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Comparison of Groundwater Level Estimation Using Neuro-fuzzy and Ordinary Kriging

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Abstract Water level in aquifer plays the main role in groundwater modeling as one of the input data. In practice, due to aspects of time and cost, data monitoring of water levels is conducted at a limited number of sites, and interpolation technique such as kriging is widely used for estimation of this variable in unsampled sites. In this study, the efficiency of the ordinary kriging (*OK*) and adaptive network-based fuzzy inference system (*ANFIS*) was investigated in interpolation of groundwater level in an unconfined aquifer in the north of Iran. The results showed that ANFIS model is more efficient in estimating the groundwater level than *OK*.

Keywords Geostatistics · Kriging · Groundwater level · ANFIS

1 Introduction

Iran is situated in an arid and semiarid region with an average precipitation of 250 mm per year. In the last two decades, due to a rapid population growth in the country, the water demand has been highly increased in municipal, agricultural, and industrial sectors. Lack of permanent rivers in most parts of the country has caused an overexploitation of aquifers. Because of this withdrawal, a considerable decline has been observed in water level of many aquifers (sometimes more than 3 m per year). In this situation, groundwater simulation models can be useful as a tool to obtain a sustainable growth of water supply.

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An important part of groundwater modeling is the accuracy of input data such as hydraulic head and sink or source that should be assigned to each node of the network. On the other hand, in groundwater, due to aspects of time and cost, data monitoring (such as observation wells) is conducted at a limited number of sites. As a result, unsampled values should be usually interpolated. Statistics based on spatial distribution, which is usually referred to as geostatistics, is a very useful tool for handling spatially distributed data such as air and groundwater pollution [5, 7].

In geostatistics, kriging method is a purely linear stochastic technique that originally developed based on probability theory or statistical experiments. This method was applied to estimate the values of hydrology and hydrogeology variables at unsampled sites by many researchers [6, 11, 21, 25].

Ma et al. [13] analyzed groundwater level, bedrock, and saltwater–freshwater interface elevations in south–central Kansas using the geostatistical approach. Their study indicates that this method reproduces satisfactory results to estimate initial conditions for groundwater levels and topography of the Permian bedrock at the nodes of a finite-difference grid used in a three-dimensional numerical model.

Marsily and Ahmed [14] compared the universal kriging, cokriging, and kriging combined with linear regression methods to estimate the transmissivity and specific capacity. Their research showed that cokriging method with minimum standard deviation error is the most efficient method in comparison with other geostatistical methods. In addition, kriging is applied to optimize the long-term and/or develop monitoring network [1].

In practice, due to high cost, time limit, the changing dynamic nature of the data, and numerous other difficulties, repeated measurements of any given spatial pattern are seldom carried out. This lack of repetition is not suited for the basic assumptions of probability theory in kriging [12]. To make up

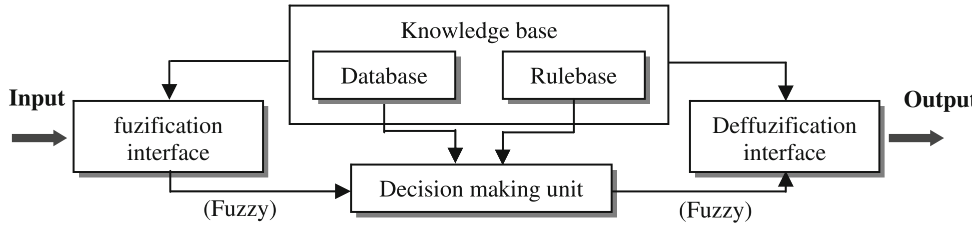

Fig. 1 Fuzzy inference system with crisp output

these absent data, combinations with other data as covariate (cokriging) are frequently adapted. Researches show that for situation of lacking data, the fuzzy inference system (FIS) is suited to handle noisy and linguistic data (soft data) [19].

Various efforts indicate that the intelligent computing tools such as artificial neural network (ANN) and FIS are proved to be efficient when applied individually to modeling, simulation, optimization, and parameter estimation of groundwater [15, 18]. Combining both ANN and FIS models is a new approach that has been used widely in engineering applications [4, 2, 8, 17].

Adaptive network-based fuzzy inference system (ANFIS) models are attractive since they can learn the underlying relations from numerical data, while the fuzzy rules obtained can provide a transparent linguistic description for the working of the model. Fuzzy systems provide the possibility of integrating (logical) information processing with the attractive mathematical properties of general function approximators [22].

Tutmez et al. [24] studied the modeling of electrical conductivity (EC) in the water by using an ANFIS using real-world data regarding the water sources in the Mersin region of southern Turkey. Their results indicate that the ANFIS model outperforms more traditional methods of modeling EC based on the total solids dissolved in the water, even though ANFIS uses less information.

In this study, the efficiency of the ordinary kriging (OK) estimator is compared to ANFIS model in interpolation of groundwater level. The next sections discuss more about the OK and ANFIS models.

2 Material and Methods

2.1 Ordinary Kriging

Ordinary kriging is a linear weighted-average technique, which is unbiased in regard to expected value of residuals.

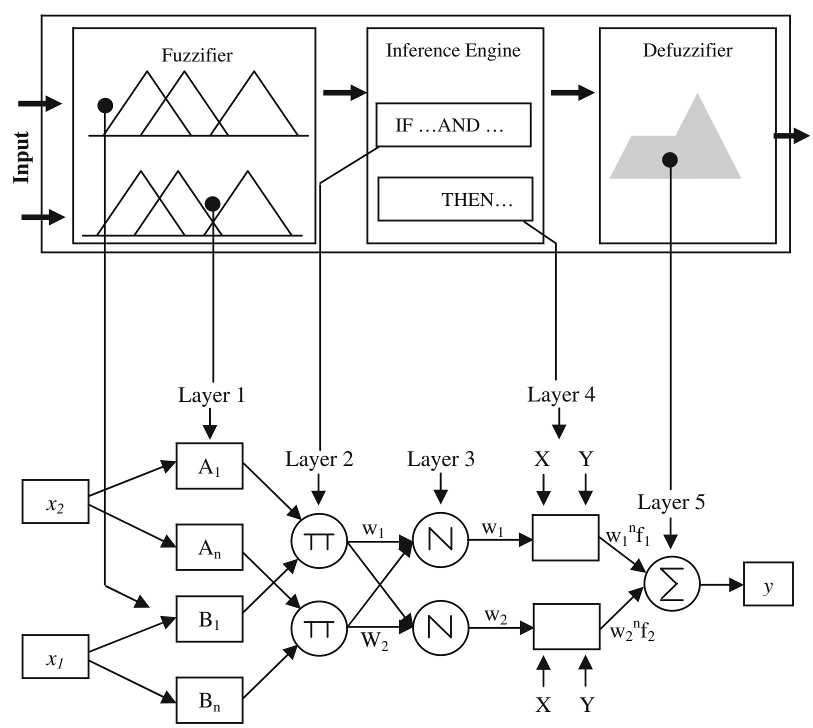

Fig. 2 Adaptive ANFIS architecture

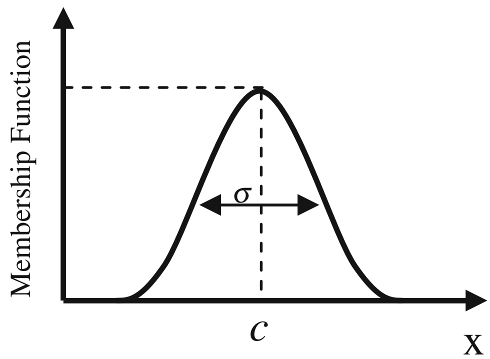

Fig. 3 Gaussian membership function: Gaussian (x; σ, c)

It is extensively used to find the linear unbiased estimation of a second-order stationary random field with an unknown constant mean as follows:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{1}$$

where $\hat{Z}(x_i)$ is kriging estimate at location x_0; $Z(x_i)$ sampled value at x_i; and λ_i is weighting factor associated with $Z(x_i)$. The estimation error or residual is defined as:

$$R(x_0) = \hat{Z}(x_0) - Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) - Z(x_0) \tag{2}$$

where $Z(x_0)$ is the true value of regionalized variable at spatial location x_0 and $R(x_0)$ is the estimation error. In an unbiased estimator, the expected value of the residual has to be 0.

$$E[R(x_0)] = 0 \tag{3}$$

After implementing Eq. 2, unbiasedness condition will be obtained which is $\sum_{i=1}^{n} \lambda_i = 1$.

In ordinary kriging, the weighting coefficient λ_i can be calculated by solving an optimization problem whereby the variance of residuals will be minimized subjected to unbiasedness condition. By using Lagrange multiplier μ, a constraint optimization problem could be converted to an unconstrained optimization problem. After solving this unconstrained optimization problem, the resulting system of linear algebraic equations in terms of λ_is can be written as:

$$\begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{1n} & 1 \\ \gamma_{21} & & \gamma_{2n} & 1 \\ & & & 1 \\ \gamma_{n1} & \gamma_{n2} & \gamma_{mn} & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \\ \gamma_{0n} \\ 1 \end{bmatrix} \tag{4}$$

The variogram γ can be defined as one half the variance of the difference between the attribute values at all points separated by h as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{5}$$

where $\gamma(h)$ is estimated variogram at separation distance h, and $N(h)$ is the total number of pairs of attributes that are

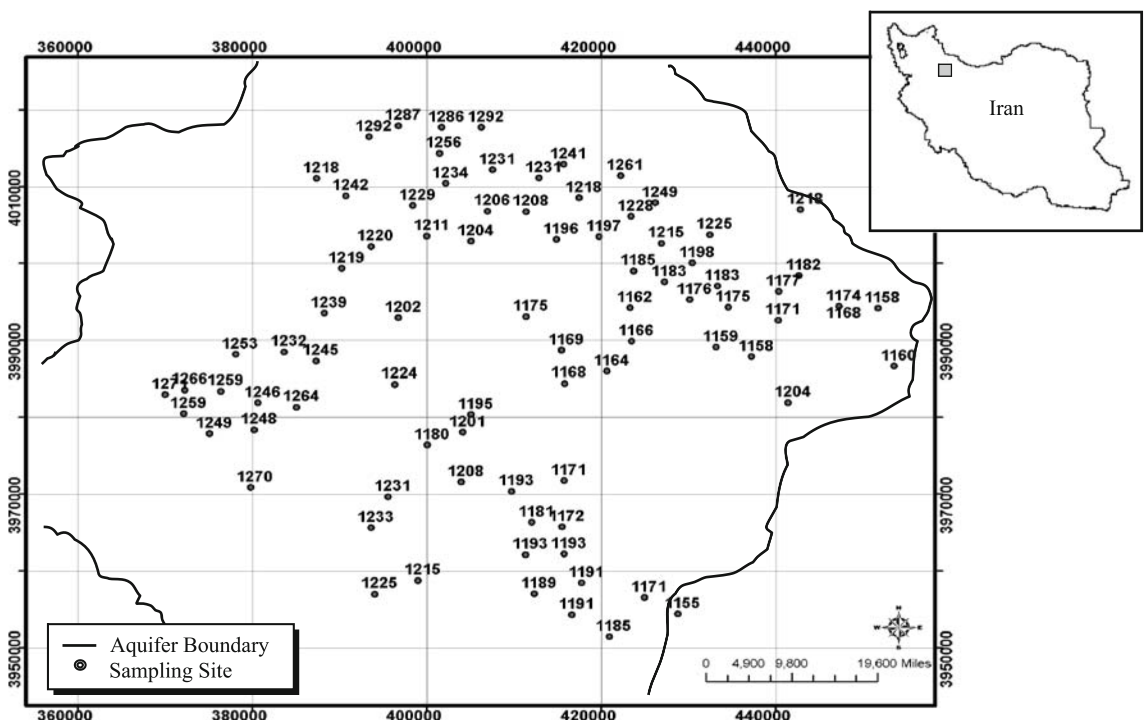

Fig. 4 Study area and location of sampling sites

Table 1 Summary of descriptive statistics

Descriptions	Year 2003
Number of sites (−)	95
Minimum (m)	1,158
Maximum (m)	1,292
Mean (m)	1,214±3.46[a]
Median (m)	1,214
SD (m)	33.80
Skewness (−)	0.312

[a] Standard error

separated by a distance h [9]. The important characteristics or properties of the traditional variogram are range, sill, and nugget effect. The most commonly used models applicable to compute theoretical variogram are spherical, Gaussian, and exponential model. In this study, the Geostatistics for the Environmental Science Software (GS+) is used for variogram modeling and estimation.

2.2 Neuro-Fuzzy Approach

ANFIS is a powerful universal approximation tool for vague and fuzzy systems [12]. The basic structure of adaptive network consists of two main conceptual parts: a FIS which is made up of three components: a rule base, a database, a reasoning mechanism demonstrated in Fig. 1 schematically, and a learning mechanism consisting of a multilayer feed forward network [17].

The adaptive network based on Sugeno fuzzy inference model provides a deterministic system of output equations and, thus, the parameters can be estimated easily [23]. The architect of ANFIS consists of five layers summarized in Fig. 2 which a brief account of the operation for each layer is provided in the following paragraph [3, 10, 17].

The first layer called input layer is composed of nodes which generates membership grades according to the appropriate membership functions and the set of parameters to be determined via minimization of an appropriate objective function:

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(x_1) \\ O_{1,i+2} &= \mu_{B_i}(x_2) \quad \text{for } i = 1,2 \end{aligned} \tag{6}$$

where x_1 and x_2 are the crisp inputs to node i, and A_i and B_i are the linguistic labels characterized by appropriate membership function μ_{A_i} and μ_{B_i}, respectively. In fact, the outputs $O_{1,i}$ and $O_{1,i+2}$ of this layer are membership functions of A_i and B_i. In this study, the Gaussian-shaped function is chosen as a membership function. A Gaussian membership function is specified by two parameters σ and c:

$$\text{Gaussian}(x;\sigma,c) = e^{-\left(\frac{x-c}{\sigma}\right)^2} \tag{7}$$

where c represents the MF's center and σ determines the MF's width (Fig. 3).

The second layer is the so called rule nodes with AND and/or OR operator to be used to compute every possible conjunction of the decision rules. The output $O_{2,m}$ of this layer is the products of the corresponding degree from layer 1:

$$O_{2,m} = W_m = \mu_{A_i}(x_1) \times \mu_{B_j}(x_2) \qquad m = 1,\ldots 4; i,j = 1,2 \tag{8}$$

The third layer is the so called average nodes whereby the main purpose is to normalize the conjunctive membership functions in order to rescale the inputs:

$$O_{3,i} = \overline{W}_i = \frac{W_i}{\sum_{i=1}^{4} W_i} \qquad i = 1,\ldots,4 \tag{9}$$

The fourth layer called consequent node is a standard perceptron [20] whereby Sugeno fuzzy inference model is used to associate the normalized membership function toward

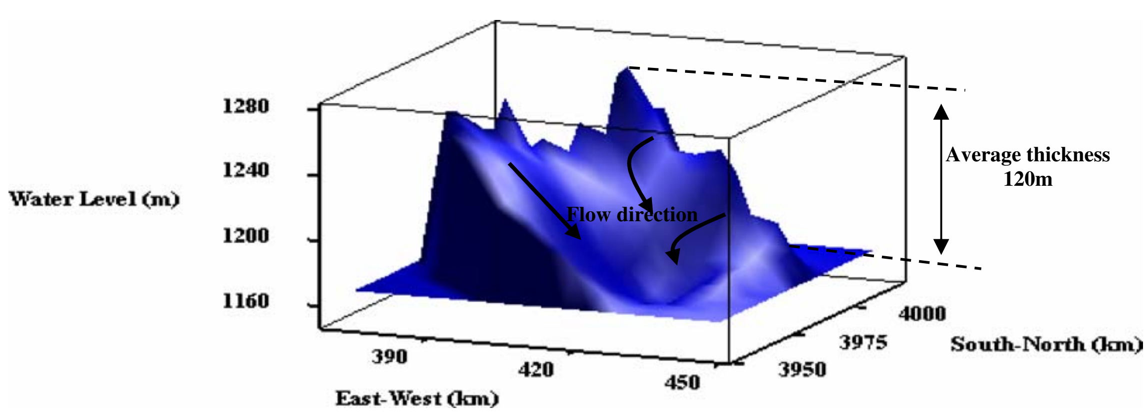

Fig. 5 3-D surface plot of groundwater level

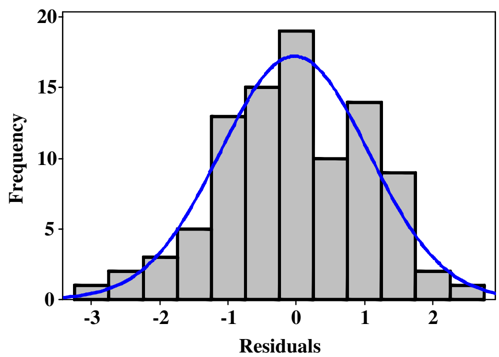

Fig. 6 Histogram of residuals and normal plot

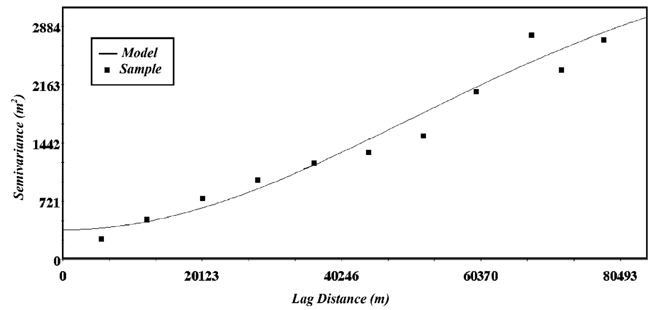

Fig. 7 Plot of sampled vs. computed variogram model

the total output. In other words, the contribution of each rule is computed at this layer:

$$O_{4,i} = \overline{W}_i f_i = \overline{W}_i (p_i x_1 + q_i x_2 + r_i) \qquad i = 1, \ldots, 4 \qquad (10)$$

where (p_i, q_i, r_i) are the coefficients of this linear combination.

The fifth layer, output nodes, will compute the overall output by summing the incoming evidences. The sum of all incoming signals is used to generate the decision crisp output:

$$O_{5,1} = y = \sum_{i=1}^{4} \overline{W}_i f_i = \frac{\sum_{i=1}^{4} W_i f_i}{\sum_{i=1}^{4} W_i} \qquad (11)$$

In the training step, the goal is to train adaptive networks to be able to appropriate unknown function given by training set data and then find the precise value of the above parameters. An integrated of least-square method and back propagation algorithm (hybrid model) is used to optimize the function parameters.

In the ANFIS model, the clustering via fuzzy subtractive clustering is also conducted for each input variable. In an M-dimensional space, there are N data points $\{x_1, \ldots, x_n\}$ to be grouped. Each data point is considered as a potential cluster center. The ith cluster center x_i can be decomposed into two components: the first N element of x_i (P_i) and the last two M–N elements of x_i (Q_i):

$$\mu_i = \exp\left[-\frac{\|x - P_i\|^2}{(r_a/2)^2}\right] \qquad (12)$$

where μ_I is the degree of the membership function to the ith node; P_i is the input vector; r_a is the radius defining a neighborhood of a cluster center. The objective of the fuzzy subtractive clustering is to prevent the increasing number of parameters which altered according to the number of rules.

3 Study Area and Dataset

Our study area is the aquifer of the Qazvin plain which is part of the Qazvin province located in the west of Tehran, capital of Iran. The storage volume of this aquifer is about 20×10^9 m^3 to be one of the largest aquifer in Iran.

In this plain, no permanent river exists; therefore, the supply of water demands in agriculture, industry, and domestic sectors in 4,000-km^2 area around this plain highly depends on groundwater. Increasing the pumping wells in two recent decades has been the main cause of groundwater decline rating to 1 m per year. This decline in water level has resulted in the negative balance of 300 million cubic meters in this aquifer. This problem has caused the decrease of groundwater quality as well. In this regard, for a sustainable

Table 2 Properties of fitted variograms and goodness-of-fit criteria

Model	R^2	RSS	Nugget (m^2)	Sill (m^2)	Range (km)
Spherical	0.934	227,404.00	70.00	3,250.00	144.00
Exponential	0.908	338,980.00	1.00	3,112.00	67.40
Gaussian	0.939	209,125.00	390.00	3,890.00	74.60

Table 3 Result of evaluation criteria for best pattern of ANFIS model

	Evaluation criteria		
	MSE	MAE	CE
Training	143.12	7.12	0.97
Testing	152.25	4.63	0.93
Validation	122.21	7.65	0.86

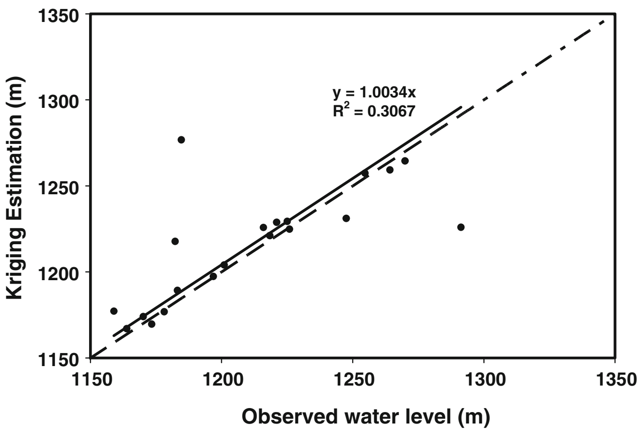

Fig. 8 The kriged groundwater level versus observed values and the best-fitted linear regression

groundwater management, development of a simulation model is the first step.

The data of 95 observation wells at this plain have been used in this study. Dataset was collected by the Iranian Ministry of Energy (IMOE). The spatial distribution of measured groundwater level is shown in Fig. 4. The descriptive statistics for the cited dataset were summarized in Table 1.

The 3-D surface plot of groundwater level based on the sampled sites is shown in Fig. 5. The average thickness of this aquifer is 120 m.

3.1 Data Preparation

In the first step, the normality test for observed data must be conducted. The normality test of residuals satisfies the stationary condition for kriging. In this regard, a second-degree polynomial was calculated from the original data as follows:

$$Z = 1.860X^2 + 0.015Y^2 - 0.347XY + 1.536X - 0.662Y - 0.849 \quad (13)$$

where Z is groundwater level elevation vector; X and Y are longitude and latitude of sampling points in UTM unit, respectively. The coefficient of determination of this interpolated polynomial is 0.92. The Kolmogorov–Smirnov test in 95% level is used to the normality of residuals (Fig. 6).

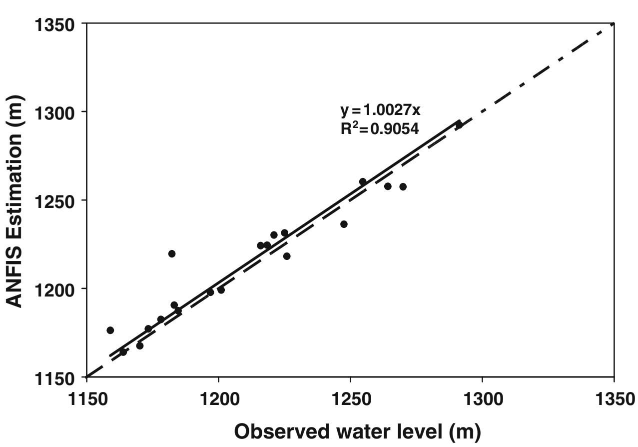

Fig. 9 The ANFIS-estimated groundwater level versus observed values and the best-fitted linear regression

4 Results and Discussions

For mapping groundwater level, an appropriate theoretical variogram model must be determined. Three nonlinear models, Gaussian, spherical, and exponential, were examined with the following mathematical model:

1. Gaussian model:

$$\gamma(h) = \begin{cases} C_0 + C_1\left(1 - \exp\left(-\frac{h^2}{a^2}\right)\right), & h \leq a \\ C_1, & h > a \end{cases} \quad (14)$$

2. Spherical model:

$$\gamma(h) = \begin{cases} C_0 + C_1\left(1.5 \times \frac{|h|}{a} - 0.5 \times \left(\frac{|h|}{a}\right)^3\right), & h \leq a \\ C_1, & h > a \end{cases} \quad (15)$$

3. Exponential model:

$$\gamma(h) = \begin{cases} C_0 + \frac{C_1|h|^2}{\left(1+\frac{|h|^2}{a}\right)}, & h \neq 0 \\ 0, & h = 0 \end{cases} \quad (16)$$

where the C_0 is the nugget; C_0+C_1 is the sill; a is the range; and h=lag distance.

A few criteria including coefficient of determination between the estimated values and observed values and residual sum of squares are used to select the best model. Table 2 indicates the properties of fitted variograms and the criteria which were considered to determine the goodness of fit for each variogram.

Table 4 The performance of estimations with ANFIS and ordinary kriging models

Model	MSE	MAE	CE
Ordinary kriging	747.32	14.40	0.896
ANFIS	122.21	7.65	0.30

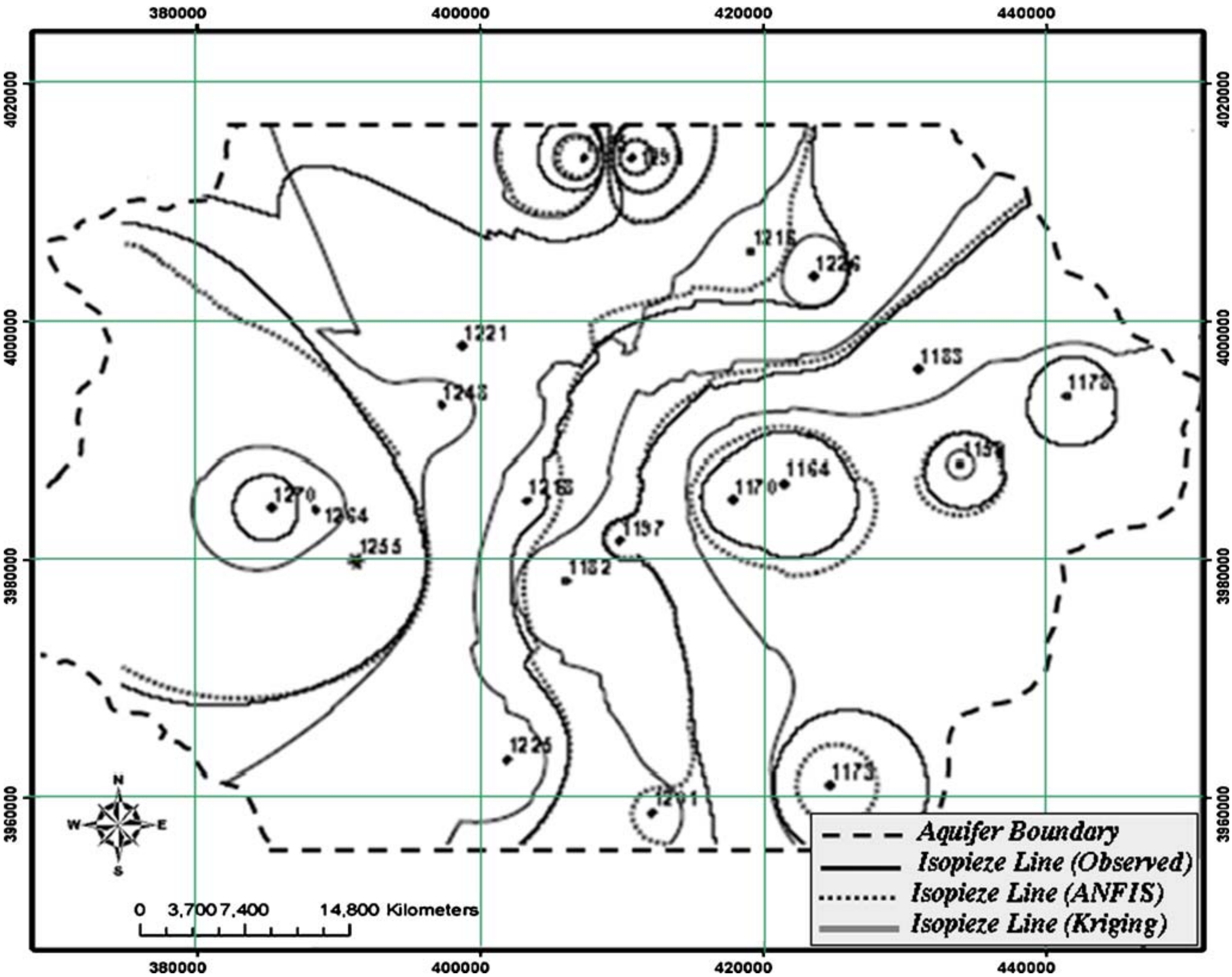

Fig. 10 Contour plot of isopieze lines estimated by kriging and ANFIS models

The results summarized in Table 2 indicate that the best-fitted variogram has a Gaussian structure. The plot of the Gaussian variogram and the sample data are shown in Fig. 7.

$$\gamma(h) = \begin{cases} 390 + 3400\left(1 - \exp\left(-\frac{h^2}{(74.60)^2}\right)\right) & h \leq 74.60 \\ 3400 & h > 74.60 \end{cases} \tag{17}$$

In the ANFIS model, each input variable, which vary within a range, might be clustered into several class values in the first layer to build up fuzzy rules. Accordingly, as the number of rules increased, the number of parameters that must be optimized becomes enormous. To prevent this problem, subtractive fuzzy clustering is used to establish the rule-based relationship between the input and output variables [3].

The observed data were divided into three sets randomly, training set (65% of total data), checking set or validation set (15% of total data), and testing set (20% of total data). The longitude and latitude of sampled sites are considered as the input variables, and the groundwater level elevations are considered as the output variable. In the training step, the influence clustering radius is evaluated by trial and error. In this study, the range of influence of 0.5 and squash factor amounting to 0.987 have the best performance, which produced six membership functions Gaussian type in first layer. In addition, the criteria of mean square error, mean absolute error, and the coefficient of efficiency [16] are considered for selecting the best architecture of the ANFIS model, as follows:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}\left(\hat{Z}_i - Z_i\right)^2}{n} \tag{18}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \left| \hat{Z}_i - Z_i \right|}{n} \tag{19}$$

$$\mathrm{CE} = 1 - \frac{\sum_{i=1}^{n} \left(\hat{Z}_i - Z_i \right)^2}{\sum_{i=1}^{n} \left(Z_i - \overline{Z}_i \right)^2} \tag{20}$$

where Z_i is the observed value at the site I; $\hat{Z}_i$ is the estimated value at site i, and $\overline{Z}_i$ is the average of observed values. The best architecture of ANFIS model has the errors as shown in Table 3.

The testing dataset selected in ANFIS model is considered to evaluate the performance of ANFIS and *OK* models. To investigate the degree of similarity between estimated and measured values, scatterplot of estimated versus observed values for both kernels are depicted in Figs. 8 and 9.

The fitted regression line between estimated and observed values for groundwater level based on both models has a greater slope than the 1:1 indicating that the predictions has smaller variance than the observed data.

The criteria (12)–(14) were also utilized to evaluate and verify the effectiveness of various models used. Table 4 indicates the summary of the results of applying these criteria. The higher efficiency of the ANFIS model compared to ordinary kriging can be seen based on the results of Table 4.

The observed isopieze contour lines and simulated contour lines by ANFIS and kriging model are shown in Fig. 10. This figure clearly showed that the contour lines based on predictions of ANFIS model have better agreement with observed values than kriged contour line. The absolute error at sampled sites which are considered for model verification are shown as contour surface plot form in Fig. 11 which reveals that the ANFIS model has less absolute errors compared to ordinary kriging method. The reduction of absolute error based on the kriging method is uniformly distributed in all of the aquifer sampled sites.

5 Conclusion

In this study, the performance of the *ANFIS* model and the *OK* has been evaluated in the estimation of groundwater level with a case study in the Qazvin plain (Iran). The

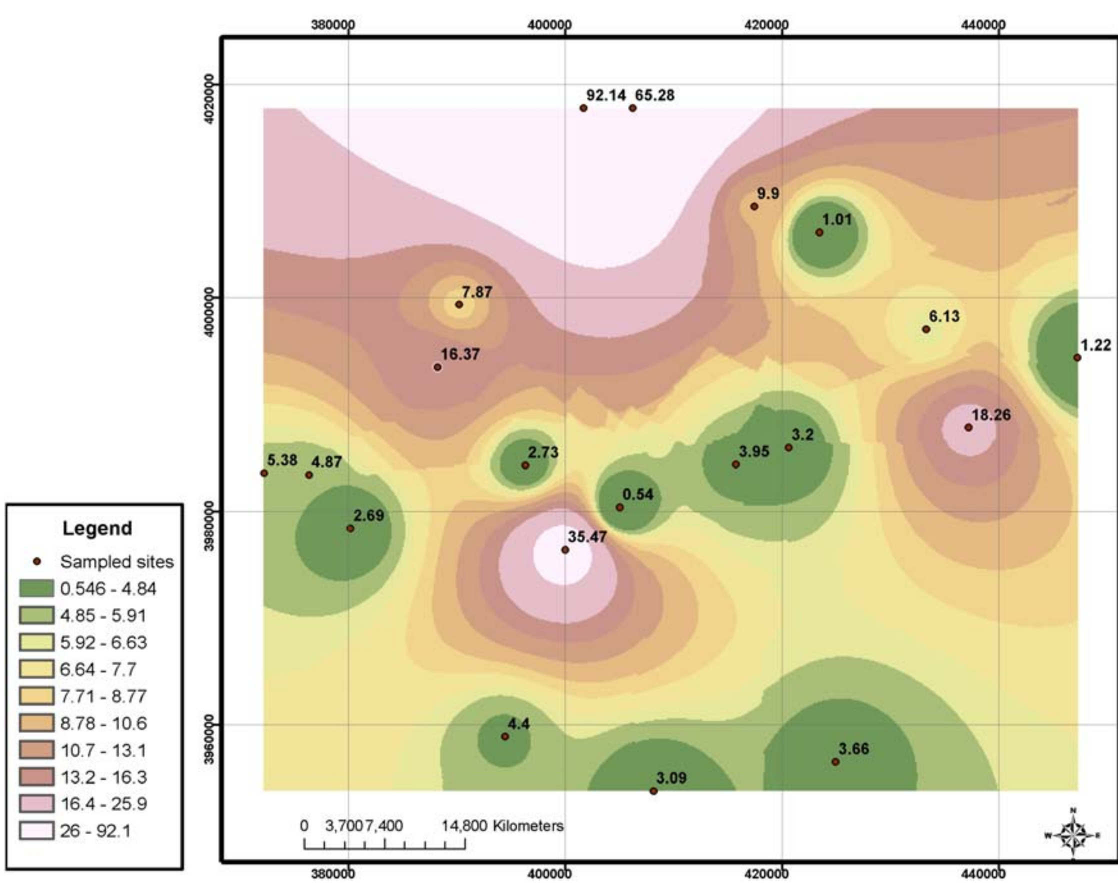

Fig. 11 The estimated standard errors of water level given by *OK* method

ANFIS model indicated the higher efficiency in estimation of the groundwater level than the *OK* method. It could be due to the ANFIS model consisting of two major approaches: one, FIS which can reflect the ambiguity and imprecision which is an inherent part of observed data and, two, applying the ANN in optimization of the system parameters which is a pure nonlinear model. It should be mentioned that the kriging is capable of calculating the standard error of estimations (as shown in Fig. 11) that can be used in finding the optimal pattern and developing of existing monitoring network; this is a special advantage of kriging than other interpolation methods and ANFIS model.

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