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Supervised Intelligent Committee Machine Method for Hydraulic Conductivity Estimation

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Abstract Hydraulic conductivity is the essential parameter for groundwater modeling and management. Yet estimation of hydraulic conductivity in a heterogeneous aquifer is expensive and time consuming. In this study; artificial intelligence (AI) models of Sugeno Fuzzy Logic (SFL), Mamdani Fuzzy Logic (MFL), Multilayer Perceptron Neural Network associated with Levenberg–Marquardt (ANN), and Neuro-Fuzzy (NF) were applied to estimate hydraulic conductivity using hydrogeological and geoelectrical survey data obtained from Tasuj Plain Aquifer, Northwest of Iran. The results revealed that SFL and NF produced acceptable performance while ANN and MFL had poor prediciton. A supervised intelligent committee machine (SICM), which combines the results of individual AI models using a supervised artificial neural network, was developed for better prediction of the hydraulic conductivity in Tasuj plain. The performance of SICM was also compared to those of the simple averaging and weighted averaging intelligent committee machine (ICM) methods. The SICM model produced reliable estimates of hydraulic conductivity in heterogeneous aquifers.

Keyword Hydraulic conductivity · Artificial intelligence methods · Supervised intelligence committee machine · Tasuj plain · Heteregenous aquifer

1 Introduction

Estimation of hydrogeological parameters is crucial for managing groundwater resources, contaminant transport, and designing remediation measures. Variety of numerical models were developed for parameter estimation, such as hydraulic conductivity, porosity, soil water retention (Tsai and Li 2008). However, due to some limitations of the numerical models such

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as low flexibility, high complexity, cost, and time consuming, other methodologies such as artificial intelligence (AI) models were recently developed for this purpose.

Hitherto, artificial intelligence (AI) models such as fuzzy logic (FL) (Bárdossy and Disse, 1993; Batyrshin et al. 2005; Tutmez and Hatipoglu 2007; Chu and Chang 2009; Helmy et al. 2010; Anifowose and Abdulraheem 2011; Tayfur 2012; Morankar et al. 2013), artificial neural network (ANN) (Schaap and Leij 1998; Merdun et al. 2006; Nayak et al. 2006; Samani et al. 2007; Tayfur et al. 2007; Mohanty et al. 2010; Motaghian and Mohammadi 2011; Shirmohammadi et al. 2013;), and neuro-fuzzy (NF) (Tutmez 2010; Huang et al. 2010; Moosavi et al. 2013; Safavi et al. 2013) have gained popularity for the hydrogeological parameter estimation.

Hydrogeological parameters such as hydraulic conductivity are not clear-cut and most of the time they are associated with uncertainties. Hence, for hydraulic conductivity estimation, the researchers have tried to evaluate different AI methods with various abilities such as fuzzy logic (FL) (Ross et al. 2007; Olatunji et al. 2011; Colin et al. 2011), artificial neural network (ANN) (Tamari et al. 1996; Garcia and Shigidi 2006; Sun et al. 2011; Inan and Tayfur 2012; Gaur et al. 2013), and neuro-fuzzy (NF) (Malki and Baldwin 2002; Hurtado et al. 2009; Sezer et al. 2010; Dhar and Patil 2012).

Generally, more than one AI model provides a similar acceptable fit to the observations (Tayfur and Singh 2011). Therefore, usage of multi-model interface can be advantages. For hydraulic conductivity estimation, intelligent committee machine (ICM) which is an artificial intelligence multi-model interface and used in different disciplines (Lim 2005; Chen and Lin 2006) can be utilized. The ICM uses the results of AI models in order to arrive at overall decision that is supposed to be superior to that of any individual AI model acting alone (Hornik et al. 1989; Naftaly et al. 1997).

The ICM can combine AI model results with a simple averaging (Naftaly et al. 1997; Chen and Lin 2006) or by weighted averaging. Using simple averaging produces the final output by linearly combining the outputs of individual AI models through the same weights. Although, it can produce better results, the AI models should have different weights based on their efficiencies. Using weighted averaging ascribes different weights to AI models which are generally optimized by genetic algorithm (GA) (Kadkhodaie-Ilkhchi et al. 2009; Labani et al. 2010) to find the best fit of the ICM output to the measurements. This method has linear nature to combine the AI models.

Instead of linearly combining AI model results, this study introduces a supervised intelligent committee machine (SICM) that replaces linear combination with artificial neural network (ANN). In SICM, the ANN receives individual model estimations as input and derives a new estimation.

Each AI method has its advantages and disadvantages. For example; ANN is a powerful tool for performing nonlinear input—output mapping. However, it is a black-box model which cannot reveal insight into understanding the physics of the process. It is a good interpolator but a poor extrapolator. MFL is a fuzzy rule based method requiring construction of many fuzzy rules, which can be unattractive from a practical point of view. Yet, it is attractive since it can account for ambiguities, and uncertainity and it is more in line with human thinking since it uses verbal statetments. SFL also operates like MFL with fuzzy rules that contain mathematical expressions. Hence, this method requires parameter estimation, which cannot be always an easy task. NF in a way combines ANN and FL methods. The objective of this study is to reap advantages of each AI method by employing the SICM to predict the very fundamental aquifer parameter of hydraulic conductivity. Thus, this study, using the SICM, accomplished the estimation of hydraulic conductivity in unconfined and heterogeneous Tasuj aquifer.

2 Study Area

The Tasuj plain, which is about 302.67 km^2, is a subbasin of Urmia Lake basin (Fig. 1) and located in the northwestern part of Tabriz city in Iran. The study area is surrounded by Urmia Lake (south), Mishu Mountains (north), Salmas Plain (west) and Shabestar Plain (east). The prevailing climate in the Tasuj plain is semiarid-cold (Nadiri et al. 2013). Average annual precipitation is about 232.7 mm (based on measurements at Tasuj climatological station, 2000–2009) (Research Center of Agriculture and Natural Resources of East Azerbaijan Province 2010). In the Tasuj basin, there is no permanent river and there is only a few seasonal rivers originating from Mishu Mountains. Agriculture is the main economic activity in Tasuj City and 15 villages in the study area. The main source for drinking, industrial and agricultural demands in the plain is groundwater.

The Tasuj plain aquifer is a heterogeneous and unconfined and the groundwater in the aquifer was withdrawn through 147 water wells, 70 springs and 70 qanats (Nadiri et al. 2013). The 24 springs and 14 qanats became dry in the recent years due to over-drawing. Therefore, identification of hydrogeological parameters such as hydraulic conductivity in the study area is

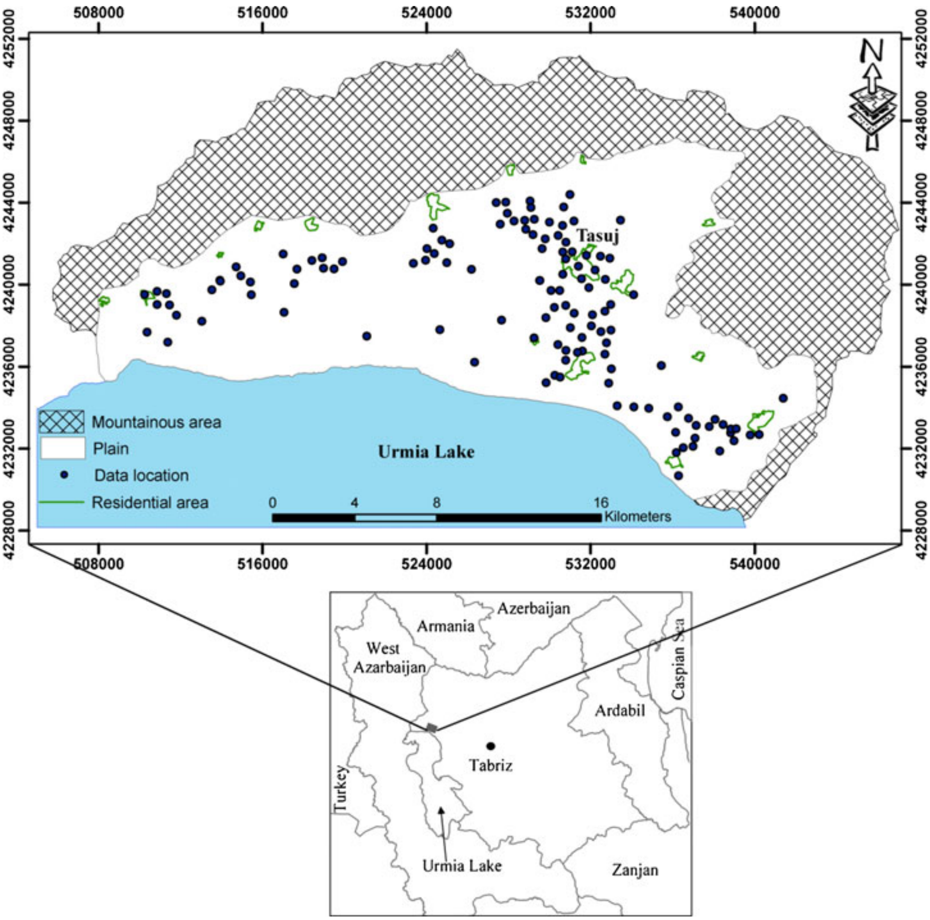

Fig. 1 Tasuj Plain and locations of hydraulic conductivity measurment

vital for groundwater management. More information about the study area is given in Nadiri et al. (2013).

Based on the a geo-electrical survey that was conducted by the Abkav Consulting Engineering Co. (1973), the saturated zone thickness in the aquifer (B) and transverse resistance (R_t) were estimated at 63 points. The maximum thickness is 182 m and the minimum thickness is 44 m. To estimate K values in each point, both parameters are needed. Therefore, B and R_t distributions were obtained by an ordinary kriging method.

Hydraulic conductivity in the saturated zone is related to electrical resistivity (ρ) which is the transverse resistance (R_t) divided by the thickness of the saturated zone (B). The electrical resistivity (ρ), on the other hand, depends on the salinity of formation water (Putvance 2000). Therefore, the electrical conductivity (EC), which responds to the salinity of formation water, is also related to hydraulic conductivity. Hence, in this study B, EC, and O, which is the distance of each estimation point to the position of down corner of the right side of the study area map (see Fig. 1) to take into account the geological and geomorphological effects, are used as input variables for the AI models.

In 132 locations of Tasuj unconfined aquifer, hydraulic conductivity was determined by the constant and step drawdown pumping tests that were carried out by the water resources authority of East Azarbaijan (Fig. 1). The maximum K is 9.74 m/day and the minimum K is 0.13 m/day. The mean and the standard deviation of K are 2.35 and 3.30 m/day, respectively (Nadiri et al. 2013).

3 Models

3.1 Fuzzy Logic (FL)

In fuzzy set theory, each element may belong to a set to a degree which can take values ranging from 0 to 1 (Zadeh 1965). The key idea in fuzzy logic is the allowance of partial belongings of any object to different subsets of a universal set. Fuzzy sets have ambiguous boundaries and gradual transitions between defined sets and this makes it to be appropriate to deal with the nature of uncertainty (Calvo and Estrada 2009). Each fuzzy set is represented by a membership function (MF), which can be Gaussian, triangular, or trapezoidal. Intuition, rank ordering, and inductive reasoning can be, among many, ways to assign membership functions to fuzzy variables. The intuitive approach is instead used commonly because it is simple and derived from the innate intelligence and understanding of human beings.

A FL model consists of four main parts i.e., Fuzzifier, Inference Engine, Fuzzy Rule Base, and Defuzzifier (Tayfur 2012). Fuzzification forms fuzzy sets for input–output variables using membership functions. The fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs. These rules are expressed in the IF-THEN format. In the Mamdani Fuzzy Logic (MFL) rule system both antecedent and consequent parts of a rule contain verbal statements. In Sugeno Fuzzy Logic (SFL), the consequent part of the rule contains mathematical expressions, relating output variable to input variables. The fuzzy inference engine takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs that are composed to form a single fuzzy subset for the output variable. Defuzzification converts the resulting fuzzy output from the fuzzy inference engine to a number. The details of MFL can be obtained from Mamdani and Assilian (1975), Mamdani (1976, 1977) and Tayfur (2012). The details of SFL can be found elsewhere (Takagi and Sugeno 1985; Sugeno 1985; Akbari et al. 2009).

3.2 Artificial Neural Network (ANN)

Artificial neural networks are imitating human brain by using mathematical methods and have been proven to be beneficial tools for simulating, predicting and forecasting hydrological variables (Nadiri 2007; Nourani et al. 2008b; Piotrowski and Napiorkowski 2011; Siou et al. 2011; Tayfur 2012). The most widely used neural network is the multi-layer perceptron (MLP) (Hornik et al. 1989; Haykin 1999; Sulaiman et al. 2011; Fijani et al. 2012; Mustafa et al. 2012). In the MLP, as a feed forward ANN, the neurons are organized in layers and each neuron is connected fully with neurons in the next layer. A typical three-layer feedforward neural network (FFNN) is shown in Fig. 2, where the input signal propagates through the network in a forward direction. In a FFNN, the input quantities (x_i) are fed into the input layer neurons which, in turn, pass them on to the hidden layer neurons (z_i) after multiplying them by the connection weights (v_{ij}) (Fig. 2). A hidden layer neuron adds up the weighted input received from each input neuron ($x_i v_{ij}$), associates it with a bias (b_j), and then passes the result (net_j) on through the activation function. Similarly, the produced outputs from the inner neurons are passed to the network output neuron. The net information received by the output neuron from the inner neurons is passed through the activiation function to produce the network output. The optimal weights are found by minimizing a predetermined error function (E) of the following form (ASCE 2000):

$$E = \sum_{\mathrm{P}} \sum_{\mathrm{p}} (y_i - t_i)^2 \tag{1}$$

where yi = the component of an ANN output vector $\boldsymbol{Y}$; t_i = the component of a target output vector $\boldsymbol{T}$; p = the number of output neurons; and P = the number of training patterns. The gradient-descent method, along with the chain rule of differentiation, is generally employed to modify the network weights as (Tayfur 2012):

$$\Delta v_{ij}(n) = -\delta \frac{\partial E}{\partial v_{ij}} + \alpha \ \ \Delta v_{ij}(n-1) \tag{2}$$

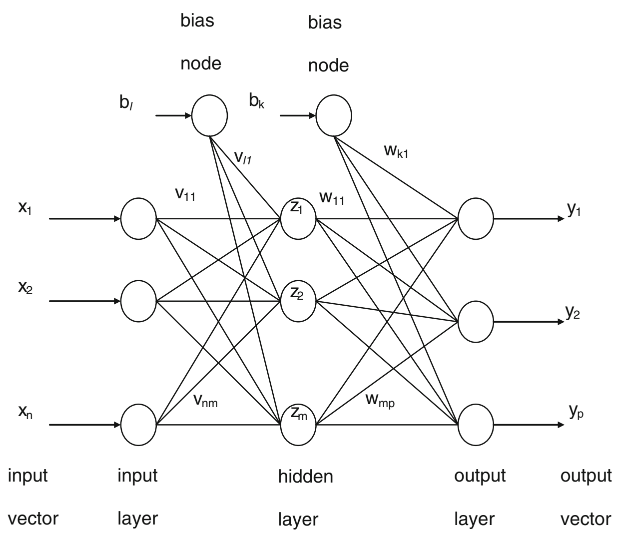

Fig. 2 A typical feedforward ANN model

where $\Delta v_{ij}(n)$ and $\Delta v_{ij}(n-1)$ = the weight increments between node i and j during the n^{th} and $(n\text{-}1)^{th}$ pass or epoch; δ = the learning rate; and α = the momentum factor.

This study adopted the hyperbolic tangent activation function (Tayfur 2012) and the training algorithm of Levenberg-Marquardt (LM) (Daliakopoulos et al. 2005; Nourani et al. 2008a, 2008b; Mustafa et al. 2012).

3.3 Neuro-Fuzzy (NF)

Neuro-fuzzy modeling is a combination technique for describing the behavior of a system using fuzzy inference rules within a neural network structure. The NF inference system consists of a given input/output data set and SFL whose MF parameters are tuned using a hybrid algorithm (Wolkenhauer 2001; Sanikhani and Kisi 2012). The most compatible method for construction of NF model is Sugeno method using subtractive clustering.

In this study, the NF architecture of a five-layer MLP network was considered in the hydraulic conductivity estimation. In the first layer, membership function of input data were generated like the SFL model. Also, a generalized Gaussian function was used to develop membership functions. In the second layer, the firing strength was calculated for the each rule via multiplication. In the third layer the normalized firing strengths were computed for each neuron. The contribution of the each rule in the model output was calculated based on the first order SFL method in the forth layer. Lastly, the final output as the weighted average of all rule outputs (aggregation) was calculated in the fifth layer. The NF parameters and membership function parameters were estimated using the hybrid algorithm, which is a combination of the gradient descent and least-squares method (Aqil et al. 2007; Akrami et al. 2013).

3.4 SICM Model

The Intelligent committee machine approach combines the artificial intelligence model results to reap advantages of all AI models to produce final output. Previous works recommended two methods of the simple averaging and the weighted averaging for construction of SICM model (Chen and Lin 2006; Labani et al. 2010). This study instead introduces a supervised intelligent committee machine (SICM) model that employs ANN as a supervised combiner of AI models.

The SICM model consists of four artificial intelligence models shown in Fig. 3 and includes two major steps. In the first step, hydraulic conductivity is estimated using the artificial intelligence models including MFL, SFL, ANN and NF. In the second step, a supervised

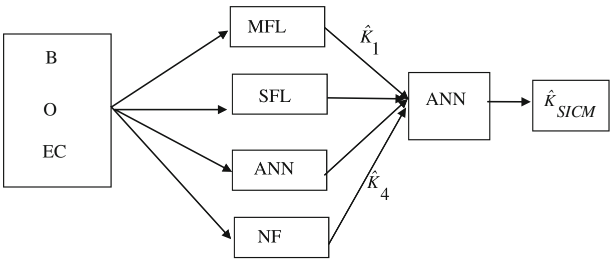

Fig. 3 The Schematic structure of SICM model

artificial neural network is constructed as a nonlinear and supervised combiner. The mathematical expression of the SICM model can be expressed as follows:

$$\widehat{K}_i = AI_i(O,\ EC,\ B) \tag{3}$$

$\widehat{K}_i$ is the output of the each AI model which is used as i^{th} input to the SICM model.

4 Model Calibration and Testing

4.1 Mamdani Fuzzy Model

Fuzzy c-means (FCM) clustering for MFL (Arrell et al. 2007; Kannan et al. 2012) was used for the construction of a fuzzy rule base (Li et al. 2001). Gaussian membership functions were employed for the input variables. Results showed that the optimum number of clusters for the hydraulic conductivity is 12. The parameters of Gaussian membership function are summarised in Table 1. The model was calibrated with 105 data sets, with the root mean square (RMSE) of 1.21 m/day and the determination coefficient (R^2) of 0.77. The model was then tested against 27 data sets, with a performance of RMSE=1.89 m/day and R^2=0.63.

4.2 Sugeno Fuzzy Model

Subtractive Clustering (SC) for SFL (Chiu 1994) was applied for the data clustering. Radius clustering was selected based on the minimum RMSE. Choosing a value of 0.4 for clustering radius was associated with the lowest RMSE of 0.99 m/day which generated six fuzzy IF-THEN rules. The model was calibrated with 105 data sets with RMSE=0.98 m/day and the R^2=0.77. The model was then tested against 27 data sets, with a performance of RMSE= 1.67 m/day and R^2=0.72.

Table 1 The parameters of Gaussian membership functions for MFL model (**σ** : standard daviation of normal distribution, **c**: mean of data)

Input	O(m)		EC(micro.s/cm)		B(m)		Output $\widehat{K}$ (m/d)	
Parameter MF No.	σ	c	σ	c	σ	c	σ	c
1	2525	19220	277.5	2429	5.565	106.8	0.6044	0.6074
2	1995	22710	121.1	1530	16.53	158.8	0.7073	0.3167
3	1880	31900	132.2	1454	6.123	114.2	0.7032	1.353
4	1613	30370	164.5	1123	6.295	119	1.13	3.588
5	1885	23880	205.1	2002	8.147	98.35	0.8993	2.489
6	2404	34400	145.8	1631	6.715	93.75	1.405	4.262
7	2740	17900	293.6	2516	5.229	110.1	0.6001	0.565
8	1498	27840	135.2	1432	7.986	109	1.717	4.129
9	3905	12250	140.5	1501	5.48	98.53	0.4931	1.445
10	1448	27720	122.5	1301	6.438	98.87	0.6457	11.31
11	1480	29090	141.6	1279	7.187	109.9	1.162	3.688
12	3154	15720	304.5	2497	6.596	107.5	0.6449	1.122

4.3 Artificial Neural Network (ANN)

A three layer network with Levenberg-Marquardt (LM) training algorithm, which is denoted as MLP-LM, was used for K estimation. The training was accomplished with RMSE=1.03 m/day and R^2=0.82. The testing performance was RMSE=1.85 m/day and R^2=0.63.

4.4 Neuro-Fuzzy(NF)

The same clusters of input and outputs and rules were used for NF construction. The hybrid algorithm which is a combination of the least-squares method and the back propagation gradient descent method was applied to optimize and adjust Gaussian membership function parameter and the coefficients of output linear equation (Zounemat-Kermani and Teshnehlab 2008). RMSE=0.83 m/day and R^2=0.85 for the training and RMSE=1.51 m/day and R^2= 0.76 for the testing stages were obtained.

Based on the above RMSE and R^2 results; it can be stated that MFL and ANN showed poor performance compared to those of SFL and NF models. At this stage, we can take advantage of using the supervised intelligence committee machine (SICM) to obtain better estimations of K values.

5 SICM Model

5.1 SICM Model Training and Testing

The SICM method shown in Fig. 3 adopts a simple ANN method to re-estimate hydraulic conductivity values, predicted by the SFL, MFL, ANN, and NF in the training step (105 sample data). The ANN model had 4 neurons ($\widehat{K}$ via SFL, MFL, ANN, and NF) in the input layer, three neurons in the hidden layer and single neuron in the output layer for the target $\widehat{K}_{SICM}$. The network was successfully trained with 500 epochs and RMSE of 0.42 m/day. Then, the SICM model was tested against 27 data sets. The RMSE and R^2 for SICM predictions were computed as 0.62 m/day and 0.94, respectively. Comparing the error measure values with those of individual models above, it is seen that SICM outperforms individual AI models with low RMSE and high R^2 values. This result implies that SICM model shows high performance for predicting the hydraulic conductivity values in the heterogeneous unconfined aquifer in Tasuj Plain. Figure 4 shows the distribution of K in Tasuj Plain which was interpolated from the estimated values by the SICM model.

5.2 Comparative Analysis

Here, SICM model performance was compared against that of the ICM model. For the simple averaging method, the ICM estimated hydraulic conductivity using SFL, MFL, ANN, and NF with equal weights as follows:

$$\widehat{K}_{SICM} = 0.25\widehat{K}_{SFL} + 0.25\widehat{K}_{MFL} + 0.25\widehat{K}_{ANN} + 0.25\widehat{K}_{NF} \tag{4}$$

For the weighted averaging method, optimal weights, w_i were determined by minimizing the mean squared error (MSE):

$$MSE = \sum_{i=1}^{m} \frac{1}{m}\left(w_1\widehat{K}_{i,SFL} + w_2\widehat{K}_{i,MFL} + w_3\widehat{K}_{i,ANN} + w_4\widehat{K}_{i,NF} - K_i\right)^2 \tag{5}$$

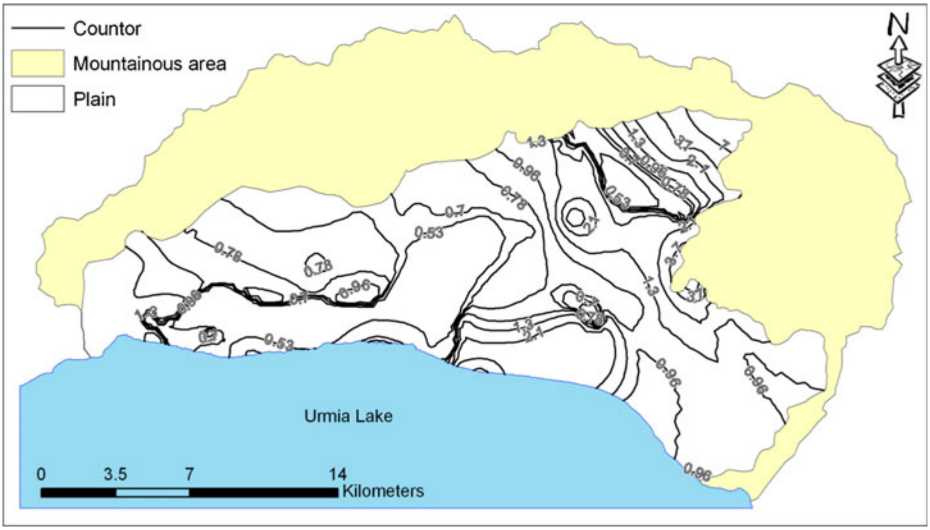

Fig. 4 Distribution of estimated hydraulic conductivity via SICM model

where m is the number of training data (105 samples). The weights, w_i range between 0 and 1 and the sum of weights is unity, $\sum_i w_i = 1$.

A GA optimizer in MATLAB toolbox was used to minimize the MSE. The initial population size was set to 25. The maximum number of generations went up to 140. The probability for crossover operation was 80 % and the mutation function was Gaussian. After optimal weights were obtained by GA, the ICM model estimated hydraulic conductivity by the following equation:

$$\widehat{K}_{CMIS} = 0.27\widehat{K}_{SFL} + 0.17\widehat{K}_{MLF} + 0.21\widehat{K}_{ANN} + 0.34\widehat{K}_{NF} \quad (6)$$

The performance results of the SICM and ICM are shown in Table 2 for K data for the testing stage. As seen, the SICM better performed than the ICM, which in turn also outperformed the individual models, presented above. According to Table 2, ICM with weighted averaging performs better than ICM with simple averaging, which agrees to Kadkhodaie-Ilkhchi et al. (2009) and Labani et al. (2010).

6 Conclusions

This study introduced a supervised intelligent committee machine (SICM) algorithm, which combines the outcomes of individual AI models, to predict the hydraulic conductivity of Tasuj aquifer. In SICM, the ANN receives predictions of four individual models—Sugeno fuzzy

Table 2 Performance measures for SICM and ICM (testing stage)

Criteria	SICM	ICM with simple averaging	ICM with weighted averaging
R^2	0.94	0.83	0.87
RMSE (m/d)	0.62	1.40	1.28

logic (SFL), Mamdani fuzzy logic (MFL), neuro-fuzzy (NF), and artificial neural network (ANN) — as input and derives a new estimation.

Following conclusions can be drawn from this study:

1. MFL and ANN showed poor performance compared to those of SFL and NF models in predicting hydraulic conductivity values. It can be stated that SFL and NF are more applicable for the estimation of hydraulic conductivity in the heterogeneous and unconfined Tasuj aquifer.
2. SICM model can be employed to predict hydraulic conductivity values.
3. ICM and SICM models produced better performance than the individual ones.
4. The SICM is more capable than ICM in predicting hydraulic conductivities of the heterogeneous and unconfined aquifer, Tasuj plain, as a case study.
5. Most of the aquifers in nature are heterogeneous and complex. Therefore, the presented method (SICM) can be used for prediction of different hydrogeological parameters such as porosity, water content and etc., in various case studies.

Note that in SICM method, the main focus is to maximize the performance by optimizing the weights assigned to each AI model. Yet, the main limitation of this method is that it cannot consider the parsimony and uncertainty of the assigned weights to individual models, which can be researched in future. Also, the influence of Kriging interpolation of B and Rt on the output of AI models was not investigated in this study. It could be a topic of a future research.

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