

A method of groundwater quality assessment based on fuzzy network-CANFIS and geographic information system (GIS)

V. Gholami¹ · M. R. Khaleghi² · M. Sebghati¹

Received: 3 May 2016 / Accepted: 22 November 2016 / Published online: 7 December 2016
© The Author(s) 2016. This article is published with open access at Springerlink.com

Abstract The process of water quality testing is money/time-consuming, quite important and difficult stage for routine measurements. Therefore, use of models has become commonplace in simulating water quality. In this study, the coactive neuro-fuzzy inference system (CANFIS) was used to simulate groundwater quality. Further, geographic information system (GIS) was used as the pre-processor and post-processor tool to demonstrate spatial variation of groundwater quality. All important factors were quantified and groundwater quality index (GWQI) was developed. The proposed model was trained and validated by taking a case study of Mazandaran Plain located in northern part of Iran. The factors affecting groundwater quality were the input variables for the simulation, whereas GWQI index was the output. The developed model was validated to simulate groundwater quality. Network validation was performed via comparison between the estimated and actual GWQI values. In GIS, the study area was separated to raster format in the pixel dimensions of 1 km and also by incorporation of input data layers of the Fuzzy Network-CANFIS model; the geo-referenced layers of the effective factors in groundwater quality were earned. Therefore, numeric values of each pixel with geographical coordinates were entered to the Fuzzy Network-CANFIS model and thus simulation of groundwater quality was accessed in the study area. Finally, the simulated GWQI indices using the Fuzzy Network-CANFIS model were

entered into GIS, and hence groundwater quality map (raster layer) based on the results of the network simulation was earned. The study's results confirm the high efficiency of incorporation of neuro-fuzzy techniques and GIS. It is also worth noting that the general quality of the groundwater in the most studied plain is fairly low.

Keywords GWQI · Model validation · Groundwater quality map · Mazandaran Plain

Introduction

In the developing countries such as Iran, there is a need of efficient water supply especially in view of scarce water resources and water pollution problems. These water resources should be utilized optimally by appropriate planning, development management sufficient decision-making information (Mohsen-Bandpei and Yousefi 2013). It is clear that the problem of water resources pollution is one of the most important challenges to be encountered in the close future, particularly in arid and semiarid areas, such as Iran (Celik et al. 1996; Kolpin et al. 1998; Dixon 2005; Ouyang et al. 2013). According to Kördel et al. (2013) since the soundness of policy decisions in groundwater management almost directly depends on the reliability of the water resource management monitoring programs, therefore an accurate and routine assessment of the groundwater quality (as an essential component of groundwater environment evaluation), and also accurate prediction of the groundwater level and, is necessary to establishing optimal strategies for regional water resource management (Zhang et al. 2009; Li et al. 2012; Singh et al. 2014). Therefore, to access this important purpose, namely to make the best and optimal use of the available water, it

✉ M. R. Khaleghi
dmrkhaleghi@gmail.com

¹ Department of Range and Watershed Management, Faculty of Natural Resources, University of Guilan, Sowmeh Sara, Guilan 1144, Iran

² Taybad Branch, Islamic Azad University, Taybad, Iran

is necessary to extent a comprehensive index that is representative of the overall water quality (Chang and Chang 2006). First time, the water quality index (WQI) was developed by the national sanitation foundation (NSF) as a standard index for assessment of the water quality and also as a technique of rating water quality (Ott 1978; Al-hadithi 2012; Gharibi et al. 2012). WQI has sufficient efficiency to assess any changes in groundwater quality. The development of WQI for groundwater quality assessment is described in the several studies (Nasiri et al. 2007; Gharibi et al. 2012). Moreover, groundwater quality index (GWQI) was used for evaluating groundwater quality in different studies (Gholami et al. 2015). GWQI was first introduced by Ribeiro et al. (2002), since the needed quantitative parameters are available. In order to eliminate the problem of the number of parameters and related limitations in water quality assessment, Ocampo-Duque et al. (2007) developed the fuzzy water quality index (FWQI). In recent years, artificial intelligence (AI) computational methods, such as the neuro-fuzzy systems have been increasingly applied to environmental issues (Chau 2006; Gharibi et al. 2012). The neuro-fuzzy systems are the result of the combination of neural networks and fuzzy logic (Zadeh 1965; Pramanik and Panda 2009). Adaptive neuro-fuzzy inference system (ANFIS) as a multilayer feed-forward network is capable of combining the benefits of both these fields and also uses Gaussian functions for fuzzy sets, linear functions for the rule outputs and Surgeon's inference mechanism and mainly has been used for mapping input–output relationship based on available data sets (Chang and Chang 2006; Nourani et al. 2011; Subbaraj and Kannapiran 2010; Ullah and Choudhury 2013).

One of the most intelligent and soft computing tools based on fuzzy logic is CANFIS model that is based on fuzzy logic and hence as in many other analytical fields, application of this model for data processing has significantly been increased during the recent years in different fields with superior performances, so that examples of the use and application of this technique to almost every aspect of water analysis can be found in the literature. For instance, neuro-fuzzy has been used successfully for prediction of flow through rock-fill dams (Heydari and Talaei 2011), river flow (Nayak et al. 2004, 2005; Pramanik and Panda 2009; Kisi 2010), suspended sediment estimation (Kisi et al. 2008; Cobaner et al. 2009; Mirbagheri et al. 2010), groundwater vulnerability (Dixon 2005), groundwater quality problems (Lu and Lo 2002; Zhou et al. 2007; Hass et al. 2012; Rapantova et al. 2012; Jang and Chen 2015), daily evaporation (Dogan et al. 2010; Karimi-Googhari 2012) and rainfall–runoff modeling (Chang and Chen 2001; Gautam and Holz 2001; Xiong et al. 2001; Jacquin and Shamseldin 2006). However, little research has been undertaken to study the problem of groundwater

quality using ANN and GIS. Today, Takagi–Sugeno fuzzy inference (TS) system is widely used for hydrological parameters simulation. Takagi–Sugeno fuzzy inference (TS) system was introduced for the first time by Takagi and Sugeno in 1985 and up to now, particularly in recent years, this method has been used widely in hydrological processes and has achieved to satisfactory performances and results (Vernieuwe et al. 2005; Hong and White 2009; Zhang et al. 2009). Jacquin and Shamseldin (2006) investigated the use of TS for rainfall–runoff modeling and their results showed that the superior performance of this method (TS) to the traditional methods (Ullah and Choudhury 2013). During the recent years, artificial neural network (ANN) as a dynamic estimator, has been used increasingly as well (Koike and Matsuda 2003; Samanta et al. 2004; Mahmoudabadi et al. 2009; Tahmasebi and Hezarkhani 2012; Gholami et al. 2016). Khatibi et al. (2011) compared performance of three artificial intelligence techniques for discharge routing; artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS) and genetic programming (GP) and concluded that the performance of GP is better than the other two modeling approaches in most of the respects. Khadangi et al. (2009) compared ANFIS with radial basis function (RBF) models in daily stream flow forecasting and demonstrated that ANFIS give better results than RBF. Moreover, geographic information system (GIS) is a powerful tool for use in environmental problem solving and in conducting groundwater modeling such as mapping the groundwater quality parameters, interpretation of groundwater quality data, evaluation of the groundwater quality feasibility zones for irrigational purposes, creating groundwater contamination vulnerability maps as the most common application of this technique and so on (Saraf et al. 1994; Durbude and Vararajan 2007; Karunanidhi et al. 2013; Bouzourra et al. 2014). Therefore, in order to develop a model using neuro-fuzzy techniques in a GIS to simulate water quality, it is very useful to combine the GIS technique with a neuro-fuzzy model that is very applicable and also has the potential for creating a successful modeling tool (Dixon 2004). Chang and Chang (2006) used ANFIS to build a prediction model for water level forecasting and reservoir management. Their results showed that the ANFIS can be applied successfully and provide high accuracy and reliability for reservoir water level forecasting. Zhang et al. (2009) implemented the Takagi–Sugeno fuzzy system (TS) and the simple average method (SAM) to combine forecasts of three individual models and the performance of modeling results was compared in five catchments of semiarid areas. They concluded that the TS combination model gives good predictions. In this study, we present a novel neuro-fuzzy approach, which combines two approaches, ANN and FL (Ross 2006; Tahmasebi and Hezarkhani 2012), namely

coactive neuro-fuzzy inference system (CANFIS), to have a rapid and more accurate predictor in forecasting groundwater quality. To verify its applicability, the Mazandaran Plain, was chosen as the study area. The specific objective of this research was to develop a modeling approach that loosely couples neuro-fuzzy techniques and GIS to predict groundwater quality in Mazandaran Plain. The overall objective of this research is to examine the sensitivity of neuro-fuzzy models used for assessing groundwater quality in a spatial context by integrating GIS and neuro-fuzzy techniques. The result can be as a tool for planning in order to manage and reduce the risk of the groundwater pollution.

Materials and methods

Study area

The study plain is located at $50^{\circ}30'$ to $53^{\circ}50'E$ longitude and $35^{\circ}55'$ to $36^{\circ}45'N$ latitude in northern Iran (Fig. 1), which is located in the southern Caspian coasts (Mazandaran Province). Study area has an area about $10,000 \text{ km}^2$. The Mazandaran coasts include plains made of alluvial sediments. Moreover, the changes in elevation and slope are inconsiderable on the Caspian coasts. Mazandaran Province is the second province in terms of rice production and is one of the main agricultural regions in Iran (Gholami

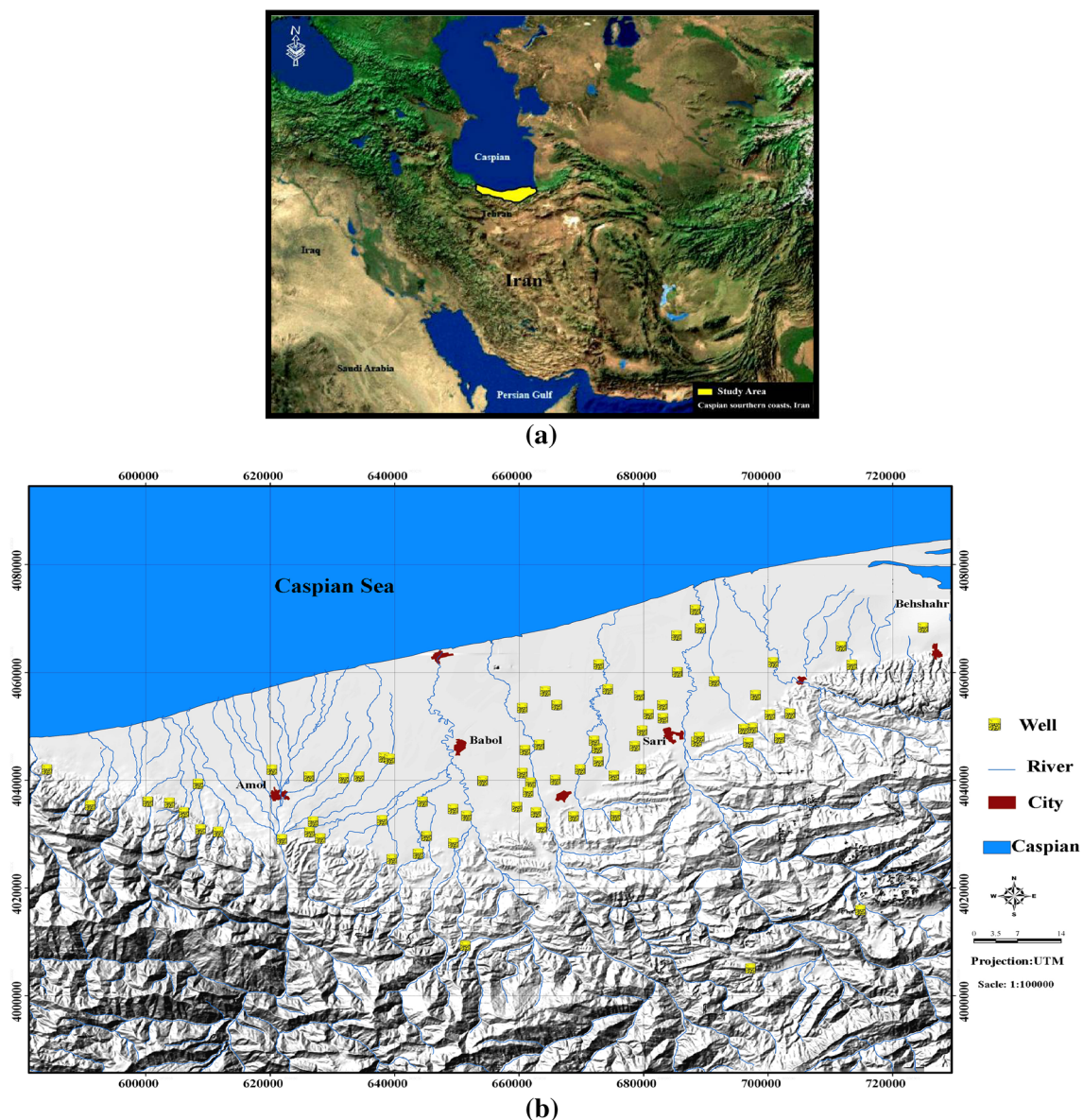


Fig. 1 Location of the study area (a) and location of the study drinking wells (b) in the Mazandaran Plain

and Khaleigh 2013). The mean annual precipitation for the west of study area is 1300 mm and decrease gradually toward of east to 600 mm. Most of the precipitation falls in the cloudy sea-seasons. Based on the modified Demartan's method, the area's climate is humid and moderate. In water quality studies, we need an index for water quality assessment.

Determination of groundwater quality index

We selected eight parameters of water quality such as cation and anion (K^+ , Na^+ , Ca^{2+} , Cl^- , Mg^{2+} , SO_4^{2-}), pH, total dissolved solids (TDS). Unfortunately, due to the lack of microbial pollution measurements in the study plain, we faced with a limitation in selecting the type of the groundwater quality index. In this study, at first about 200 drinking water wells identified in the Mazandaran Plain and then by examining the number of qualitative measurements, 85 drinking water wells related to Mazandaran Rural Water and Wastewater Company were selected. The selected wells have a high number of samples and regularly quality testing during the years 2008–2013. Figure 1 shows the location of understudy wells. In order to provide water quality index and also to check the status of groundwater quality drinking water wells, to determine the minimums, it must provide a standard index. National standards related to the quality parameters in drinking water are presented in Table 1.

Horton (1965) developed a compound index of ten water quality variables and suggested that water quality parameters can be completed through the use of other parameters, and hence, has firstly used the concept of WQI then developed by Brown et al. (1970) and improved by Scottish Development Department (1975). In this study, to check groundwater quality, ground water quality index (GWQI) was intended. One of the main reasons for the use of the mentioned index is the ease of access to available qualitative data. Suitable indicators need to have bacterial tests and we do not have access to such a data. The overall groundwater quality index (GWQI) is calculated as (Eq. 1):

$$GWQI = \sum_{i=1}^8 w_i \cdot \frac{C_i}{C_{si}} \quad (1)$$

where C_i is parameter concentration in mg/L, C_{si} is the national standard concentration of parameter for potable water, and W_i is the relative weight of each chemical parameter. Each of these parameters has a

Table 2 The relative weight of participation of each parameter involved in the creation in the ground water quality index (GWQI) (Saeedi et al. 2010)

Parameter	The relative weight of each parameter
K^+	0.07
Na^+	0.08
Mg^{2+}	0.15
Ca^{2+}	0.2
SO_4^{2-}	0.1
Cl^-	0.1
pH	0.2
TDS	0.1

different weight in terms of its contribution to groundwater quality.

The corresponding weight rates of the factors are then aggregated using some types of sum or mean (e.g., arithmetic, geometric), frequently including individual weighing factors (Horton 1965). Final GWQI index is calculated by aggregating all the normalized parameters. The extent of the parameters participation in the water quality determination defines the relative importance or the weights of parameters in the final GWQI. Table 2 shows the weights of participation of the parameters in the final GWQI. In this study, finally 85 GWQI indices were estimated for the studied drinking water wells in the Mazandaran Plain. Each of these indices represents a qualitative status of groundwater in the area and total indices indicate general states of groundwater quality in the area.

Groundwater quality simulation using fuzzy network-CANFIS

In this research, neuro-fuzzy hybrid model was used for groundwater quality modeling. Neural-fuzzy network is a feed-forward network that uses a neural network learning algorithm through back propagation during network training. Here we used from various input vectors and an output vector. In the designing of neuro-fuzzy hybrid model, the structure of optimized inputs was determined by a trial-and-error process. The difference between the rate of changes in the observed and simulated water quality indices is as the objective function and in case of equality of both quantity, the rate of instantaneous error (the total error) will be equal to zero according to Eq. (2):

Table 1 Potable water quality standards of Iran (mg/l) (Saeedi et al. 2010)

K^+	Na^+	Ca^{2+}	Mg^{2+}	SO_4^{2-}	Cl^-	pH	TDS
12	200	200	150	400	600	6.5–8.5	2000

$$J_i(n) = t_i(n) - a_i(n) \tag{2}$$

where $J_i(n)$ is the network moment error and represents the total error for the neuron i in output layer, $t_i(n)$ represents the desired target output of i th network in n th iteration and $a_i(n)$ represents the predicted from the system and is the actual output at each iteration. By estimation of the output error and application of the back-propagation process (to the system), the selected weight in model was modified. Weights correction was done using gradient descent method and according to Eq. (3):

$$W_{ij}(n + 1) = w_{ij}(n) + \eta \delta_i(n) x_i(n) \tag{3}$$

where $W_{ij}(n + 1)$ is the synaptic weight to i th neuron in the output layer from the j th neuron in the previous layer, $w_{ij}(n)$ is the rate of mentioned weight in n th iteration, n denotes the steps of the iteration, η is the extent of step size or the learning rate coefficient because controls the speed at which we do the error correction or decides for the rate at which the network learns (Loganathan and Girija 2013), $\delta_i(n)$ is standard deviation of the modeling error (local error) and has been estimated from $j_i(n)$ in n th iteration, $x_i(n)$ is the regressor vector and $\delta_i(n)x_i(n)$ is the gradient vector of the performance surface at iteration (n) for the i th input node.

Coactive neuro-fuzzy inference system

Neuro-fuzzy inference systems were implemented to integrate the fuzzy inputs and CANFIS technique due to its applicability in solving very complex and poorly defined problems quickly (Singh et al. 2007). Neuro-fuzzy inference systems consist of four main components comprising: fuzzifier input, fuzzy knowledge base, inference engine and defuzzifier output. At the beginning of processing, fuzzifier, as one of main components of the fuzzy inference

system convert observed data to acceptable form of fuzzy membership functions (MFs) and then fuzzifier outputs are used as fuzzy inference productive inputs (Tay and Zhang 2000; Gharibi et al. 2012). The major components of CANFIS are (a) a fuzzy axon, which applies membership functions to the inputs and (b) a modular network that applies functional rules to the inputs (Heydari and Talaee 2011). The most common type of fuzzy inference system that has the ability to placement in an adaptive network is Sugeno fuzzy inference system and its output is based on a linear regression equation. In this study, we used the Gaussian, bell-shaped membership functions (due to smoothness and concise notation) and Sugeno fuzzy inference system. Membership function (MF), presents the fuzzy value of a fuzzy set. At first, it was determined the number of membership functions assigned to each input network in a process of trial-and-error and then in the output layer it was used from the momentum, the back propagation gradient descent (GD) method (as the most common neural network training algorithm) and the step function learning rate algorithms to achieve the best structure and to improve the performance of system (Pranik and Panda 2009; Tahmasebi and Hezarkhani 2012). It is notable that in all cases, the transfer function in the output layer is linear. In the neuro-fuzzy networks, coactive neuro-fuzzy inference system (CANFIS) is used as a feed forward network structure. Fuzzy system is a system based on reasonable fuzzy if-then rules and logical fuzzy set operators (Fig. 2).

We used NeuroSolutions software for modeling of groundwater quality using neuro-fuzzy network. For training and then testing the performance of a network, it is very important to choose the number and type of input parameters to the model. For this reason, eight input patterns are given below (Eqs. 4–11):

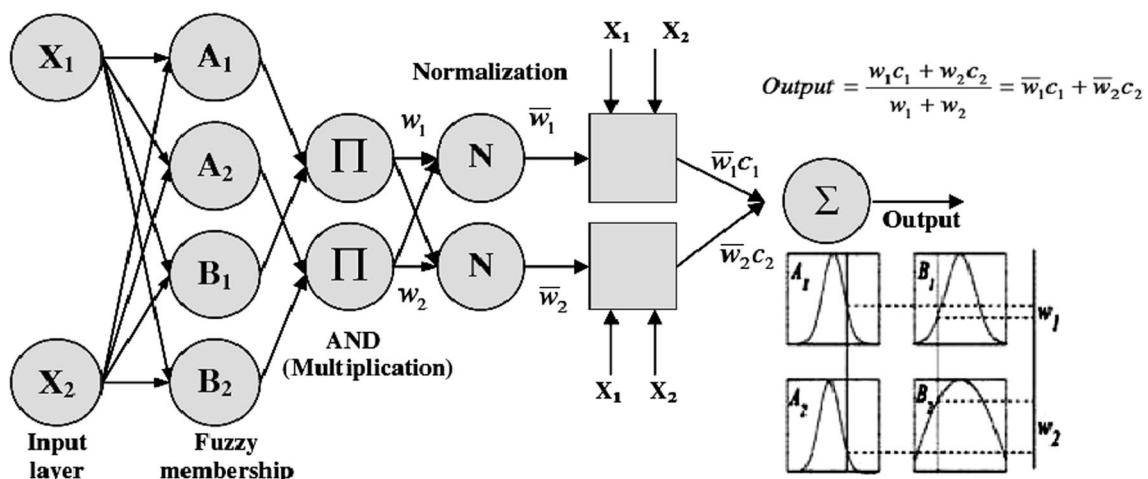


Fig. 2 CANFIS architecture

$$\text{GWQI} = f(T, G_{\text{wTable}}) \quad (4)$$

$$\text{GWQI} = f(T, G_{\text{wTable}}, L_C) \quad (5)$$

$$\text{GWQI} = f(T, G_{\text{wTable}}, L_C, E) \quad (6)$$

$$\text{GWQI} = f(T, G_{\text{wTable}}, L_C, E, P) \quad (7)$$

$$\text{GWQI} = f(T, G_{\text{wTable}}, L_C, E, P, H) \quad (8)$$

$$\text{GWQI} = f(G_{\text{wTable}}, L_C, E, P, H) \quad (9)$$

$$\text{GWQI} = f(T, L_C, E, P, H) \quad (10)$$

$$\text{GWQI} = f(T, G_{\text{wTable}}, E, P, H) \quad (11)$$

where GWQI is groundwater quality index, T is the transmissivity of aquifer formations (m^2/day), G_{wTable} is the mean water table depth (m), L_C is the distance from the pollutant centers (m), E is the site elevation (m), H is the number of households in the area of a square kilometer and P is the population in a square kilometer. These eight input patterns with fixed network architecture were implemented to simulate groundwater quality and the results show that optimized structure of network inputs consists of three inputs included the mean water table depth, the transmissivity of aquifer formations and distance from the pollutant centers. Finally, we determined the optimized network structure by determining the optimal inputs, transfer function and learning technique and re-training of network. In this study, in the training phase, different transfer functions were used in order to identify the one which gives the best results (Heydari and Talaei 2011). Moreover, we used Quick-prop and Momentum of the network to determine the optimal structure of Step systems. Finally, the network efficiency was evaluated using the mean squared error (MSE) and the coefficient of determination (R^2). These performance evaluation criteria (the MSE and R^2) are given below (Eqs. 12, 13):

$$\text{MSE} = \frac{\sum (Q_i - \hat{Q}_i)^2}{n} \quad (12)$$

$$\text{Rsqr} = \left[\frac{\sum_{i=1}^n (Q_i - \bar{Q}_i) \cdot (\hat{Q}_i - \bar{\hat{Q}}_i)}{\sqrt{\sum_{i=1}^n (Q_i - \bar{Q}_i)^2 \cdot \sum_{i=1}^n (\hat{Q}_i - \bar{\hat{Q}}_i)^2}} \right]^2 \quad (13)$$

where Q_i is the actual value, \hat{Q}_i is the simulated value, \bar{Q}_i is the mean of the observed data, $\bar{\hat{Q}}_i$ is the mean of the actual data, and n_i is the number of data points. Above-mentioned standard performance indices were used to compare the performance of the CANFIS model, as well as the training techniques.

Integration of fuzzy network-CANFIS and geographic information system (GIS)

Neuro-fuzzy technique has a high potential in simulating quantitative values of hydrological parameters, but it cannot preset its results in the forms of map and geo-referenced data. In this study, we applied integration of neuro-fuzzy and GIS techniques for assessment of groundwater quality. We used neuro-fuzzy technique as a system to simulate groundwater quality and GIS used as pre-processor and post-processor system of data. At first, quantitative values of the network input parameters included the mean water table depth, the transmissivity of aquifer formations, distance from the pollutant centers, site elevation and the numbers of households were estimated using the secondary data of water resources, maps and digital layers in the GIS environment for the 85 studied drinking water wells. After the quantifying of the parameters, modeling process was performed to simulate the groundwater quality index. In this stage, network training, optimizing and then network test or validation were conducted. Finally, the validated neuro-fuzzy network was presented. Here, GIS will be used as a pre-processor. The purpose of this study is use of fuzzy neural network to simulate groundwater quality for the areas where no data (as graphical geo-referenced). In training stage, we found that the optimized structure of fuzzy neural network for simulating groundwater quality needs to three inputs included the average depth of the water table, the transmissivity of the aquifer formations and the distance from the pollutant centers. Therefore, raster layers of the three input parameters were prepared and those were combined using overlay analysis with a pixel size 1×1 km (similar pixel size). Therefore, Mazandaran Plain was separated to over than 10,000 geo-referenced pixels in GIS. These pixels had values of network inputs or the groundwater quality parameters (water table depth, transmissivity of aquifer formation and the distance from contaminant centers). It is clear that the size of the cellular network can be considered smaller which leads to more accurate results on the inputs such as the distance from the pollutant centers, but a high number of input pixels accompany a limitation in simulation process. Moreover, we have not accessed the exact secondary data for two main inputs, namely, water table depth and transmissivity of aquifer formations. Pixels coordinate was inserted automatically in GIS environment. Afterwards, pixels data (networks inputs and coordinate) were exported from GIS and then these data were imported to NeuroSolutions software. Finally, we estimated the GWQI values of the all pixels using the validated fuzzy network and the optimal inputs. Here, the estimated GWQI values along

with their coordinates were entered from the network environment into the GIS environment. In order words, GIS plays the role of the post-processor. Finally, the ground water quality (GWQI) map was generated using GWQI values (throughout geographic coordinate as an agent for distinguishing geographic coordinate) and GIS capabilities in the study area. The groundwater quality index (GWQI) values of 85 studied drinking water wells were overlapped on the simulated raster layer of the groundwater quality to evaluate and approve the accuracy of the results. In fact, we evaluated the results accuracy through comparison between the simulated GWQI and the actual GWQI in GIS. Finally, the layer of groundwater quality was presented as groundwater quality map after classification. In this study, we simulated groundwater quality using neuro-fuzzy network and GIS capabilities and the simulation was performed with precision and speeds up in large-scale and results were presented as the geo-referenced graphical (map).

Results

We estimated GWQI values of the studied drinking water wells based on the sampling of a 5-year period. GWQI values change from 0.05 to 0.35 in the studied plain. Quantitative amounts of the factors affecting groundwater

quality included the average depth of water table, the transmissivity of aquifer formations, distance from the pollutant centers, site elevation and the number of households were estimated based on the secondary data, digital maps and field studies. Some examples of the estimated values are given in Table 3. After the quantitative estimation of groundwater quality indices and the factors affecting water quality for 85 studied wells, the process of entering data and using them in the neural fuzzy network was carried out. In the training phase, by changing the pattern of data entry and analysis the neuro-fuzzy network sensitivity to input data, it was concluded those three parameters: the mean water table, the aquifer formations transmissivity, and distance from the pollutant centers are the main factors affecting groundwater quality inputs (Gholami et al. 2015). Digital maps of these three factors were prepared in the GIS environment and are presented in Figs. 4, 5 and 6. According to the results, the mean water table depth changes from 1 to 30 m and the mean transmissivity of the aquifer formations changes from 75 to 3250 (m²/day) in the studied plain. The results of the performance evaluation of the neuro-fuzzy network in the simulation of groundwater quality in the training stage are presented in Table 4. In fact, Table 4 reflects the error in the training phase and according to that, good results were obtained in the training phase. The LinearTanhAxon optimal transfer function and the Levenberg–Marquardt (LM)

Table 3 Parameters affecting groundwater quality and GWQI indices in the some drinking water wells

No.	GWQI	Transmissivity (m ² /day)	Water table depth (m)	Elevation (m)	Distance from contaminant centers (m)	No. of households	Population (person)
1	0.2715	1500	12.90	50	6.4	52	460
2	0.2401	750	3.00	−11	153.8	239	1077
3	0.2267	175	5.00	−13	99.4	32	144
4	0.2165	750	4.00	−10	1121.2	21	98
5	0.2125	1500	5.00	11	0	22	93
6	0.2070	500	4.17	6	20	246	1105
7	0.1971	1000	5.00	11	0	22	93
8	0.1969	750	6.50	20	20	161	666
9	0.1553	500	31.00	1062	830	30	95
10	0.1483	300	23.00	453	1100	13	62
11	0.1252	300	25.00	69	709	53	287
12	0.0568	100	38.00	1670	1023	53	342
13	0.2578	500	4.70	6	44	109	495
14	0.2042	750	3.50	−8	451	92	434
15	0.3413	3000	5.00	20	15.42	574	2770
16	0.3252	2000	3.00	2	66.37	118	820
17	0.3243	1000	1.00	3	28.07	239	1187
18	0.3146	1000	1.00	1	21.27	136	800
19	0.2597	750	5.00	12	9.21	607	2931
20	0.2571	1500	8.00	33	194.20	144	693

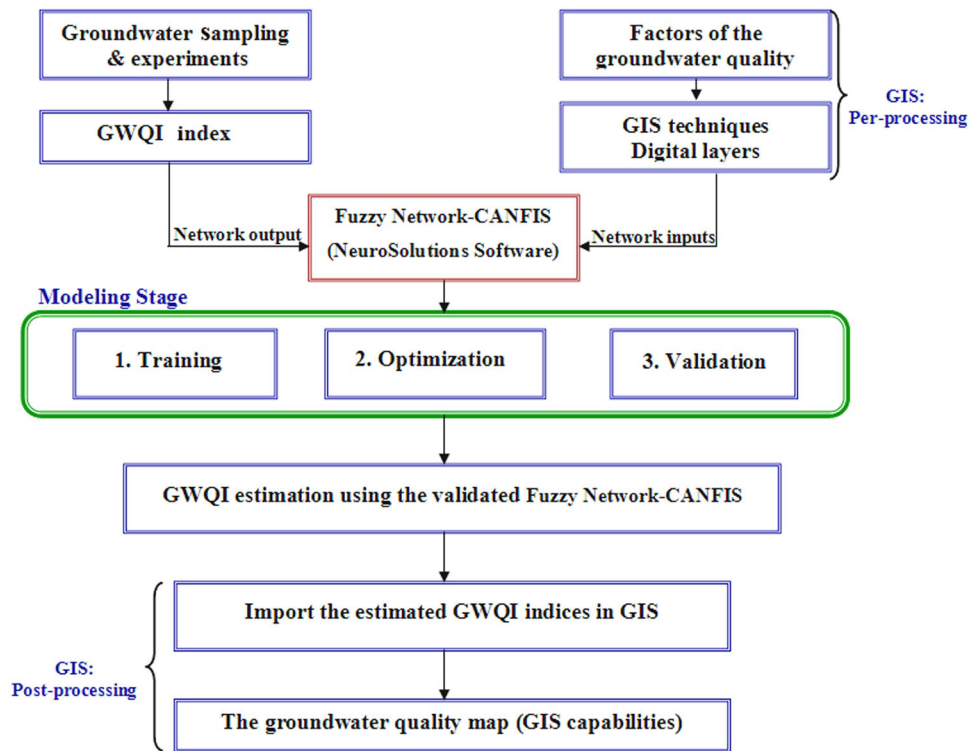


Fig. 3 The flowchart of the methodology stages used for groundwater quality assessment based on Fuzzy Network-CANFIS and GIS

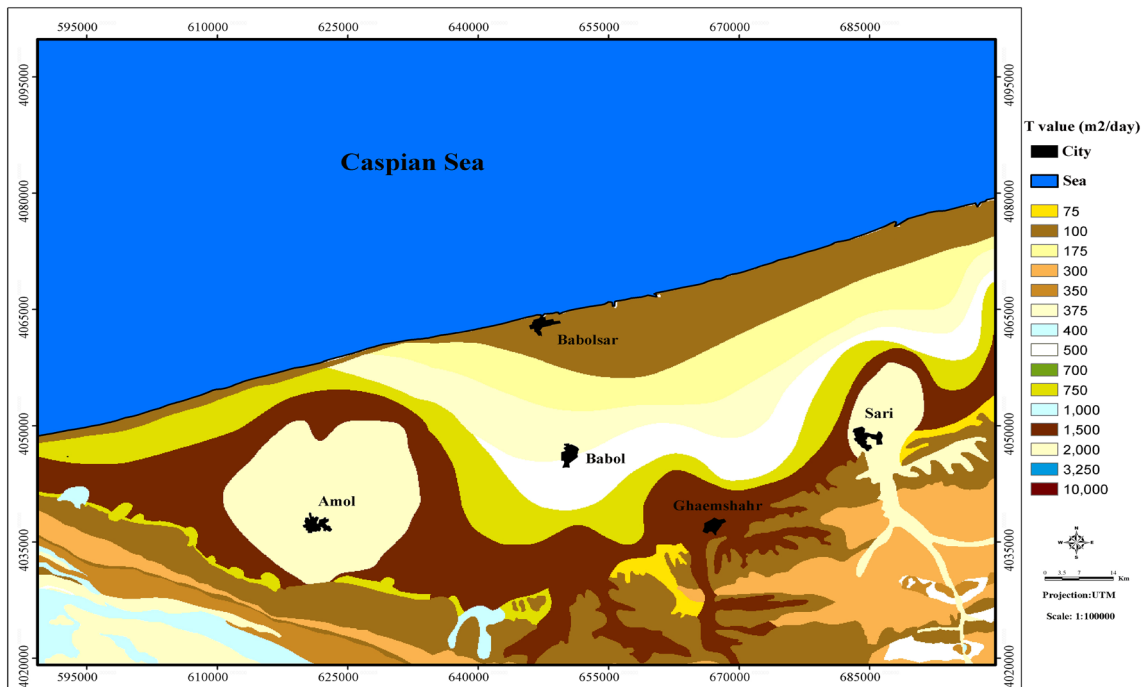


Fig. 4 The map of the mean transmissivity of aquifer formations in the study plain (m^2/day)

optimal learning techniques (as the best algorithms for training the network and also as the modern second-order back-propagation algorithm) were used to train the network

(Bishop 1995). Correlation between the observed and simulated values (R) in the training stage is equal to 0.9. Moreover, Table 5 shows the results of the evaluation of

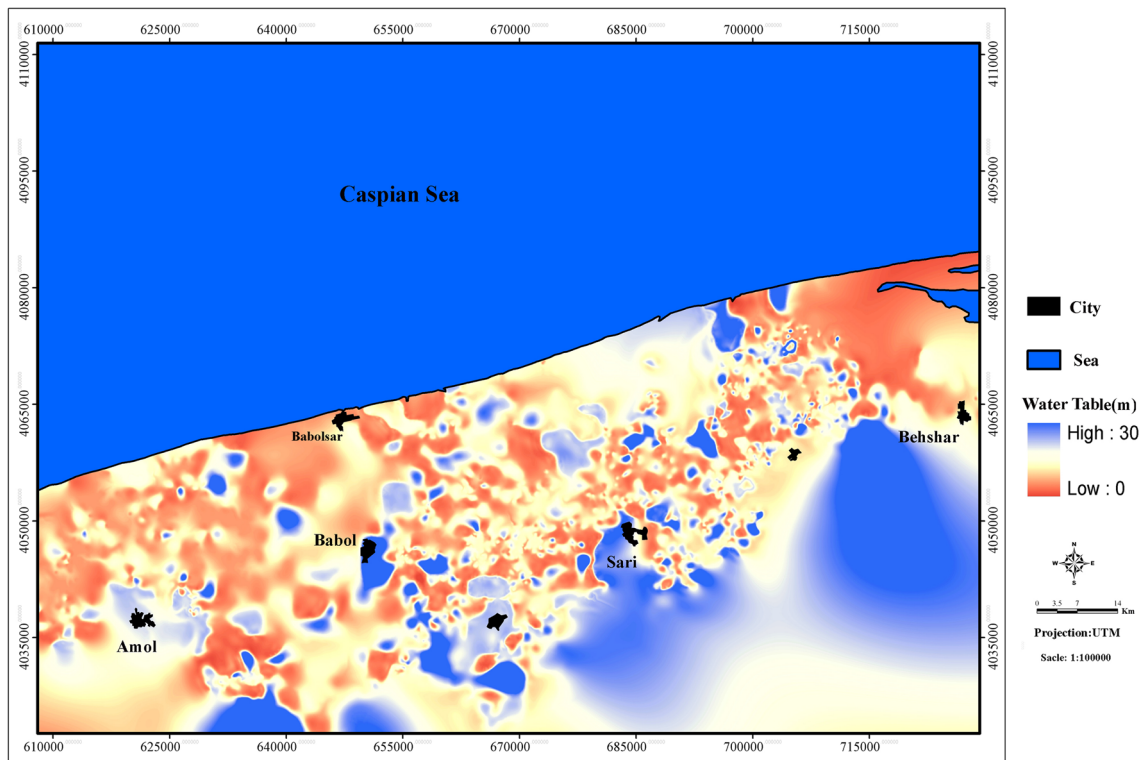


Fig. 5 The map of the mean water table depth in the study plain (m)

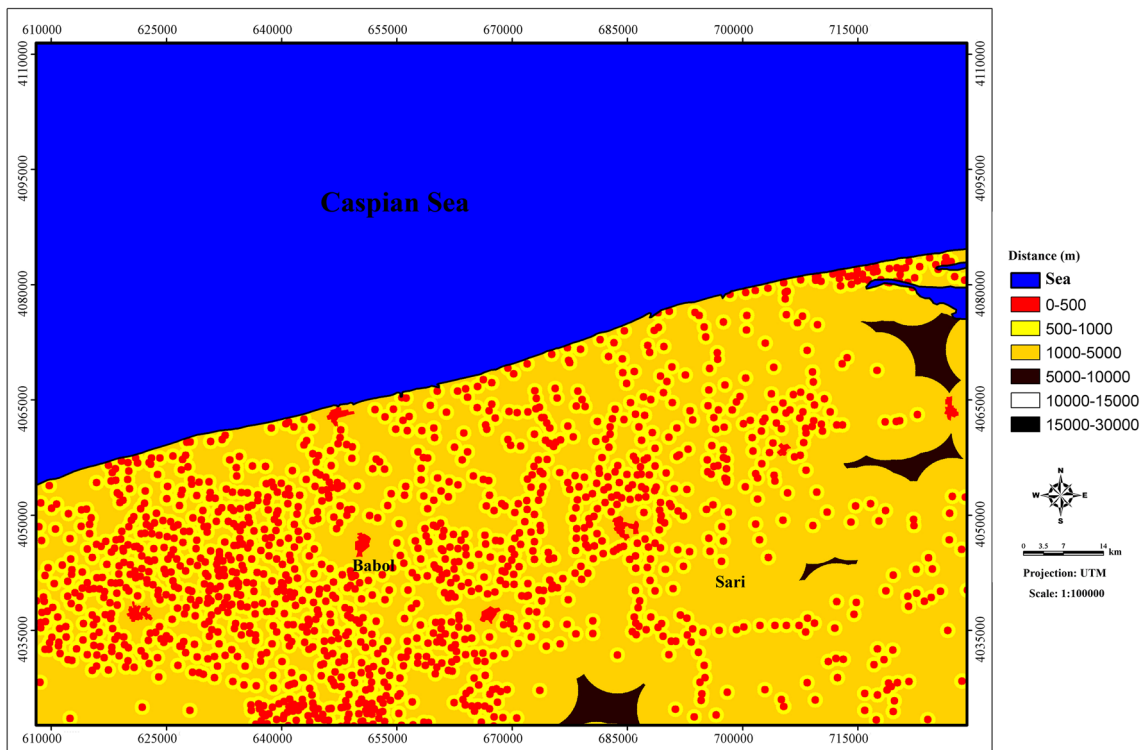


Fig. 6 The map of distance from contaminant centers (villages, cities and industries) in the Mazandaran Plain (m)

Table 4 The results of neuro-fuzzy network training and optimization (training stage)

All runs	Training minimum	Training standard deviation	Cross-validation minimum	Cross-validation standard deviation
Average of minimum MSEs	0.006	0.001	0.008	0.001
Average of final MSEs	0.006	0.001	0.024	0.014

Table 5 The results of neuro-fuzzy testing for validating network

Performance	GWQIA
MSE	0.0004
NMSE	0.24
MAE	0.018
Min Abs error	0.001
Max Abs error	0.052
<i>R</i>	0.9

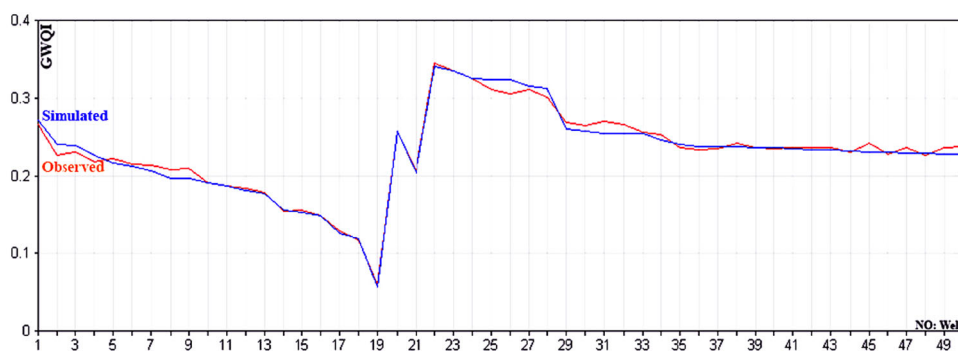
the neuro-fuzzy network efficiency in the simulation of groundwater quality in the test or validation stage. In the test stage, the simulated and actual GWQI values were compared and this comparison is presented in Fig. 8. The results show that the neuro-fuzzy network has acceptable accuracy in simulating of the groundwater quality index ($R = 0.89$). Such results are consistent with the results of other researchers (Samani et al. 2007). The aim of this study is to simulate groundwater quality in the places with no secondary data. Therefore, neuro-fuzzy network can be applied to evaluate groundwater quality with an acceptable accuracy. For this purpose, the raster layers of the groundwater quality factors or the neuro-fuzzy network inputs were prepared in GIS with the similar pixel sizes (1×1 m) and then were combined with each other. After combining these layers, a geo-referenced raster layer was generated that contains three input parameters associated with network. Data of the pixels with coordinates was entered from GIS to the neuro-fuzzy network. Then, it was used from the validated optimal neuro-fuzzy network to estimate GWQI index for all of the pixels. The neuro-fuzzy network estimated the GWQI value for each pixel and then the estimated values with coordinates (X, Y) were

imported to ArcGIS environment. In this stage, GIS will be as the post-processor. Here, GIS capabilities were used for monitoring the results of the neuro-fuzzy network as the raster layer of groundwater quality and finally the results are presented in Fig. 9. As can be seen in this figure, in order to evaluate the results accuracy, the location of the 85 drinking water wells and their GWQI values were inserted on the layer or the groundwater quality map. Comparison between the observed and estimated GWQI values (groundwater quality classes in Fig. 10) shows the performance of the neuro-fuzzy network and also high performance of the approach of integrating the neuro-fuzzy network and GIS in groundwater quality modeling (Gangopadhyay et al. 1999; Krishna et al. 2008). The groundwater quality based on GWQI index is classified into three categories included very good quality ($GWQI > 0.15$), good quality ($0.04 < GWQI < 0.15$) and poor quality ($GWQI < 0.04$) (Saeedi et al. 2010). As can be seen in the resulting map, the presented methodology in this study could provide an acceptable simulation for the classification of groundwater quality and the current error in simulation, not enter any prejudice to the water quality classification accuracy of a plain or a watershed (Figs. 3, 7).

Discussion

Based on the various studies conducted on the superior performance of neuro-fuzzy network in modeling and prediction of time-series hydrologic problems and variables (Ullah and Choudhury 2013), it is clear that the capabilities of a CANFIS model depends on its structure and the nature of the problem that we have to solve, is

Fig. 7 Evaluation of CANFIS efficiency for groundwater quality simulation during training stage throughout comparison between the estimated and actual GWQI values ($R^2 = 0.9$)



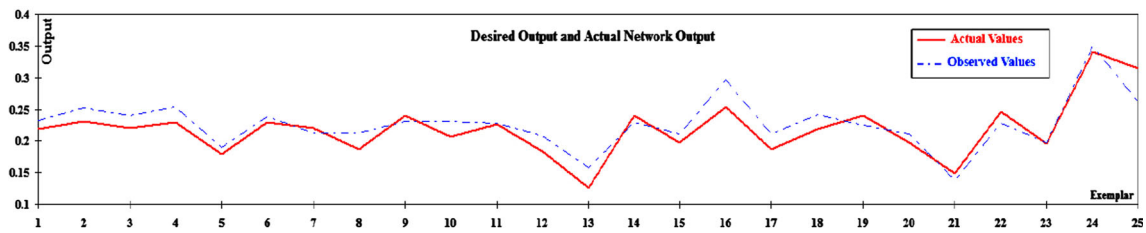


Fig. 8 Evaluation of CANFIS efficiency for groundwater quality simulation during test stage (validation) throughout comparison between the estimated and actual GWQI values

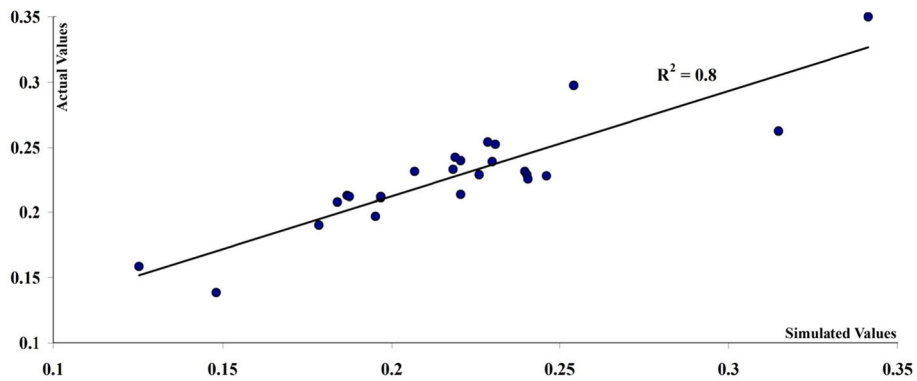


Fig. 9 Evaluation of CANFIS efficiency for groundwater quality simulation during test (validation) stage throughout comparison between the estimated and actual GWQI values ($R^2 = 0.8$)

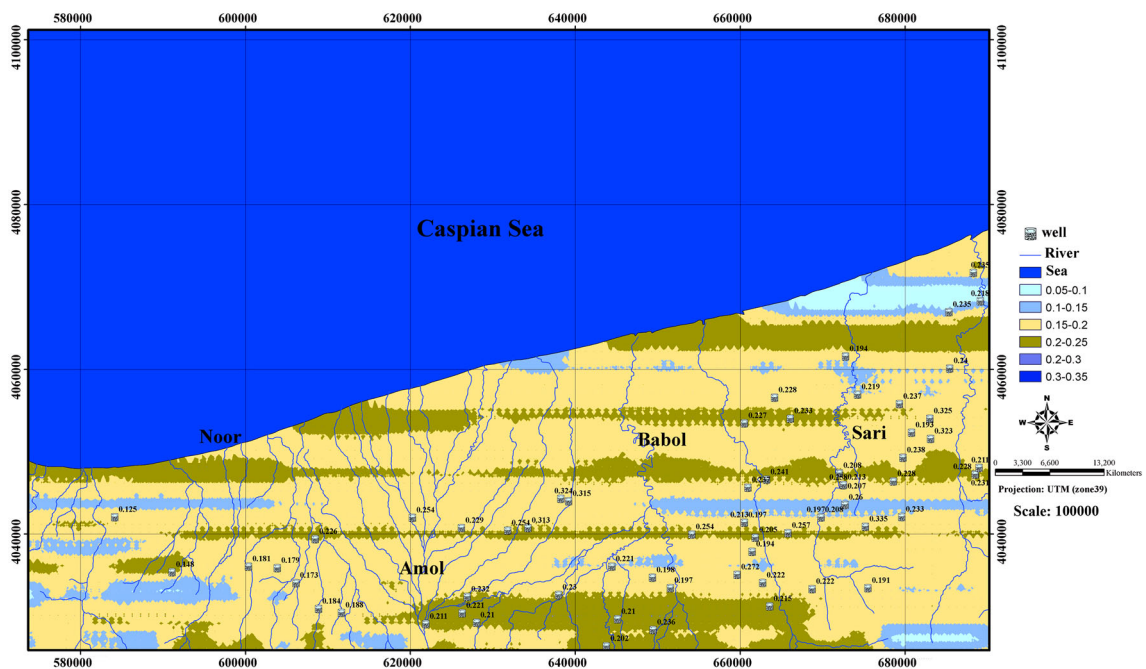


Fig. 10 The map of groundwater quality (GWQI index) is resulted from integration of neuro-fuzzy inference system and GIS capabilities. In this map, we evaluated the results accuracy using a comparison between the simulated GWQI values with the actual GWQI values

different. By selecting the appropriate type and the number of MFs for each input and the use of appropriate and adaptive fuzzy neural network and its proper calibration, we can say that this technique is very effective and useful and can therefore be used as a comprehensive tool for groundwater quality assessment.

The results of this study show a high capability of the neuro-fuzzy network in simulation of groundwater quality. According to the results of the neuro-fuzzy network performance for different makeup and compared the results with observed data, it can be said that three factors included the mean water table, the aquifer formations transmissivity and distance from the pollutant centers are the most important factors affecting groundwater quality in the study plain. Neuro-fuzzy network modeling is an efficient tool, but an important point in this regard, is the application of its results. We used neuro-fuzzy network to simulate groundwater quality and also GIS was used to increase the accuracy and rapidness of modeling and monitoring of the results of the neuro-fuzzy network in large-scale. Previous researches results show the high performance of the neuro-fuzzy network with the structure of the Takagi–Sugeno–Kang (TSK) model in hydrologic simulations as well (Jang et al. 1997; Jacquin and Shamseldin 2006; Lohani et al. 2006; Talei et al. 2010; Heydari and Talae 2011). In terrain and optimization stages, we found that TSK model is the best structure for neuro-fuzzy network in the groundwater quality simulation. The main focus of this study is the automatic connection of the neuro-fuzzy network with GIS in order to use the results for all users. Moreover, we selected the Levenberg–Marquardt learning technique as the best algorithms for training the network. In training stage, that the mean square error (MSE) and coefficient of determination (R^2) were estimated 0.01 and 0.9, respectively. After network training and optimization, the optimal neuro-fuzzy network structure was defined. In the testing stage, mean square error (MSE) and coefficient of determination (R^2) measures were 0.0004 and 0.8, respectively. Therefore, the results show that the neuro-fuzzy network can be used in the groundwater quality simulation with an acceptable accuracy. The base of this study is automatic relation between neuro-fuzzy network and GIS for simulating groundwater quality and mapping of the results. However, the results should have capability of overlay with other digital geo-referenced data. We can provide a high volume of input data in a short time using GIS and neuro-fuzzy network can simulate hydrologic parameters in a short time for the sites without the groundwater quality data. Finally, the integration of neuro-fuzzy network and GIS can present the simulated results in a manner of digital maps. Moreover, the groundwater quality map shows that the quality of groundwater is improper in terms of potable water quality standards of Iran in the most of the

studied area. Therefore, it is necessary to plan to conserve and optimize usage of water resources. In modeling process, the main thing is the accuracy of input and output. Thus, integration of neuro-fuzzy network and geographic information system can be used for water quality simulation and the efficiency of this methodology is dependent on the accuracy of the input data and to select the appropriate input parameters for the network correctly.

Conclusion

This paper introduces an integrated CANFIS model for assessing groundwater quality. Input data of CANFIS network for groundwater modeling include the mean water table, the aquifer formations transmissivity and distance from the pollutant centers. The output of the CANFIS network was groundwater quality index. We evaluated the CANFIS performance by the statistical evolution criteria; which shows that this method significantly outperforms the assessing process and has a very good and acceptable performance for assessing groundwater quality. To sum up, the findings of this study indicated that groundwater quality assessed using the CANFIS model were in good agreement with experimental data, indicating CANFIS model gives the best results and hence, can be employed successfully in assessing groundwater quality. Thus, the results of this study confirm the general enhancement achieved by using neuro-fuzzy network in many other hydrological fields (Heydari and Talae 2011; Wu et al. 2014). It is clear that we could select a smaller size of the pixels that causes the more exact input about distance from contaminant centers, but a high number of the input pixels impose a limitation for simulating in CANFIS model (ANN software). Also, we have not accessed the exact data for two main inputs, namely, water table depth and transmissivity of aquifer formation. According to the results, groundwater quality in the most of the study plain has a fairly low quality in terms of potable water standards. Hence, the move towards conservation and optimal utilization is necessary and the aquifers of the study area needs respective degree of quality improvement (Yousefi and Naeef 2008; Sharma and Patel 2010). It is important to note that according to the results obtained from this study, to access optimal conditions, study area needs frequent monitoring as well as appropriate management practices. As a consequence, the findings of this study clearly indicate the possibility for using CANFIS and GIS for highly successful assessment of groundwater quality. Also, artificial intelligence computational methods, such as CANFIS model can be applied successfully as a very useful and accurate tool for assessing groundwater quality, therefore suggested for assessing groundwater quality in similar problems.

Acknowledgements We wish to thank the ABFAR (Mazandaran Rural Water and Sewer Company) for their great help in provision of the water quality data.

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

References

- Al-hadithi M (2012) Application of water quality index to assess suitability of groundwater quality for drinking purposes in Ratmao–Pathri Rao watershed, Haridwar District, India. *Am J Sci Ind Res* 3(6):395–402. doi:10.5251/ajsir.2012.3.6.395.402
- Bishop CM (1995) *Neural networks for pattern recognition*. Clarendon Press, Oxford
- Bouzourra H, Bouhlila R, Elango L, Slama F, Ouslati N (2014) Characterization of mechanisms and processes of groundwater salinization in irrigated coastal area using statistics, GIS, and hydro-geochemical investigations. *Environ Sci Pollut Res*. doi:10.1007/s11356-014-3428-0
- Brown RM, McClelland NI, Deininger RA, Tozer RG (1970) A water quality index: do we dare? *Water Sewage Works* 117:339–343
- Celik I, Camas H, Arslan O, Kufrevioglu O (1996) The effects of some pesticides on human and bovine erythrocyte carbonic anhydrase enzyme activities in vitro. *Environ Sci Health* 10:2651–2657. doi:10.1080/10934529609376516
- Chang FJ, Chang YT (2006) Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. *Adv Water Resour* 29:1–10. doi:10.1016/j.advwatres.2005.04.015
- Chang FJ, Chen YC (2001) A counter-propagation fuzzy-neural network modeling approach to real time stream-flow prediction. *J Hydrol* 245:153–164. doi:10.1016/S0022-1694(01)00350-X
- Chau KW (2006) A review on integration of artificial intelligence into water quality modelling. *Mar Poll Bull* 52:726–733. doi:10.1016/j.marpolbul.2006.04.003
- Cobaner M, Unal B, Kisi O (2009) Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydro-meteorological data. *J Hydrol* 367(1–2):52–61. doi:10.1016/j.jhydrol.2008.12.024
- Dixon B (2004) Prediction of ground water vulnerability using an integrated GIS-based neuro-fuzzy techniques. *J Spat Hydrol* 4(2):1–38
- Dixon B (2005) Applicability of neuro-fuzzy techniques in predicting ground-water vulnerability: a GIS-based sensitivity analysis. *J Hydrol* 309(1–4):17–38. doi:10.1016/j.jhydrol.2004.11.010
- Dogan E, Gumrukcuoglu M, Sandalci M, Opan M (2010) Modeling of evaporation from the reservoir of Yuvacik dam using adaptive neuro-fuzzy inference systems. *Eng Appl Artif Intell* 23(6):961–967. doi:10.1016/j.engappai.2010.03.007
- Durbude DG, Vararajan N (2007) Monitoring and mapping of groundwater quality. *J App Hydrol* xx(1–2):22–30
- Gangopadhyay S, Gautam TR, Gupta AD (1999) Subsurface characterization using artificial neural network and GIS. *J Comput Civ Eng* 13(3):153–161. doi:10.1061/(ASCE)0887-3801(1999)13:3(153)
- Gautam DK, Holz KP (2001) Rainfall–runoff modelling using adaptive neuro-fuzzy systems. *J Hydroinf* 3:3–10
- Gharibi H, Mahvi AH, Nabizadeh R, Arabalibeik H, Yunesian M, Sowlat MH (2012) A novel approach in water quality assessment based on fuzzy logic. *J Environ Manag* 112:87–95. doi:10.1016/j.jenvman.2012.07.007
- Gholami V, Khaleigh MR (2013) The impact of vegetation on the bank erosion (case study: the Haraz river). *Soil Water Res* 8(4):158–164
- Gholami V, Aghagoli H, Kalteh AM (2015) Modeling sanitary boundaries of drinking water wells on the Caspian Sea southern coasts, Iran. *Environ Earth Sci* 74(4):2981–2990. doi:10.1007/s12665-015-4329-3
- Gholami V, Ahmadi Jolandan M, Torkaman J (2016) Evaluation of climate change in northern Iran during the last four centuries by using dendroclimatology. *J Nat Hazards*. doi:10.1007/s11069-016-2667-4
- Hass U, Dünbier U, Massmann G (2012) Occurrence of psychoactive compounds and their metabolites in groundwater down gradient of a decommissioned sewage farm in Berlin (Germany). *Environ Sci Pollut Res* 19:2096–2106. doi:10.1007/s11356-011-0707-x
- Heydari M, Talaei PH (2011) Prediction of flow through rockfill dams using a neuro-fuzzy computing technique. *J Math Comput Sci* 2(3):515–528
- Hong YT, White PA (2009) Hydrological modeling using a dynamic neuro-fuzzy system with on-line and local learning algorithm. *Adv Water Resour* 32(1):110–119. doi:10.1016/j.advwatres.2008.10.006
- Horton RK (1965) An index-number system for rating water quality. *J Water Pollut Control Fed* 37(3):300–305
- Jacquín AP, Shamseldin AY (2006) Development of rainfall–runoff models using Takagi–Sugeno fuzzy inference systems. *J Hydrol* 329(1–2):154–173. doi:10.1016/j.jhydrol.2006.02.009
- Jang C, Chen S (2015) Integrating indicator-based geostatistical estimation and aquifer vulnerability of nitrate-N for establishing groundwater protection zones. *J Hydrol* 523:441–451. doi:10.1016/j.jhydrol.2015.01.077
- Jang JSR, Sun CT, Mizutani E (1997) *Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence*. Prentice-Hall, New Jersey
- Karimi-Googhari S (2012) Daily pan evaporation estimation using a neuro-fuzzy-based model. *J Agric Sci Technol* 1(4):159–163
- Karunanidhi D, Vennila G, Suresh M, Subramanian SK (2013) Evaluation of the groundwater quality feasibility zones for irrigation purposes through GIS in Omalur Taluk, Salem District, South India. *Environ Sci Pollut Res*. doi:10.1007/s11356-013-1746-2
- Khadangi E, Madvar HR, Edazadeh MM (2009) Comparison of ANFIS and RBF models in daily stream flow forecasting. *Computer control and communication: 2nd international conference on digital object identifier*, pp 1–6. doi:10.1109/IC4.2009.4909240
- Khatibi R, Ghorbani MA, Hasanpour Kashani M, Kisi O (2011) Comparison of three artificial intelligence techniques for discharge routing. *J Hydrol* 403:201–212. doi:10.1016/j.jhydrol.2011.03.007
- Kisi O (2010) Discussion of “Application of neural network and adaptive neuro-fuzzy inference systems for river flow prediction”. *Hydrol Sci J* 55(8):1453–1454. doi:10.1080/02626667.2010.527848
- Kisi O, Haktanir T, Ardiclioglu M, Ozturk O, Yalcin E, Uludag S (2008) Adaptive neuro-fuzzy computing technique for suspended sediment estimation. *Adv Eng Softw* 40(6):438–444. doi:10.1016/j.advengsoft.2008.06.004
- Koike K, Matsuda S (2003) Characterizing content distributions of impurities in a limestone mine using a feed forward neural

- network. *Nat Resour Res* 12(3):209–223. doi:[10.1023/a:1025180005454](https://doi.org/10.1023/a:1025180005454)
- Kolpin DW, Thurman EM, Linhart SM (1998) The environmental occurrence of herbicides: the importance of degradates in groundwater. *Arch Environ Contam Toxicol* 35(3):385–390. doi:[10.1007/s002449900392](https://doi.org/10.1007/s002449900392)
- Kördel W, Garelick H, Gawlik BM, Kandile NG, Peijnenburg WJGM, Rüdell H (2013) Substance-related environmental monitoring strategies regarding soil, groundwater and surface water—an overview. *Environ Sci Pollut Res* 20:2810–2827. doi:[10.1007/s11356-013-1531-2](https://doi.org/10.1007/s11356-013-1531-2)
- Krishna B, Satyaji Rao YR, Vijaya T (2008) Modeling groundwater levels in an urban coastal aquifer using artificial neural networks. *Hydrol Proc* 22(8):1180–1188. doi:[10.1002/hyp.6686](https://doi.org/10.1002/hyp.6686)
- Li P, Wu J, Qian H (2012) Groundwater quality assessment based on rough sets attribute reduction and TOPSIS method in a semi-arid area, China. *Environ Monit Assess* 184:4841–4854. doi:[10.1007/s10661-011-2306-1](https://doi.org/10.1007/s10661-011-2306-1)
- Loganathan C, Girija KV (2013) Hybrid learning for adaptive neuro fuzzy inference system. *Int J Eng Sci* 2(11):6–13
- Lohani AK, Goel NK, Bhatia KKS (2006) Takagi–Sugeno fuzzy inference system for modeling stage–discharge relationship. *J Hydrol* 331(1–2):146–160. doi:[10.1016/j.jhydrol.2006.05.007](https://doi.org/10.1016/j.jhydrol.2006.05.007)
- Lu RS, Lo SL (2002) Diagnosing reservoir water quality using self organizing maps and fuzzy theory. *Water Resour* 36(9):2265–2274. doi:[10.1016/S0043-1354\(01\)00449-3](https://doi.org/10.1016/S0043-1354(01)00449-3)
- Mahmoudabadi H, Izadi M, Menhaj MB (2009) A hybrid method for grade estimation using genetic algorithm and neural networks. *Comput Geosci* 13(1):91–101. doi:[10.1007/s10596-008-9107-9](https://doi.org/10.1007/s10596-008-9107-9)
- Mirbagheri SA, Nourani V, Rajae T, Alikhani A (2010) Neuro-fuzzy models employing wavelet analysis for suspended sediment concentration prediction in rivers. *Hydrol Sci J* 55(7):1175–1189. doi:[10.1080/02626667.2010.508871](https://doi.org/10.1080/02626667.2010.508871)
- Mohsen-Bandpei A, Yousefi Z (2013) Status of water quality parameters along Haraz river. *Int J Environ Res* 7(4):1029–1038
- Nasiri F, Maqsood I, Huang G, Fuller N (2007) Water quality index: a fuzzy river pollution decision support expert system. *J Water Resour Plan Manag* 133(2):95–105. doi:[10.1061/\(ASCE\)0733-9496](https://doi.org/10.1061/(ASCE)0733-9496)
- Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS (2004) A neuro-fuzzy computing technique for modeling hydrological time series. *J Hydrol* 291(1–2):52–66. doi:[10.1016/j.jhydrol.2003.12.010](https://doi.org/10.1016/j.jhydrol.2003.12.010)
- Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS (2005) Short-term flood forecasting with a neurofuzzy model. *Water Resour Res* 41(4):2517–2530. doi:[10.1029/2004WR003562](https://doi.org/10.1029/2004WR003562)
- Nourani V, Kisi O, Komasi M (2011) Two hybrid artificial intelligence approaches for modeling rainfall–runoff process. *J Hydrol* 402:41–59. doi:[10.1016/j.jhydrol.2011.03.002](https://doi.org/10.1016/j.jhydrol.2011.03.002)
- Ocampo-Duque W, Schumacher M, Domingo JL (2007) A neural-fuzzy approach to classify the ecological status in surface waters. *Environ Pollut* 148(2):634–641. doi:[10.1016/j.envpol.2006.11.027](https://doi.org/10.1016/j.envpol.2006.11.027)
- Ott WR (1978) water quality indices: a survey of indices used in the United States. US Environmental Protection Agency, Washington, DC, p 138
- Ouyang Y, Zhang JE, Parajuli P (2013) Characterization of shallow groundwater quality in the Lower St. Johns River Basin: a case study. *Environ Sci Pollut Res* 20(12):8860–8870. doi:[10.1007/s11356-013-1864-x](https://doi.org/10.1007/s11356-013-1864-x)
- Pramanik N, Panda RK (2009) Application of neural network and adaptive neuro-fuzzy inference systems for river flow prediction. *Hydrol Sci J* 54(2):247–260. doi:[10.1623/hysj.54.2.247](https://doi.org/10.1623/hysj.54.2.247)
- Rapantova N, Licbinska M, Babka O, Grmela A, Pospisil P (2012) Impact of uranium mines closure and abandonment on groundwater quality. *Environ Sci Pollut Res* 20(11):7590–7602. doi:[10.1007/s11356-012-1340-z](https://doi.org/10.1007/s11356-012-1340-z)
- Ribeiro L, Paralta E, Nascimento J, Amaro S, Oliveira E, Salgueiro R (2002) A agricultural a delimitação das zonas vulneráveis aos nitratosdeorigem agrícola segundo a Directiva 91/676/CE. *Proceedings III Congreso Ibérico sobre Gestión e Ianificación del Agua*. Universidad de Sevilla, Spain, pp 508–513
- Ross TJ (2006) Fuzzy logic with engineering applications. McGraw Hill Inc., New York, p 628
- Saeedi M, Abessi O, Sharifi F, Meraji H (2010) Development of groundwater quality index. *J Environ Monit Assess* 163:327–335. doi:[10.1007/s10661-009-0837-5](https://doi.org/10.1007/s10661-009-0837-5)
- Samani N, Gohari-Moghadam M, Safavi AA (2007) A simple neural network model for the determination of aquifer parameters. *J Hydrol* 340(1):1–11. doi:[10.1016/j.jhydrol.2007.03.017](https://doi.org/10.1016/j.jhydrol.2007.03.017)
- Samanta B, Bandyopadhyay S, Ganguli R (2004) Data segmentation and genetic algorithms for sparse data division in Nome placer gold grade estimation using neural network and geostatistics. *Min Explor Geol* 11(1–4):69–76. doi:[10.2113/11.1.4.69](https://doi.org/10.2113/11.1.4.69)
- Saraf AK, Gupta RP, Jain RK, Srivastava NK (1994) GIS based processing and interpretation of ground water quality data. In: *Proceedings of regional workshop on environmental aspects of ground water development*, Oct. 17–19, Kurukshetra, India
- Scottish Development Department (1975) Towards cleaner water. HMSO, Report of a River Pollution Survey of Scotland, Edinburgh
- Sharma ND, Patel JN (2010) Evaluation of groundwater quality index of the urban segments of Surat City, India. *Int J Geol* 1(4):1–4
- Singh TN, Verma AK, Sharma PK (2007) A neuro-genetic approach for prediction of time dependent deformational characteristic of rock and its sensitivity analysis. *Geotechnol Geol Eng* 25(4):395–407. doi:[10.1007/s10706-006-9117-0](https://doi.org/10.1007/s10706-006-9117-0)
- Singh KP, Gupta S, Rai P (2014) Investigating hydrochemistry of groundwater in Indo-Gangetic alluvial plain using multivariate chemometric approaches. *Environ Sci Pollut Res*. doi:[10.1007/s11356-014-2517-4](https://doi.org/10.1007/s11356-014-2517-4)
- Subbaraj P, Kannapiran B (2010) Artificial neural network approach for fault detection in pneumatic valve in cooler water spray system. *Int J Comput App* 9(7):43–52. doi:[10.5120/1395-1881](https://doi.org/10.5120/1395-1881)
- Tahmasebi P, Hezarkhani A (2012) A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. *Comput Geosci* 42:18–27. doi:[10.1016/j.cageo.2012.02.004](https://doi.org/10.1016/j.cageo.2012.02.004)
- Talei A, Chua LHC, Quek C (2010) A novel application of a neuro-fuzzy computational technique in event-based rainfall–runoff modeling. *Expert Syst Appl* 37(12):7456–7468. doi:[10.1016/j.eswa.2010.04.015](https://doi.org/10.1016/j.eswa.2010.04.015)
- Tay JH, Zhang X (2000) A fast predicting neural fuzzy model for high rate anaerobic waste water treatment systems. *Water Res* 34(11):2849–2860
- Ullah N, Choudhury P (2013) Flood flow modeling in a river system using adaptive neuro-fuzzy inference system. *Environ Manag Sustain Develop* 2(2):54–68. doi:[10.5296/emsd.v2i2.3738](https://doi.org/10.5296/emsd.v2i2.3738)
- Vernieuwe H, Georgieva O, Baets BD, Pauwels VRN, Verhoest NEC, Troch DFP (2005) Comparison of data-driven Takagi–Sugeno models of rainfall–discharge dynamics. *J Hydrol* 302:173–186. doi:[10.1016/j.jhydrol.2004.07.001](https://doi.org/10.1016/j.jhydrol.2004.07.001)
- Wu W, Dandy GC, Maier HR (2014) Protocol for developing ANN models and its application to the assessment of the quality of the ANN model development process in drinking water quality modelling. *Environ Modell Softw* 54:108–127
- Xiong LH, Shamseldin AY, O'Connor KM (2001) A nonlinear combination of the forecasts of rainfall–runoff models by the first order Takagi–Sugeno fuzzy system. *J Hydrol* 245(1–4):196–217. doi:[10.1016/S0022-1694\(01\)00349-3](https://doi.org/10.1016/S0022-1694(01)00349-3)
- Yousefi Z, Naeef O (2008) Study on nitrate value in rural area in Amol city. *J Mazand Univ Med Sci* 17(61):161–165
- Zadeh LA (1965) Fuzzy sets. *Inf Control* 8:338–353

Zhang L, Zhao W, He Z, Liu H (2009) Application of the Takagi–Sugeno fuzzy system for combination forecasting of river flow in semiarid mountain regions. *Hydrol Process*. doi:[10.1002/hyp.7265](https://doi.org/10.1002/hyp.7265) (John Wiley Sons Ltd.)

Zhou F, Liu Y, Guo H (2007) Application of multivariate statistical methods to water quality assessment of the watercourses in Northwestern New Territories, Hong Kong. *Environ Monit Assess* 132(1):1–13. doi:[10.1007/s10661-006-9497-x](https://doi.org/10.1007/s10661-006-9497-x)