0.84	0.90	2.23	1.68	0.81	0.93	1.84	1.38	0.86
			Test	0.80	1.06	0.95	0.55	0.42	1.84	1.44	-0.04	0.58	1.56	1.20	0.22
	Combination 2	2, 0.5	Train	0.98	1.22	0.95	0.93	0.93	1.89	1.22	0.86	0.95	1.51	0.97	0.91
			Test	0.87	0.89	0.77	0.68	0.67	1.69	1.37	0.12	0.68	1.38	1.15	0.39
	Combination 3	2, 0.5	Train	0.91	1.59	1.14	0.88	0.97	1.33	1.06	0.93	0.96	1.39	1.05	0.92
			Test	0.78	1.14	0.95	0.51	0.62	1.59	1.33	0.22	0.72	1.64	1.30	0.14



of nodes in the hidden layer for combination 3 was specified as 5 (Table 2). The observed and predicted groundwater levels obtained in the observation well

using the ANN, FL, ANFIS, GMDH and LSSVM models (Table 2) for the best combinations are presented in Figure 3.



**Figure 3** | The observed and predicted groundwater levels in observation well using the (a) ANN model in the  $H_{t+1}$  for the combination 3 (top panel), (b) FL model in the  $H_{t+1}$  (top middle panel) for the combination 3, (c) ANFIS model in the  $H_{t+1}$  (middle panel) for the combination 3. (d) GMDH model in the  $H_{t+2}$  (bottom middle panel) for the combination 2. (e) LSSVM model in the  $H_{t+1}$  (bottom panel) for the combination 2.

## Results of the FL model

Performance of the FL models up to three different combinations in training and testing were evaluated based on their outputs:  $H_{t+1}$ ,  $H_{t+2}$  and  $H_{t+3}$  (Table 2).

The range of the parameter radius used in the FL model development was determined to be between 0.2 and 0.9. Table 2 displays the results of the parameter radius of the most optimized FL model. Similar to the ANN model, the FL model with Combination 3 as input and  $H_{t+1}$  as output showed the optimal values of RMSE, MAE, R and NSE for the training and testing periods and was selected as the best-fit model for groundwater level prediction using FL (Figure 3).

## Results of the ANFIS model

An ANFIS model retains the advantages of a fuzzy expert system, while removing (or at least reducing) the need for an expert. The ANFIS model with three different combinations was evaluated based on outputs,  $H_{t+1}$ ,  $H_{t+2}$ ,  $H_{t+3}$ . The final structures of the ANFIS model were determined by an extensive trial and error process for each input combination. A suitable cluster radius is required in order to establish fuzzy rules using ANFIS-SC. This radius can indicate the range of influence of a cluster when the data space is assumed to be a unit hypercube; the radius can be between 0 and 1. Normally, smaller radii result in many small clusters (having many rules), whereas large radii result in a few large clusters in the data (having fewer rules) (Sanikhani & Kisi 2012).

Performances of the different combinations for training and testing periods using the ANFIS model are given in Table 2. Again, the ANFIS model with combination 3 as the input and  $H_{t+1}$  as the output had the best RMSE, MAE, R and NSE values and was selected as the best-fit model for groundwater level prediction (Figure 3).

## Results of the GMDH model

In a GMDH model, successive layers that have complex connections are formulated and built using second-order polynomial functions. The first layer is built by computing regressions of the input variables and the second layer is

built by computing regressions of the output values. Only the best are chosen at each layer and this process continues until a pre-specified selection criterion is finally found (Samsudin et al. 2010). The success and performance of GMDH models depend on the choices of the number of input variables. We evaluated GMDH models with different combinations based on their outputs at  $H_{t+1}$ ,  $H_{t+2}$  and  $H_{t+3}$ , for both training and testing data sets (Table 2). The GMDH model with Combination 2 as input was considered the best-fit model for groundwater level prediction in this study. Figure 3 shows observed and predicted groundwater level values obtained using the selected GMDH model.

## Results of the LSSVM model

Performance of LSSVM models with different combinations of input variables were evaluated based on their output results at  $H_{t+1}$ ,  $H_{t+2}$  and  $H_{t+3}$ , in training and testing data sets (Table 2). The LSSVM model with Combination 2 as input and  $H_{t+1}$  as output had the optimal RMSE, MAE, R and NSE values in training and testing periods and was selected as the best-fit model for groundwater level prediction. The RBF-kernel was chosen as it was a nonlinear function and able to decrease the computational complexity of the training process while providing suitable performance. The penalty parameter  $C$  and kernel function's parameter  $\gamma$  for the SVM were determined by a trial and error approach. The optimal number of  $C$  and  $\gamma$  for the different combinations are given in Table 2. Figure 3 shows the observed and predicted groundwater levels using the LSSVM model.

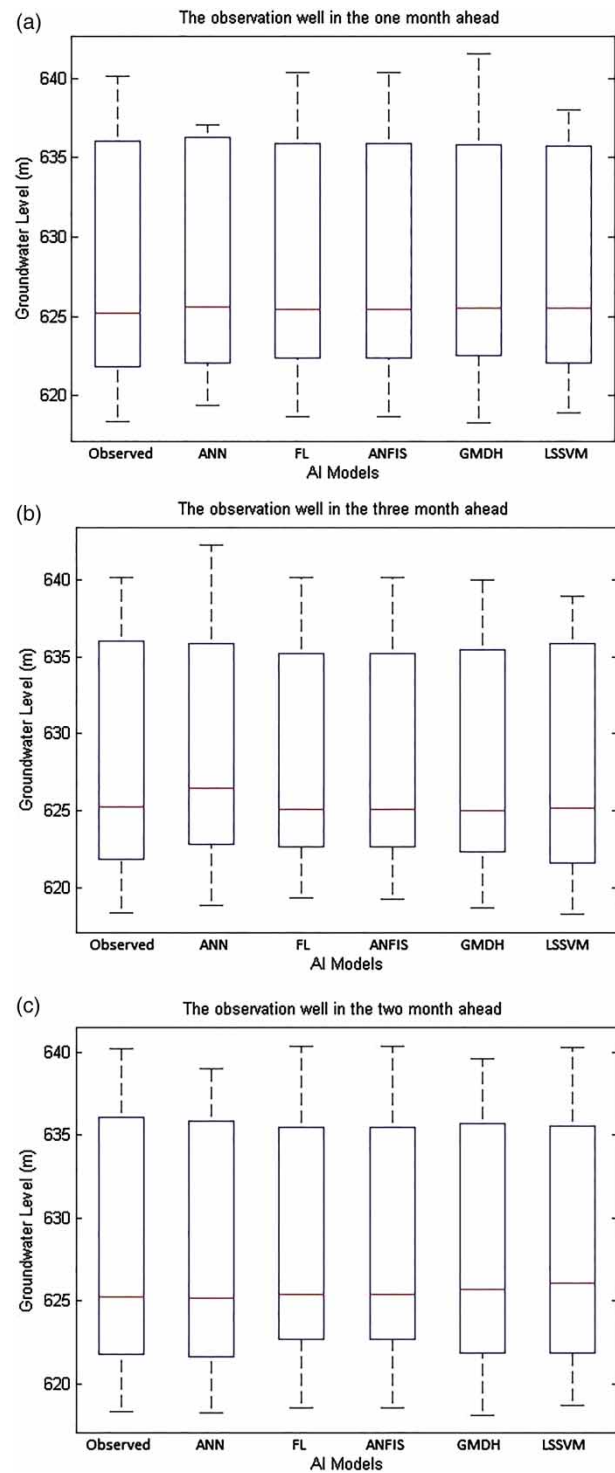
## Comparison of the different models

In order to obtain a comprehensive evaluation of the ANN, FL, ANFIS, GMDH and LSSVM models, the best input combination for the developed models (i.e. Combination three:  $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ,  $T_t$ ,  $ET_t$ ,  $P_t$ ,  $P_{t-1}$ ) for a one-month lead time was used for comparison. The best-fit model indicated that the difference between the values of the statistical criteria did not vary substantially and all five models generally showed low RMSE and MAE values and high R and NSE values.

Furthermore, one of the significant characteristics of the models in predicting the groundwater level is maintaining the main statistics of the observed groundwater level, including mean, median, minimum, maximum, and upper and lower quintiles. The box-plot presented in Figure 4 indicates that the five models were able to maintain the main statistics of the observed data in the study area. Based on Figure 4, it can be said that the GMDH model performs best in keeping the main statistics of the observed groundwater level. Figure 4 shows the observed and predicted groundwater level values using the five models in the observation well in the  $H_{t+1}$  (a, top panel),  $H_{t+2}$  (b, middle panel),  $H_{t+3}$  (c, bottom panel) lead months.

If the NSE criterion on the estimated values is equal to 1, the model would be perfect, while it can be accurate if the value of NSE is greater than 0.8 (Shu & Ouarda 2008). The NSE values for groundwater level prediction using the LSSVM model were higher than those of the other models. This implied that, based on NSE values, the overall quality of estimation using the LSSVM model was better than the other four models. Comparing the RMSE and R values among the ANN, FL, ANFIS, GMDH and LSSVM models, the LSSVM model also had the best performance. The LSSVM model produced low RMSE and high R values (the former criterion shows a better value in terms of the performance of the LSSVM model). Also, results showed that the models could predict groundwater levels for 1 and 2 months ahead appropriately in many combinations, but for 3 months ahead the performance of the models was not satisfactory, although in some cases the results of models generally showed low RMSE and MAE values and high R and NSE values for 3 months ahead rather than 1 and 2 months.

Overall, it can be concluded that the developed ANN, FL, ANFIS, GMDH and LSSVM models produced good estimations of groundwater levels and could be used in prediction models to provide accurate and reliable results. The results obtained in this study suggest that the LSSVM model was superior to the other models in groundwater level prediction.



**Figure 4** | The observed and predicted groundwater level values using the five models in the observation well in the  $H_{t+1}$  (top panel),  $H_{t+2}$  (middle panel),  $H_{t+3}$  (bottom panel) lead months for the combination 2.

## CONCLUSIONS

This study explored the potential use of five machine learning techniques (i.e., ANN, FL, ANFIS, GMDH and LSSVM) in predicting short-term groundwater levels for 1-, 2- and 3-month lead times based on antecedent values of groundwater head, precipitation, temperature, and evapotranspiration. The use of GMDH was investigated for the first time in this research. To test the performance of the developed models, an observation level was selected and used in different techniques. The observed values obtained using the different techniques were compared and their performances were evaluated based on statistical criteria. Results suggested that the developed models could be applied successfully to establish accurate and reliable groundwater level prediction. Using seven antecedent inputs, which included  $H_{t-1}$ ,  $H_{t-2}$ ,  $H_{t-3}$ ,  $T_t$ ,  $ET_t$ ,  $P_t$ , and  $P_{t-1}$ , produced the best-fit model (for each technique). All five models generally showed low RMSE and MAE values and high R and NSE values and could model groundwater levels for 1 and 2 months ahead in many combinations appropriately, but for 3 months ahead the performance of the models was not satisfactory. Overall, the results showed that the LSSVM method was superior to the other models in predicting groundwater levels using local input and output data.

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