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Optimization of ANFIS model using wavelet transform for simulating groundwater level variations

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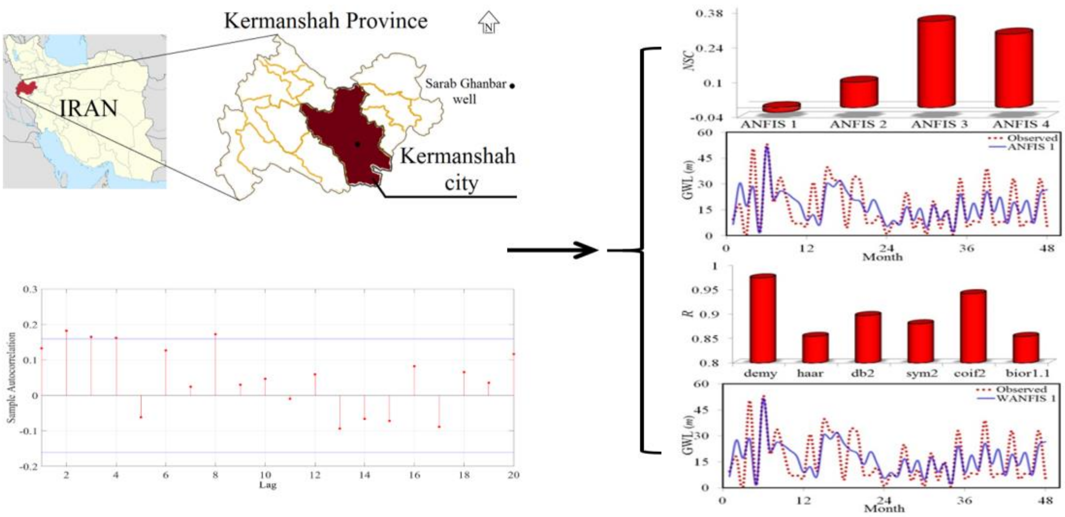
GRAPHICAL ABSTRACT



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ABSTRACT

In this study, for the first time, groundwater level (GWL) variations of the Sarab-e Qanbar well located in the city of Kermanshah, are simulated over a 13-year period by a hybrid model named WANFIS (wavelet-adaptive neuro fuzzy inference system). In order to develop the hybrid model, the wavelet transform and the adaptive neuro fuzzy inference system (ANFIS) model are utilized. Furthermore, the 9 and 4 year data are used for training and testing the artificial intelligence models, respectively. Moreover, the effective lags are detected by the autocorrelation function (ACF) and then eight different models are developed for each of the ANFIS and WANFIS models using them. After that, all mother wavelets are evaluated and Dmey mother wavelet is chosen as the most optimal. For this mother wavelet, the values of scatter index (SI), variance account for (VAF) and Root mean square error (RMSE) are obtained 0.192, 94.951 and 3.117, respectively. Next, the superior model is detected through the analysis of the results obtained by all ANFIS and WANFIS models. The superior model estimates the objective function values with reasonable accuracy. For example, the correlation coefficient (R), Scatter Index (SI) and variance account for (VAF) for this model are obtained 0.974, 0.192 and 94.951, respectively. The modeling results indicate that the wavelet transform noticeably enhances the ANFIS model accuracy. Finally, the lags of the time series data for the Sarab-e Qanbar well including (t-1), (t-2), (t-3) and (t-4) are introduced as the most effective lags.

1. Introduction

Groundwater exploitation is one of the main sources for supplying drinking water as well as agriculture and other purposes in dry and semi-dry regions of the planet. In recent years, due to sequent droughts and climate change, the water extraction amount has increased. In som e areas of Iran, groundwater levels have been dropped significantly. Thus, the estimation and modeling groundwater level fluctuations are

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vitally important. Additionally, various numerical models such as artificial intelligence (AI) algorithms and soft computing (SC) methods have been implemented by many researchers for modeling various problems (Akhbari et al. 2017; Azimi et al. 2018) and this phenomenon. For instance, Dash et al. (2010) and Kisi and Shiri (2012) estimated different groundwater parameters by artificial intelligence algorithms or neuro-fuzzy models. Then, Chitsazan et al. (2013) simulated groundwater level variations in aquifers using the artificial intelligence network. They run their artificial intelligence network with two hidden layers and demonstrated that the simulated and observed values are close to each other in this mode. Also, Khaki et al. (2015) simulated groundwater level variations during a seven-year period using the neural model and also the (adaptive neuro fuzzy inference system) ANFIS model. They developed various models adopting time-series and effective parameters and eventually introduced the best one. They stated that the ANFIS model has higher accuracy. Additionally, Ebrahimi and Rajaee (2016) provided three hybrid AI models for forecasting groundwater levels within an eleven-year period through the combination of the wavelet model with the artificial intelligence network, the linear regression and the support vector. Barzegar et al. (2017) managed to simulate the Maraqe-Bonab aquifer for evaluating the efficiency of the wavelet-group method of data handeling (WA-GMDH) method and wavelet-extreme learning machine (WA-ELM) models as well as wavelet-based models in predicting groundwater levels. They used 367 monthly groundwater level data for testing and training the model. Finally, they concluded that the wavelet-based models improve the efficiency of the group method of data handeling (GMDH) and extreme learning machine (ELM) models in forecasting groundwater levels. Furthermore, Liu et al. (2018) proposed some hybrid models for approximating groundwater level fluctuations by combining the empirical mode decomposition (EMD), particle swarm optimization (PSO), phase space reconstruction (PSR), and extreme learning machine (ELM) models. They proved that the EMD and PSO models considerably enhance the accuracy of the ELM model. On the one hand, the simulation of groundwater levels (GWL) has attracted the attention of many researchers due to the importance of groundwater resources. This means that this water resource plays a vital role in supplying water for various purposes in different areas all over the world. On the other hand, different artificial intelligence (AI) techniques are considered as precise and efficient tools for estimating groundwater level (GWL) variations in the long-term. AI models have reasonable accuracy and using them leads to saving in time and computational costs.

Therefore, in the current study, the groundwater level variations of the Sarab-e Qanbar well located in the city of Kermanshah, are simulated for a 14-year period by means of the ANFIS model and the WANFIS hybrid technique for the first time. To develop the hybrid model, the ANFIS models are combined with the wavelet transform. To train the artificial intelligence models, the 9-year data are used and the 4-year data are employed for testing them. It should be noted that the effective lags of the time-series data are detected by the auto-correlation function. It is worth mentioning that Dmey mother wavelet is chosen as the most optimal mother wavelet. In contrast, the superior models and the most effective lags are identified through the analysis of the modeling results.

2. Materials and methods

Initially, the study area is completely introduced and then the applied numerical models including adaptive neuro fuzzy inference system (ANFIS), wavelet and hybrid model (WANFIS) are described. Then, the most important lags are identified using an autocorrelation function. After that, the results yielded by all numerical models are analyzed. Finally, the superior model and the most effective input lags are detected.

2.1. Study area

In this paper, the study area is located in the Sarab-e Qanbar region, south of Kermanshah. Sarab-e Qanbar has a warm and moderate climate. This area has rainy winters and cool summers. In this region, the average annual temperature is about 12.9 °C and the average rainfall is near 440 mm. The geographic coordinates of this area are 34.2870° N, 47.0547° E. In this paper, the observational well located within the region is utilized for verifying the artificial intelligence models. The northern and eastern margins and some parts of the northwestern region of this plain are covered with Karstic limestones, which are mostly Karstic. The East-southern and northwestern parts are restricted to altitudes with different facies. Geologically, the study area is composed of two zones including Zagros and crushed. These two zones together with the Khuzestan Plain constitute the entire Zagros structure. The oldest unit of the stones surrounding the Miandarband plain belong to Jurassic. Due to this, the thickness, the type and gravity of alluvium in this plain are different at different points. In this plain, groundwaters are in alluvials with the thickness of 50-200 m, most of which are from silicate clay, fine and coarse sand, and rug. In general, the foothills and the plains are composed of large coarse aggregates causing good permeability in these areas. The bedrock of the Kermanshah plain is formed of radiolarite rocks. In the plain of Kermanshah, there are free and artesian aquifers and reservoirs of groundwater in this area are formed in alluvial deposits of the fourth period, which are the result of erosion of the marginal heights of the plain. The constituents of sediments are in the range of water table include cobblestone, gravel, sand, silt and clay. The main recharge source of the existing groundwater table, irrespective of the atmospheric precipitation on the plain, is some streams originating from the range of adjacent heights and enter the area of the plain, as well as the presence of abundant springs, which are mainly karstic. Furthermore, the transmissivity of the groundwater table in different areas of the study area is different, so that in the margin of the table due to steep slope and low viscosity of alluvium is about 500 square meters per day and even less, and in the central areas to a maximum of 10,000 square meters per day. The observational values were used monthly in a 13-year period from 2002 to 2015. The observed values were monthly measured by the regional water company of Kermanshah over this period. The measurement of the groundwater levels was mostly performed using a submersible pressure transmitter. These hydrostatic level transmitters are small in diameter and directly suspended by their cable into wells, boreholes, deep bore wells or monitoring wells. The groundwater level measurement was logged locally or transmitted back to the control unit or PLC by telemetric systems or underground lines. The groundwater level variations, as well as the monthly rainfall in this region, were evaluated for 13 water years and based on the results it was concluded that the groundwater level variations in the plain have a decreasing trend so that during these 13 years about 5.77 m drawdown has been measured in the aquifer. The mentioned drawdown is due to the recent droughts and also increasing the withdrawal amount. The observational data were used in the form of the time-series data for 156 consecutive months. Furthermore, 9 years of these observational data were used for training and 4 years for testing the artificial intelligence models. The location of the Sarab-e Qanbar well is illustrated in Fig. 1.

2.2. Adaptive neuro fuzzy inference system (ANFIS)

ANFIS is a universal estimator provided for the first time by Jang (1993). This technique is capable to forecast complex real functions with an acceptable degree. The structure of this method consists of a number of nodes directly connected to each other. Each node has adjustable parameters (Jang et al. 1997). If a fuzzy inference system has three parameters (x, y and z) as inputs and the parameter f as the network output, assuming we have two fuzzy rules, so:

$$\begin{aligned} &Rule1: IF\ x\ is\ A_1,\ y\ is\ B_1,\ and\ z\ is\ C_1, \\ &THEN\ \ f_1 = p_1x + q_1y + r_1z + s_1 \end{aligned} \tag{1}$$

$$\begin{aligned} &Rule\ 2: IF\ x\ is\ A_2,\ y\ is\ B_2,\ and\ z\ is\ C_2, \\ &THEN\ \ f_2 = p_2x + q_2y + r_2z + s_2 \end{aligned} \tag{2}$$

where, f_1 and f_2 represents the output function related to the first and second rules, respectively. In general, the ANFIS system has five different layers. Each node in the first layer is taken into account as an adaptive node as follows:

$$O_{1,i} = \phi A_i\left(x\right) \quad i = 1,2 \tag{3}$$

where, Ol,i is the membership function of the fuzzy set A, Ai is the linguistic label like "big" or "small" depending to the node function and x denotes the ith input node. The membership function specifies the input component x which is satisfied by the quantity meter Ai. The membership function (φAi(x)) is usually chosen as Gaussian in the domain of 0 and 1.

$$\phi A_i\left(x\right) = \exp\left(-\left(\frac{x-a_i}{b_i}\right)^2\right) \tag{4}$$

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where, {ai, bi}are Gaussian parameters so that changing them leads to create Gaussian functions with different shapes. Hence, there are various functions for Ai (Jang 1993). The parameters of this layer are known as "premise parameters". Each node in the second layer is multiplied by input signals and provides the resulted product as the output. The output of each node is known as the "firing strength".

$$O_{2,i} = w_i = \phi A_i(x)\phi B_i(y)\phi C_i(z) \quad i = 1,2 \tag{5}$$

In the third layer, the ratio of the firing strength of the ith rule to the total firing strengths for the ith node is calculated as follows:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{6}$$

Each node in the fourth layer is presented as follows:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i z + s_i \right) \tag{7}$$

where, {pi, qi, ri, si}is the set of parameters and $\bar{w}$ is the output of the third layer. The parameters of this section are known as the "consequent parameters". Finally, the node existing in the fifth layer known as the output node is calculated as the sum of all input signals as follows:

$$O_{5,i} = \sum_{i=1} \bar{w}_i f_i = \frac{\sum_{i=1} w_i f_i}{\sum_{i=1} f_i} \tag{8}$$

2.3. Wavelet transform

The wavelet transform presented by Grossman and Morlet (1984) can provide data related to time and frequency simultaneously, so represents time-frequency related to time data very well. Unlike other analysis techniques, the wavelet transform is capable to take into account different aspects of a time-series like trend and instability (Adamowski and Sun 2010; Singh 2012). Unlike the Fourier transform which uses a sinusoidal wave, in the wavelet transform a pseudo-wave (ψ) is utilized which can be modified in the form of the base function (ψa,b). This function derives from variations in deviation from the initial waveform. In the following equation, a and b are scale and translation parameters, respectively.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{9}$$

2.4. WANFIS hybrid method

Before start modeling groundwater levels in different months using WANFIS, the data are divided into two groups including training and testing. All data used in this study are related to 156 different months. To train the model, 108 months (9 years) are utilized as the model training samples and the level values for the next 4 years (48 months) are forecasted by the WANFIS method. After the classification of the data and determination of the training data, the influence of different time lags and their direction and correlation level with each other should be evaluated. Thus, different time lags are examined by the autocorrelation function (ACF) (Fig 3). Based on this graph, the significant effect of the basic lags and the lack of period in time-series are shown. Therefore, various combinations are suggested as follows:

WANFIS1Q(t) = f(Q(t-1))
WANFIS2Q(t) = f(Q(t-1), Q(t-2))
WANFIS3Q(t) = f(Q(t-1), Q(t-2), Q(t-3))
WANFIS4Q(t) = f(Q(t-1), Q(t-2), Q(t-3), Q(t-4))

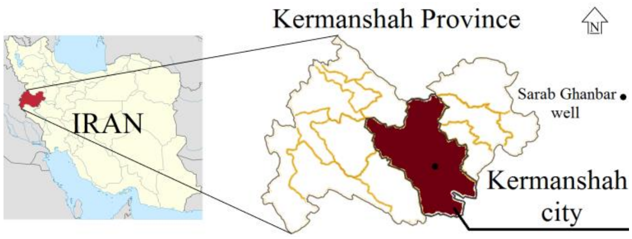

Fig. 1. Geographical location of under study well.

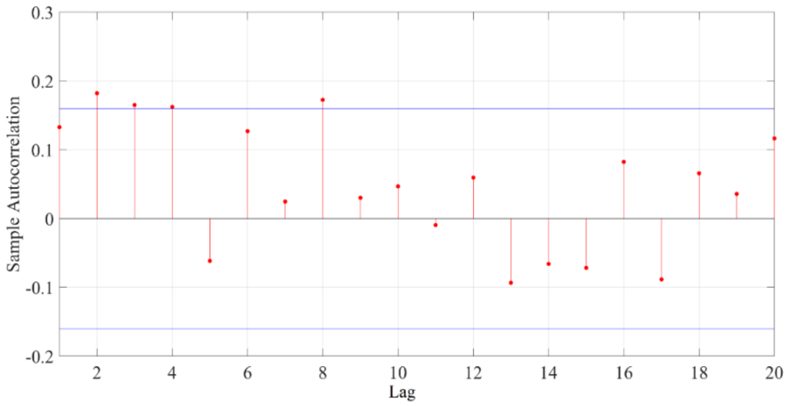

Fig. 2. ACF chart for groundwater levels.

After the determination of the samples used for training the model and also the examination of different input combinations, the type of the wavelet function and its decomposition level must be specified. The type of time-series and nature of the interested event (groundwater level) are the basic points in choosing the mother wavelet. In fact, the wavelet function must be chosen so that to be geometrically well-matched to the curve of the interested time series to perform the mapping operation with a higher ability. The wavelet functions used in this study are dmey, bior, coif, sym, haar and db. In addition, the following relationship is employed to determine the decomposition level:

$$l = \mathrm{int}\left[\log(N)\right] \tag{10}$$

where, l represents the decomposition level, N is the number of samples in the learning mode and int denotes the integer part of the l value. Given that N is equal to 108, the composition level is considered equal to 2.

2.5. Criteria for examining accuracy of numerical models

In the current study, in order to evaluate the accuracy of the introduced numerical models, the correlation coefficient (R) ،variance account for (VAF) ،root mean square error (RMSE) ،scatter index (SI) ، mean absolute relative error (MARE) and nash-sutcliffe efficiency coefficient (NSC) are used as follows:

$$R=\frac{\sum_{i=1}^{n}\left(F_i-\bar{F}\right)\left(O_i-\bar{O}\right)}{\sqrt{\sum_{i=1}^{n}\left(F_i-\bar{F}\right)^2\sum_{i=1}^{n}\left(O_i-\bar{O}\right)^2}} \quad (11)$$

$$\mathrm{VAF}=\left(1-\frac{\operatorname{var}\left(F_i-O_i\right)}{\operatorname{var}\left(F_i\right)}\right)\times 100 \quad (12)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(F_i-O_i\right)^2} \quad (13)$$

$$SI=\frac{RMSE}{\bar{O}} \quad (14)$$

$$MARE=\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|F_i-O_i\right|}{O_i}\right) \quad (15)$$

$$\mathrm{NSC}=1-\frac{\sum_{i=1}^{n}\left(O_i-F_i\right)^2}{\sum_{i=1}^{n}\left(O_i-\bar{O}\right)^2} \quad (16)$$

where, O_i , F_i , $\bar{O}$ and n represent observational values, values predicted by numerical models, the mean of observational values and the number of observational values, respectively. In the following sections, the results of different simple and hybrid artificial intelligence models along with the performance of the mother wavelets are evaluated. It should be noted that the results of these models are examined for the test mode conditions.

3. Results and discussion

3.1. ANFIS models

In this section, the accuracy of different ANFIS models is examined. The results of the statistical indices calculated for all ANFIS models are shown in Fig. 3. It should be noted that ANFIS1 estimates the groundwater level values with the lag (t-1). For this model, the values of R and SI are calculated 0.722 and 0.597, respectively. In addition, for ANFIS1, the values of RMSE, MARE and NSC are obtained 9.674, 0.880 and -0.018, respectively. It is worth noting that the ANFIS2 model simulates the objective function values by means of the lags (t-1) and (t-2). The values of different statistical indices such as VAF, R and SI for ANFIS2 are approximated 48.611, 0.700 and 0.614, respectively. For the mentioned model, RMSE and NSC are computed 9.947 and 0.103, respectively. It should be considered that ANFIS3 simulates the groundwater level values using the lags (t-1), (t-2) and (t-3). Furthermore, the values of MARE, RMSE and SI for the mentioned model are obtained 0.689, 8.174 and 0.504, respectively. For this model, VAF and R are calculated 65.342 and 0.813, respectively. It is worth mentioning that ANFIS4 estimates the groundwater level values using all input lags. In other words, this model is a function of the lags (t-1), (t-2), (t-3) and (t-4). For this model, the values of R, VAF and NSC are 0.746, 55.400 and 0.296, respectively. In addition, RMSE and SI for ANFIS4 are calculated 9.269 and 0.572, respectively. Thus, as shown, the ANFIS2 model has the lowest accuracy and ANFIS4 has the highest accuracy among all ANFIS models. Furthermore, the lags (t-1), (t-2), (t-3) and (t-4) are identified as the most effective lags. Also, the comparison of the groundwater level values forecasted by the ANFIS models versus the observed ones is shown.

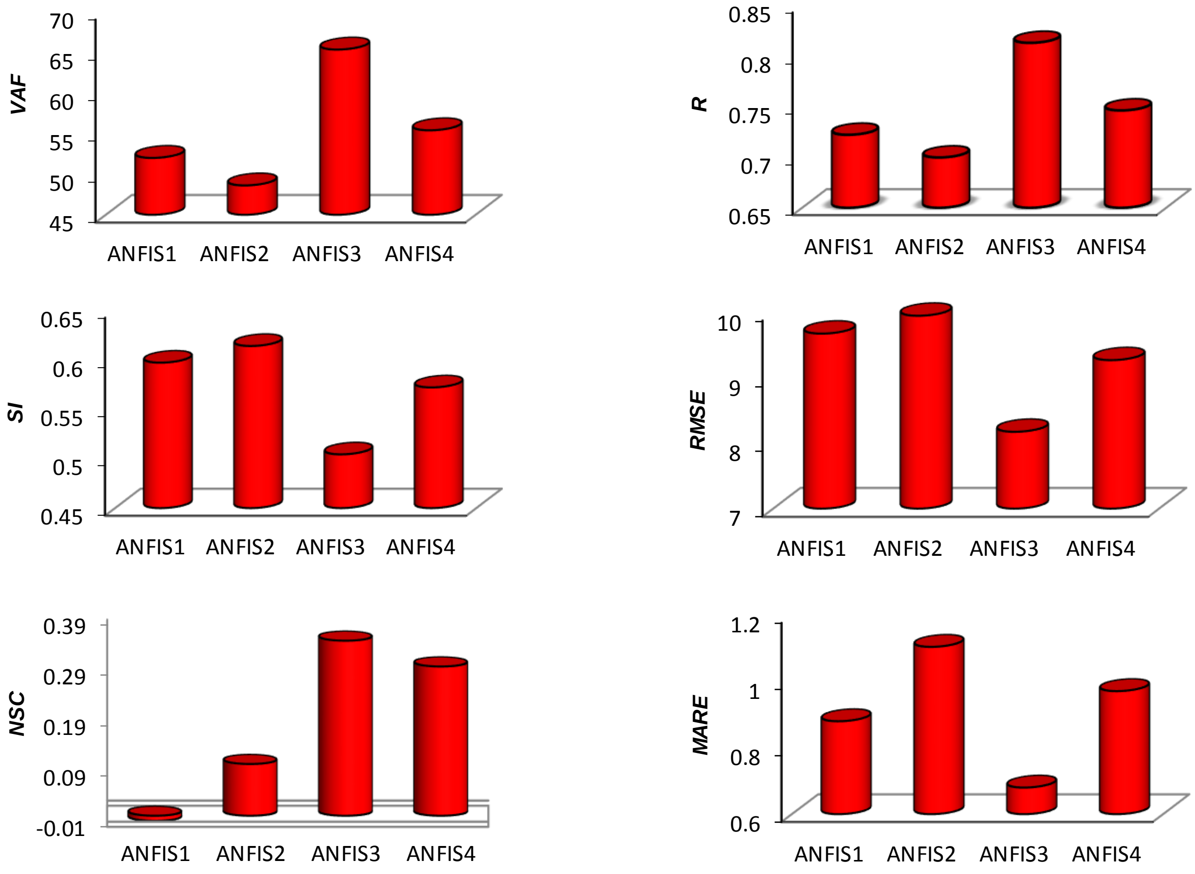

Fig. 3. Results of statistical indices for different ANFIS models.

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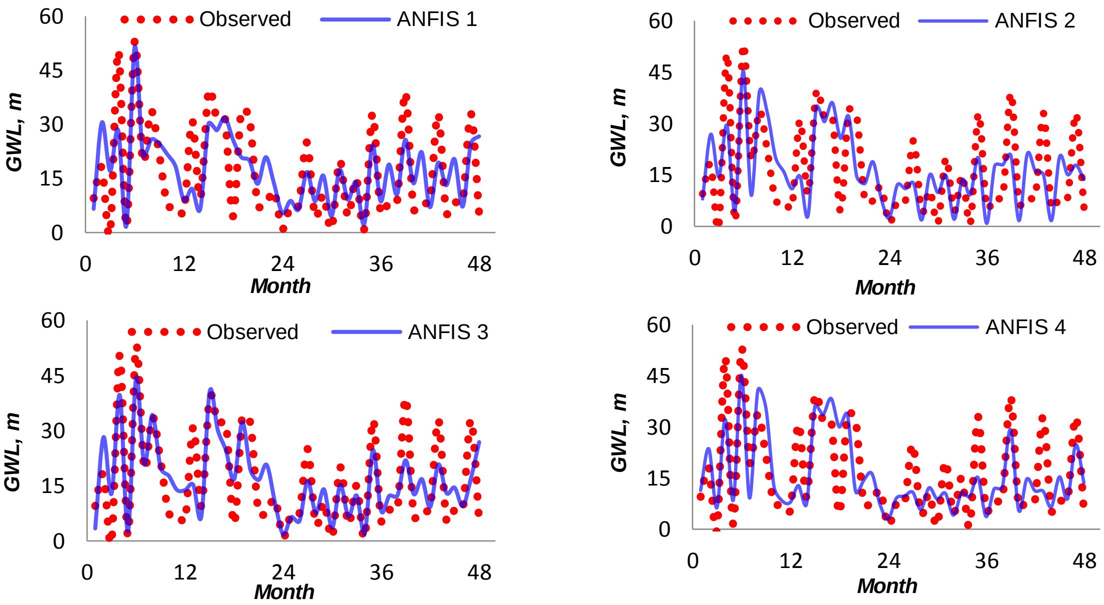


Fig. 4. Comparison of groundwater level values predicted by ANFIS models with observed values.

3.2. Mother wavelets

In this section, the mother wavelets are evaluated. Generally, the wavelet has families entitled Daubechies (db), haar, Symlets (sym), Coiflets (coif), Biorthogonal (bior) and DMeyer (dmey). In Fig. 5, the statistical indices computed for these mother wavelets are illustrated. Based on the modeling results, Dmey wavelet estimates the groundwater levels values with higher accuracy than other mother wavelets. For this mother wavelet, the values of SI, VAF and RMSE are obtained 0.192, 94.951 and 3.117, respectively. Furthermore, the values of R and MARE for dmey are approximated 0.974 and 0.437, respectively. It should be noted that for Haar mother wavelet, the values of RMS and NSC are computed 7.451 and 0.485, respectively. Among all the members of the Daubechies family, db2 estimates the groundwater level values with higher accuracy. For this mother wavelet, the values of MARE and R obtained 0.659 and 0.897, respectively. Also, according to the results of the other mother wavelets, sym2, Coif2 and bior1.1are detected as the superior members of the Symlets, Coiflets and Biorthogonal mother wavelets, respectively. For instance, VAF and R for sym2 are estimated 76.645 and 0.880, respectively. However, RMSE and MARE for Coif2 are 4.696 and 0.603, respectively. Besides, for bior1.1, SI, VAF and R are computed 0.460, 71.795 and 0.854, respectively. Based on the modeling results, Dmey mother wavelet is chosen as the best mother wavelet for combining with the ANFIS model.

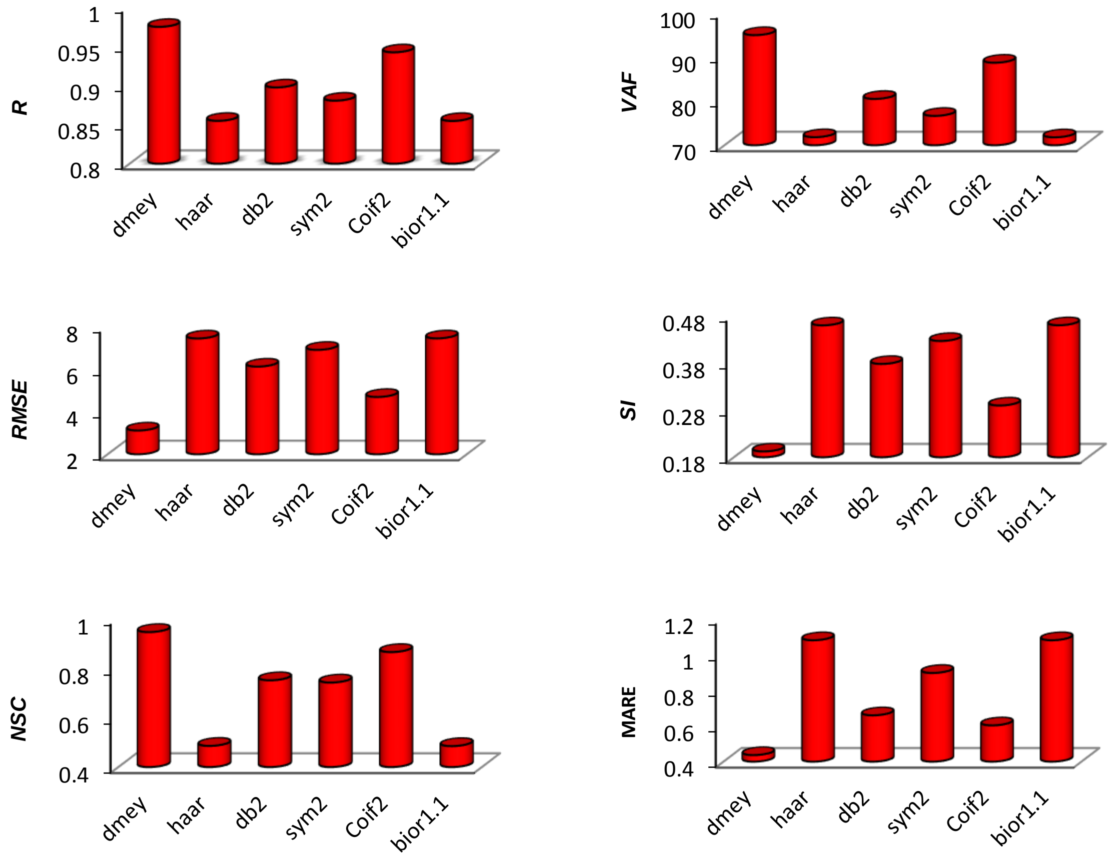


Fig. 5. Results of statistical indices for different mother wavelets.

3.3. WANFIS models

In this section, the hybrid WANFIS models are assessed. The results of different statistical indices for all WANFIS models are presented in Fig. 6. According to the modeling results, the wavelet transform significantly increases the ANFIS model efficiency. In other words, the accuracy of all WANFIS models is higher than the ANFIS models. For example, VAF for WANFIS1 is about 2 % higher than the ANFIS1 model. In addition, RMSE, SI and NSC for this hybrid model are estimated 9.559, 0.590 and -0.009, respectively. Moreover, the values of R and SI for WANFIS2 are calculated 0.858 and 0.444, respectively. It is worth mentioning that VAF for WANFIS2 increases 1.5 times compared to ANFIS2. Furthermore, NSC and RMSE for WANFIS2 are obtained 0.594 and 7.190, respectively. Moreover, the wavelet transform enhances VAF of the WANFIS3 about 1.35 times compared to the ANFIS2 model. It should be noted that MARE, R and NSC for WANFIS3 are approximated 0.487, 0.942 and 0.884, respectively. By contrast, SI, RMSE and VAF for WANFIS4 are 0.192, 3.117 and 94.951, respectively. The examination of this model exhibits that the wavelet transform increases the VAF value of WANFIS4 about 1.7 times. In Fig. 7, the comparison of the groundwater level values simulated by the hybrid models with the observed data is illustrated. Thus, the wavelet transform improves the accuracy and the efficiency of the ANFIS models. Furthermore, the WANFIS 4 model is introduced as the superior model in estimating the groundwater level values in the Sarab-e Qanbar observational well. In addition, the lags (t-1), (t-2), (t-3) and (t-4) are the most effective ones.

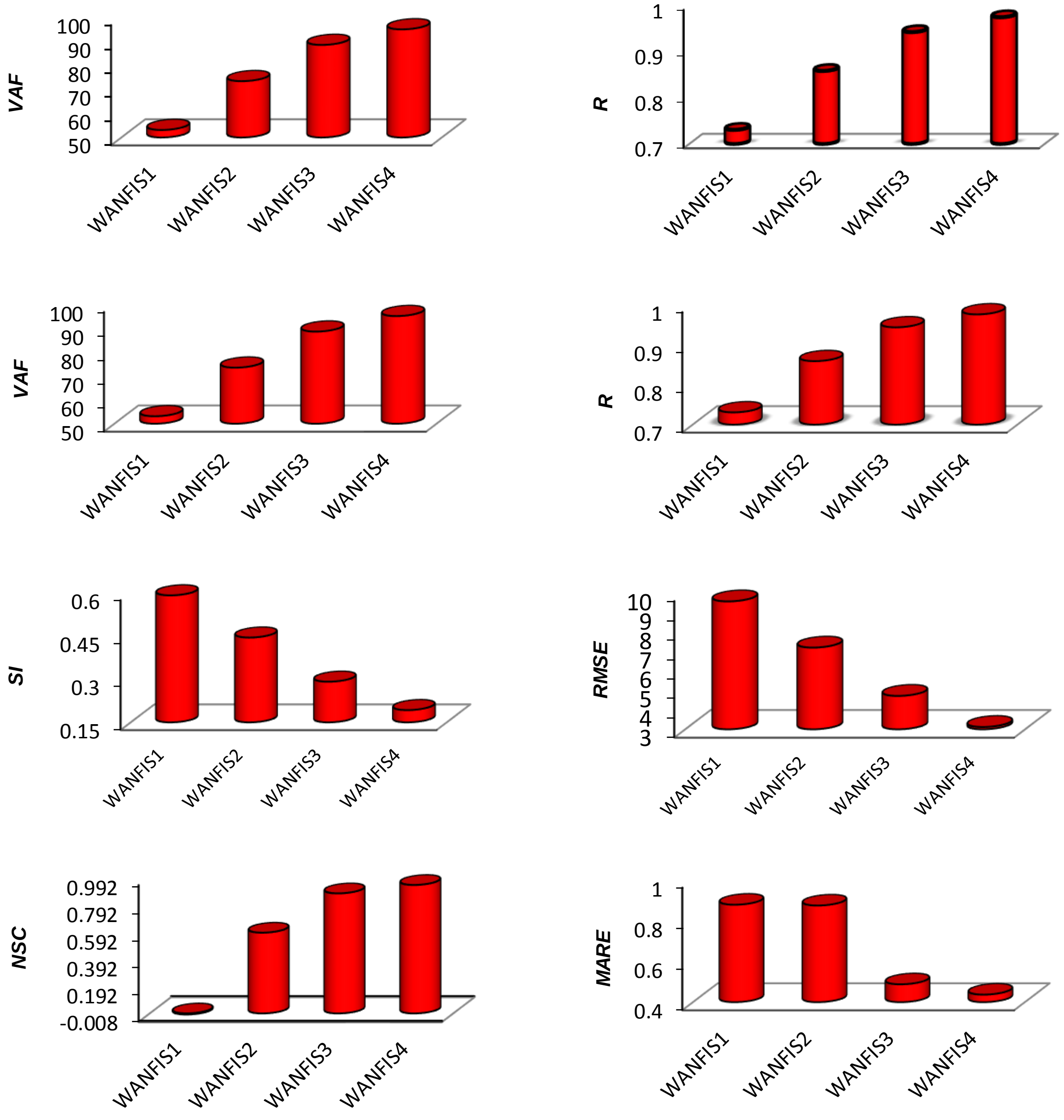
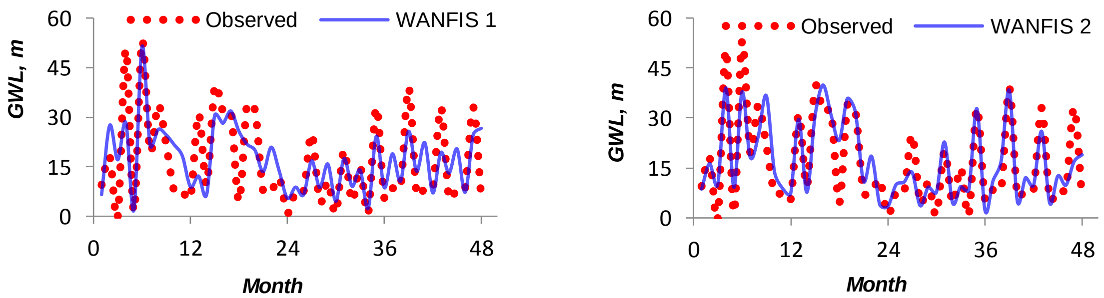


Fig. 6. Results of statistical indices for different WANFIS models.



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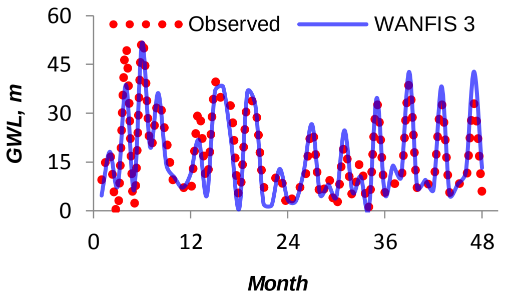

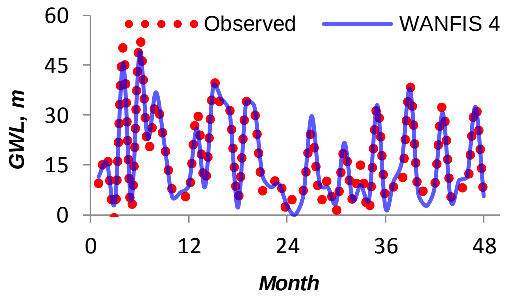

Fig. 7. Comparison of groundwater level values simulated by WANFIS models with observed data.

4. Conclusions

Owing to the importance of groundwater resources as one of the main water supply sources, the estimation and the simulation of groundwater level (GWL) variations in arid and semi-arid regions of the world like Iran is crucially important. In this paper, the long-term fluctuations of the groundwater level during a 14-year period of the Sarab-e Qanbar well located in the city of Kermanshah was simulated by means of the ANFIS model and also the WANFIS hybrid method. To develop the hybrid model, the ANFIS model and the wavelet transform were combined. Furthermore, thorough the analysis of the modeling results, Dmey mother wavelet was selected as the most optimal member of the mother wavelets. For this mother wavelet, the values of SI, VAF and RMSE were obtained 0.192, 94.951 and 3.117, respectively. In addition, the effective lags of the time-series data were detected by the autocorrelation function (AFC) and then four various models were produced for each of ANFIS and WANFIS models. The results of the simulations exhibited that the wavelet transform considerably improves the accuracy of the ANFIS model. For instance, the VAF index for the superior models of ANFIS and WANFIS were obtained 55.400 and 94.951, respectively. It is worth noting that WANFIS4 simulated the groundwater level values in the Sarab-e Qanbar observational well with reasonable accuracy. For example, the values of R and SI for this model were computed 0.974 and 0.192, respectively. Besides, RMSE and NSC for this hybrid model are estimated to be 9.559 and -0.009, respectively. Furthermore, the analysis of the simulations demonstrated that the lags (t-1), (t-2), (t-3) and (t-4) are the most effective lags.

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