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Quantity and Quality Modeling of Groundwater by Conjugation of ANN and Co-Kriging Approaches

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1. Introduction

Today, groundwater is a major source of supply for domestic and agricultural purposes; especially in arid and semi arid regions. More water is being consumed to meet of a society whose population increases steadily. Worldwide, irrigated land has increased from 50 million ha in 1900 to 267 million ha in 2000 (Cay and Uyan, 2009). The climatic changes stemming from global warming also have negative effects on water resources. Both over exploitation from aquifers, and drought events have caused severe water table level drop in many areas. However, the level of groundwater has reduced remarkably in many areas, as a result of unconscious and excessive irrigation. Depletion of groundwater supplies, conflicts between groundwater and surface water users and potential for groundwater contamination are the main concerns that will become increasingly important as further aquifer development takes place in any basin.

The natural chemical composition of groundwater is influenced predominantly by type and depth of soils and subsurface geological formations through which groundwater passes. Groundwater quality is also influenced by contribution from the atmosphere and surface water bodies. Quality of groundwater is also influenced by anthropogenic factors. For example, over exploitation of groundwater in coastal regions may result in sea water ingress and consequent increase in salinity of groundwater and excessive use of fertilizers and pesticides in agriculture and improper disposal of urban/industrial waste can cause contamination of groundwater resources.

Groundwater systems possess features such as complexity, nonlinearity, being multi-scale and random, all governed by natural and/or anthropogenic factors, which complicate the dynamic predictions. Therefore many hydrological models have been developed to simulate this complex process. Models based on their involvement of physical characteristics generally fall into three main categories: black box models, conceptual models and physical based models (Nourani and Mano, 2007). The conceptual and physically based models are the main tools for predicting hydrological variables and understanding the physical processes that are taking place in a system. In these models, the internal physical processes are modeled in a simplified way. Even if not applying the exact differential laws of conservation, conceptual models attempt to describe large scale behavior of hydrological processes in a basin. However, these models require a large quantity of good quality data, sophisticated programs for calibration using rigorous optimization techniques and a detailed understanding of the underlying physical process. Because of the recognized limitations of these models and the growing need to properly manage overdeveloped groundwater systems, significant researches have been devoted to improve their predictive capabilities. Despite large investments in time and resources, prediction accuracy attainable with numerical flow models has not improved satisfactorily for many types of groundwater management problems. Studies on groundwater levels reveal spatial and temporal information on aquifers and aquiferous systems and help us to take appropriate measures. For management of groundwater resources, traditional numerical methods, with specific boundary conditions, are able to depict the complex structures of aquifers including complicated prediction of groundwater levels. However, the vast and accurate data required to run a numerical model are difficult to obtain owing to spatial variations and the unavailability of previous hydrogeology surveys. As a result, numerical methods have been restricted in their use in remote, sparsely monitored areas. If sufficient data are not available, and accurate predictions are more important than understanding the actual physics of the situation, black box models remain a good alternative method and can provide useful predictions without the costly calibration time (Daliakopoulos et al., 2005).

In recent years, Artificial Neural Network (ANN) as a black box model has been widely used for forecasting in many areas of science and engineering. ANNs are proven to be effective in modeling virtually any nonlinear function to an arbitrary degree of accuracy. The main advantage of this approach over traditional methods is that the method does not require the complex nature of the underlying process under consideration to be explicitly described in mathematical form. This makes ANNs attractive tools for modeling water table fluctuations.

The development of ANNs began approximately 70 years ago (McCulloch and Pitts, 1943), inspired by a desire to understand the human brain and emulate its behavior. Although the idea of ANNs was proposed by McCulloch and Pitts, the development of these techniques has experienced a renaissance only in the last decades due to Hopfield's effort (Hopfield, 1982) in iterative auto-associable neural networks. A tremendous growth in the interest of this computational mechanism has occurred since Rumelhart et al. (1986) rediscovered a mathematically rigorous theoretical framework for neural networks, i.e., back propagation algorithm. Consequently, ANNs have found applications in many engineering problems.

Since the early nineties, ANNs have been successfully used in environmental and hydrology-related areas such as rainfall-runoff modeling, stream flow forecasting, groundwater modeling, water quality, water management policy, precipitation forecasting, and reservoir operations (ASCE, 2000a,b). Also, ANN models have been used for rainfall-runoff modeling (Tayfur and Singh, 2006), precipitation forecasting and water quality modeling (Govindaraju and Ramachandra Rao, 2000). In the water level modeling context, Tayfur et al. (2005) presented an ANN model to predict water levels in piezometers placed in the body of an earthfill dam in Poland considering upstream and downstream water levels of the dam as input data. Neural networks have also been applied with success to temporal prediction of groundwater level (Coulibaly et al., 2001). Two researches have been carried out for forecasting floods in a karestic media (Beaudeau et al., 2001) and determining aquifer outflow influential parameters, and simulating aquifer outflow in a fissured chalky media (Lallahem and Mania, 2003). ANNs have been successfully used for identifying the temporal data necessary to calculate groundwater level in only one piezometer (Lallahem et al., 2005). ANNs were also employed to solve complex groundwater problems and for predicting transient water level in a multilayer groundwater system under variable pumping states and climate conditions (Coppola et al., 2003). Coppola et al. (2005) developed an ANN model for accurately predicting potentiometric surface elevations in alluvial aquifers. Relationships among lake levels, rainfall, evapotranspiration and groundwater levels were determined by Dogan et al. (2008) using ANN-based models. Nourani et al. (2008) employed ANN approach for time-space modeling of groundwater level in an urbanized basin.

In spite of reliable ability of the ANNs in temporal and time series predictions, they could not find notable application for the spatial modeling of the environmental processes. Instead, geostatistics powerful interpolating tools are extremely used for unbiased estimation of the spatial variables at a given point. Geostatistics has made rapid advances in recent years since it first developed by Matheron (1963). Recently, the term geostatistics has been used more generally to describe all applications of statistics in hydrogeology in which the attributes is a random field in space. The heterogeneity of the subsurface often is difficult to characterize adequately for use in deterministic models; therefore, geostatistical techniques often are used to generate estimates of parameters in deterministic mathematical models where parameters are random variables in space. For groundwater flow problems, attributes such as water levels are sampled at a limited number of sites whereas values at un-sampled sites usually are needed for analysis. Geostatistical techniques such as Kriging and Cokriging can be applied to estimate the values of attributes at un-sampled sites (Ma et al., 1999). For examples, various forms of geostatistical tools have been used to map potentiometric surfaces from water level data alone (Delhomme, 1978; Aboufirassi and Marino, 1983; Neuman and Jacobsen, 1984). A comprehensive review of the applications of geostatistics to hydrogeology can be found in the ASCE Task Committee report (ASCE, 1990). Also, a few applications of the geostatistics tools in groundwater level predictions can be found in the literature (e.g. Ma et al., 1999; Finke et al., 2004; Gundogdu and Guney, 2007; Barca and Passarella, 2008; Cay and Uyan, 2009; and Taany et al., 2009).

Nourani et al., (2010) proposed a hybrid model (ANNG) for spatiotemporal forecasting of groundwater level in coastal aquifers. The basic idea of the models combination in the forecasting is the use each model's unique feature to capture different pattern in the data. Both theoretical and empirical findings suggest that the combining different methods can be efficient way to improve forecasting (Zhang and Dong, 2001). Therefore, the developed hybrid model employs the ability of ANN in time series modeling and capability of Kriging in spatial estimation in a unique framework and may be considered as a more general groundwater level modeling tool. According to the inherent capability of ANNs in temporal forecasting and geostatistics tools in spatial estimating, a new modified hybrid ANN-Geostatistic (MANNG) black box model is proposed in this text and its potential is evaluated for spatio-temporal prediction of groundwater level and salinity in a coastal aquifer located in Iran.

2. Study area and data

The data used in this study are from the Shabestar plain (Figure 1) which is located in northwest Iran at Azerbaijan province (between 45^o 26' and 46^o 2' north latitude and 38^o 3' and 38^o 23' east longitude). The plain area is 1300 km^2 and its main channel is Daryanchai which discharges to Urmieh Lake. The headwaters of the river are situated in the Misho Mountain. Plain elevation is varying between 1278 m to 3135 m above sea level and its longest waterway has 15 km length.

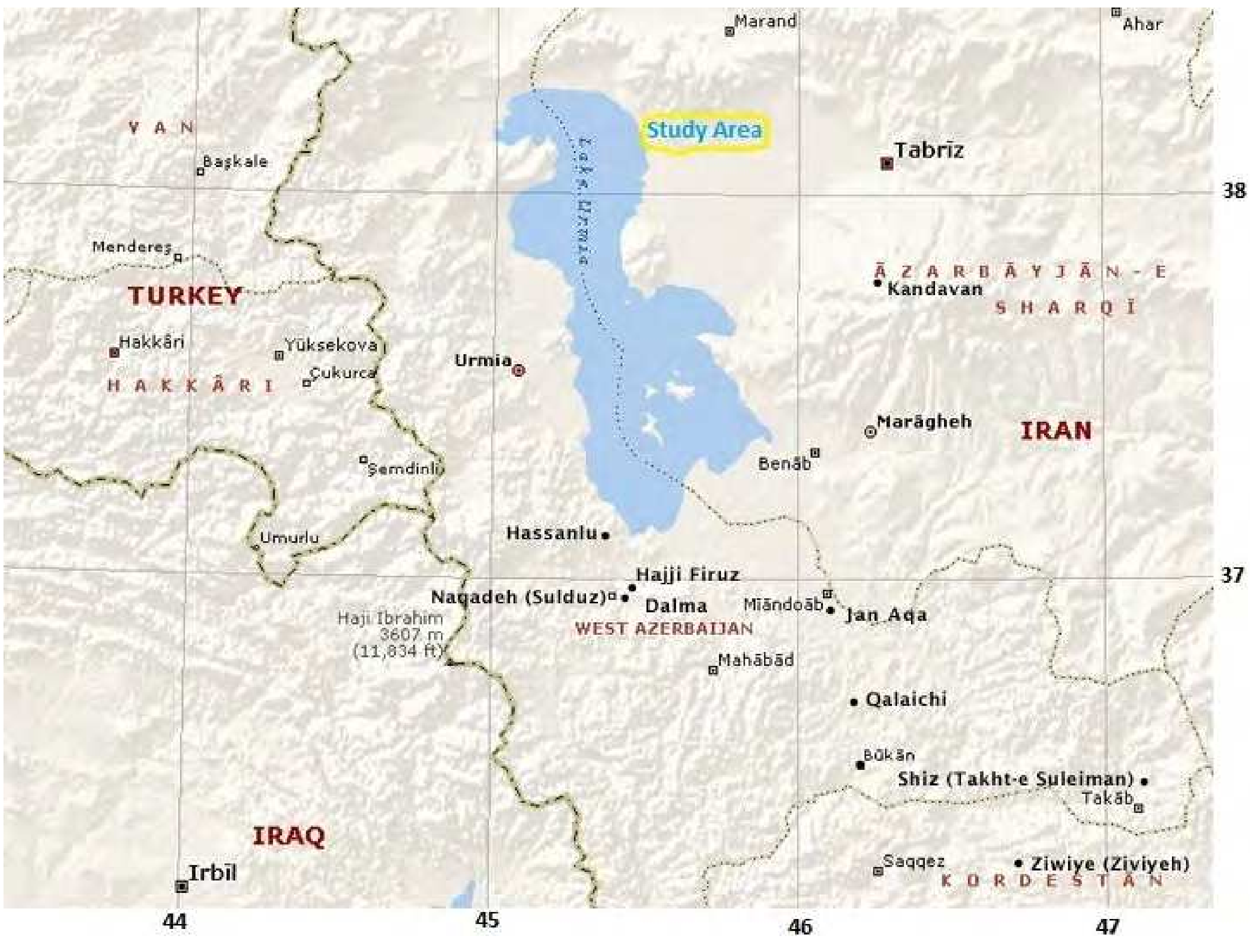


Fig. 1. Study area

The mean daily temperature varies from -19°C in January up to 42°C in July with a yearly average of 11°C and the average annual rainfall is about 250 mm.

Urmieh Lake, located in northwestern Iran, is an oligotrophic lake of thalassohaline origin and the20th largest, and the second hyper saline lake in the world with a total surface area between 4750 and 6100km^2 and a maximum depth of 16 m at an altitude of 1250 m. The lake is divided into north and south parts separated by a causeway in which a 1500 m gap provides little exchange of water between the two parts. Due to drought and increased demands for agricultural water in the lake's basin, the salinity of the lake has risen to more than 300g/l during recent years, and large areas of the lake bed have been desiccated. The possible causes of rising salinity are likely to be surface flow diversions, groundwater extractions and unsuitable climate condition.

Fluctuation of Urmieh Lake water levels has tremendous environmental impacts, especially on the adjoining groundwater resources. About 4.4 million people live in the Urmieh Lake basin, whose irrigation economy is strongly dependent on existing surface and groundwater resources in the area. Accordingly, human population growth in the lake's basin has seriously increased the need for agricultural and potable water in recent years, all of which are supplied from surface and groundwater sources in the area. These issues, together with poor weather conditions, have reduced significantly the volume of water entering the lake so that, at present, Urmieh Lake has shrunk significantly and large areas of the former lake bed have been exposed. According to the interaction between the water depth of the lake and groundwater level of the plain, decreasing of the water depth of the lake leads to decrease of groundwater level of the plain and also increase the groundwater salinity. In this research, it is tried to utilize the ANN and geostatistic concepts in order to investigate the effects of the lake's water depth and other hydro-meteorological parameters on the groundwater level and salinity via a spatiotemporal modeling.

The data utilized in this study were collected over 13years (from April 1994 to March 2006) with one month time interval. Table 1 shows the statistical analysis of the observed groundwater levels of piezometers.

Piez. No.	X(UTM) (m)	Y(UTM) (m)	Piezometer Elevations (m)	Mean (m)	Min. (m)	Max. (m)	Variance	Standard deviation (m)	Skewness coefficient
P1	586050	4238025	1401.48	1390.0	1389.6	1391.1	0.069140	0.262944	1.224652
P2	562800	4230450	1583.24	1547.8	1540.9	1553.8	8.785094	2.963966	-0.12895
P3	561450	4217350	1277.70	1333.7	1331.4	1336.8	1.211814	1.100824	0.132759
P4	562250	4221350	1322.79	1272.0	1268.1	1276.2	3.930377	1.982518	0.026029
P5	576925	4223350	1309.97	1297.7	1295.4	1303.4	3.523323	1.877052	1.473395
P6	577600	4222950	1303.96	1302.5	1301.7	1303.6	0.235159	0.484932	0.611962
P7	584800	4229250	1325.98	1299.1	1298.1	1301.3	0.399340	0.631933	1.321099
P8	546600	4223900	1301.86	1321.8	1319.5	1323.7	1.302649	1.141337	-0.374780
P9	551700	4220350	1292.05	1282.2	1279.0	1284.4	3.338116	1.827051	-0.346380
P10	554550	4220050	1289.02	1284.2	1282.4	1285.8	0.970875	0.985330	0.031911
P11	555050	4220250	1288.98	1285.9	1283.6	1287.3	0.805980	0.897764	-0.651490

Table 1. Statistical analysis of observed data in piezometers

The monthly data collected consist of the following categories:

1. Observed water levels and salinities of piezometers located within the Shabestar plain (P1, P2, P3,…, P11 for training and TP1, TP2, and TP3 for cross-validation purposes). Figure 2 shows positions of the piezometers in the study area.
2. Rainfall in Sharafkhaneh station,
3. Average discharge of Daryanchai in Daryan station,
4. Urmieh Lake level,
5. Temperature in Sharafkhaneh station.

3. Artificial Neural Network

ANNs offer an effective approach for handling large amounts of dynamic, non-linear and noisy data, especially when the underlying physical relationships are not fully understood. This makes them well suited to time series modeling problems of a data-driven nature. In general the advantages of an ANNs over other statistical and conceptual models can be classified as (Nourani et al., 2008):

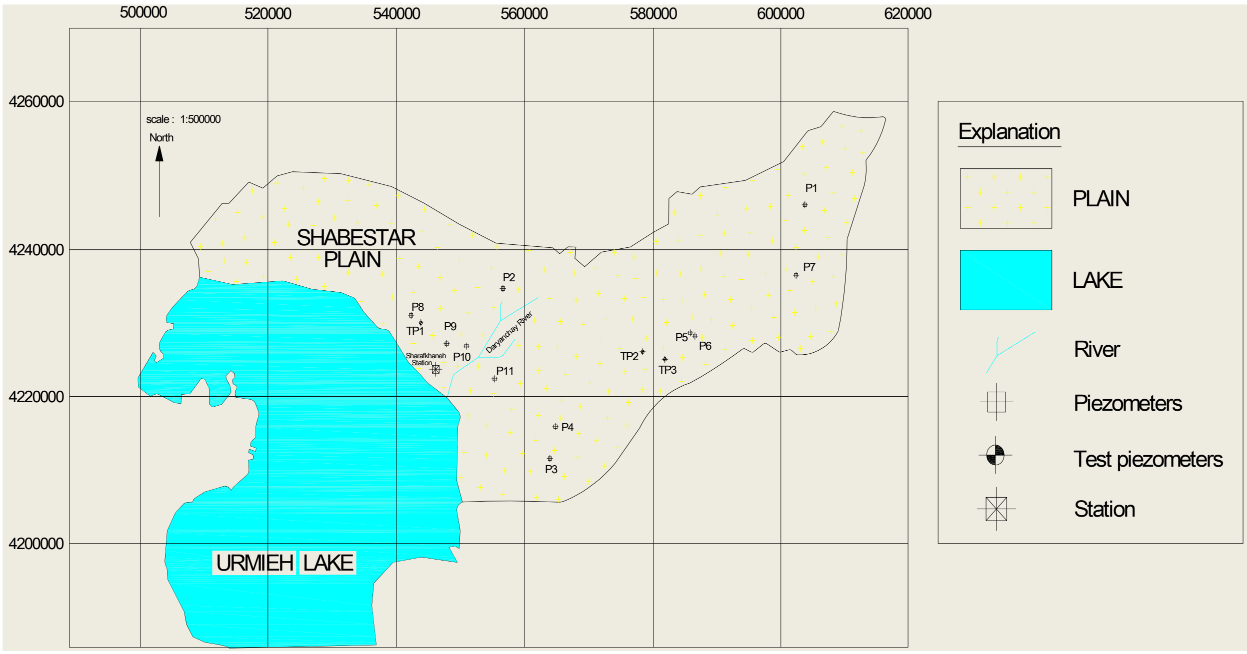


Fig. 2. Piezometers positions

1. The application of ANN does not require a prior knowledge of the process because ANNs have black-box properties,
2. ANNs have the inherent property of nonlinearity since neurons activate a nonlinear filter called an activation function,
3. ANNs can have multiple input having different characteristics, which can represent the time-space variability,
4. ANN has been proven to be effective in modeling virtually any nonlinear function to an arbitrary degree of accuracy. The main advantage of this approach over traditional methods is that it does not require the complex nature of the underlying process under consideration to be explicitly.

ANN is composed of a number of interconnected simple processing elements called neurons or nodes with the attractive attribute of information processing characteristics such as nonlinearity, parallelism, noise tolerance, and learning and generalization capability. Among the applied neural networks, the feed forward neural networks (FFNN) with back-propagation (BP) algorithm are the most common used methods in solving various engineering problems (Nourani et al., 2009).

FFNN technique consists of layers of parallel processing elements called neurons, with each layer being fully connected to the preceding layer by interconnection strengths, or weights. Initial estimated weight values are progressively corrected during a training process that compares predicted outputs with known outputs. Learning of these ANNs is generally accomplished by Back Propagation (BP) algorithm (Hornik et al., 1989). The objective of the BP algorithm is to find the optimal weights, which would generate an output vector, as close as possible to the target values of the output vector, with the selected accuracy.

The network is determined by architecture of the network, the magnitude of the weights and the processing element's mode of operation. The neuron is a processing element that takes a number of inputs, weights them, sums them up, adds a bias and uses the results as the argument for a singular valued function called the transfer function. The transfer function results in the neuron's output. At the start of training, the output of each node tends to be small. Consequently, the derivatives of the transfer function and changes in the connection weights are large with respect to the input. As learning progresses and the network reaches a local minimum in error surface, the node outputs approach stable values. Consequently the derivatives of the transfer function with respect to input, as well as changes in the connection weights, are small.

The Back Propagation (BP) neural network is the most widely used ANN in hydrologic modeling and is also used in this study. A typical BP neural network model is a full-connected neural network including input layer, hidden layer and output layer.

Back-propagation (BP) algorithms use input vectors and corresponding target vectors to train ANN. The standard BP algorithm is a gradient descent algorithm, in which the network weights are changed along the negative of the gradient of the performance function. There are a number of variations in the basic BP algorithm that is based on other optimization techniques such as conjugate gradient and Newton methods (Hornik et al., 1989).

For properly trained BP networks, a new input leads to an output similar to the correct output. This ANN property enables training of a network on a representatives set of input/target pairs and achieves sound forecasting results. A clear systematic document about the BP algorithm and the methods for designing the BP model are given by Basheer and Hajmeer (2000) and Jiang et al. (2008). Some researchers claim that networks with a single hidden layer can approximate any continuous function to a desired accuracy and is enough for most forecasting problems (Hornik et al., 1989).

In this study, at first step by using a three-layer neural network via a sensitivity analysis the effective data sets are chosen. All input values are standardized to a specific range separately after data division. Input and output variables are normalized by scaling between zero and one to eliminate their dimensions and to ensure that all variables receive equal attention during training of the models. Finally, the training and testing data sets are selected, and the network is trained.

The Levenberg-Marquardt (LM) method is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. Levenberg-Marquardt has large computational and memory requirement and thus it can only be used in small networks (Maier and Dandy, 1998). It is faster and less easily trapped in local minima than other optimization algorithms (Coulibaly et al., 2001a, b, c; Toth et al., 2000).

In this study, among the many training methods, the Levenberg- Marquuardt training algorithm was selected, considering its fast convergence ability (Sahoo et al., 2005). Also a Tangent Sigmoid transfer function was used for hidden layer and a linear transfer function for the output layer according to Qu et al. (2004). The numbers of hidden layer nodes and training epochs are determined using trial and error in the test scenarios.

4. Geostatistics

Since detailed information about geostatistics and geostatistical techniques such as Kriging and Cokriging can be found in the scientific literature (e.g., Isaaks and Srivastava, 1989), only a brief description of this methods which is employed in this research is provided.

Kriging technique is a spatial interpolation estimator $Z(x_0)$ used to find the best linear unbiased estimator of a second-order stationary random field with an unknown constant mean:

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

Where $\underline{Z}$ (x_0) is Kriging estimate at location x_0; $Z(x_i)$ is sampled value at x_i; λ_i is weighting factor for $Z(x_i)$; and i = 1, … , n in which n denotes to the numbers of samples. The estimation error can be written as:

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

Where $Z(x_0)$ is unknown true value at x_0; and $R(x_0)$ is estimation error. For an unbiased estimator, the mean of the estimates must be equal to the true mean, therefore (Ma et al., 1999):

$$E\left(R(x_0)\right) = 0 \tag{3}$$

Where E is expected value and then:

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{4}$$

The best linear unbiased estimator must have minimum variance of estimation error. The minimization of the estimation error variance under the constraint of unbiasedness leads to a set of simultaneous linear algebraic equations for the weighting factors as follows (Ma et al., 1999):

$$E\left[\left(\sum_{i=1}^{n} \lambda_i Z(x_i) - Z(x_0)\right)^2\right] = Var\left[\sum_{i=1}^{n} \lambda_i Z(x_i) - Z(x_0)\right] \tag{5}$$

Where Var, is the abbreviation of variance function. The weighting factors λ_i can be determined by solving a nonlinear optimization problem involving the minimization of the foregoing function subject to the constraint in (4) by using the Lagrange multiplier μ as:

$$L(\lambda_i, \mu) = Var\left[\sum_{i=1}^{n} \lambda_i Z(x_i) - Z(x_0)\right] - 2\mu\left(\sum_{i=1}^{n} \lambda_i - 1\right) \tag{6}$$

The necessary conditions for optimal λ_i and μ values involve setting the first derivative of Equation (6) to zero; therefore, the system of simultaneous linear algebraic equations for λ and μ can be expressed in matrix form as (Ma et al., 1999):

$$\begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} & 1 \\ \gamma_{21} & \gamma_{22} & & \gamma_{2n} & 1 \\ \vdots & & \ddots & \vdots & \\ \gamma_{n1} & \gamma_{n2} & \cdots & \gamma_{nn} & 1 \\ 1 & 1 & \ldots & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \gamma_{0n} \\ 1 \end{bmatrix} \tag{7}$$

The Variogram γ can be derived from sampled data as follows:

The presence of a spatial structure where observations close to each other are more alike than those that are far apart (spatial autocorrelation) is a prerequisite to the application of geostatistics. The experimental Variogram measures the average degree of dissimilarity between un-sampled values and a nearby data value and thus can depict autocorrelation at various distances. The value of the experimental Variogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at $z(x_i)$ and the value at $z(x_{i+h})$ as (Ma et al., 1999):

$$\gamma(h) = \frac{\left\{ \sum_{i=1}^{n} \left[Z(x_i) - Z(x_i + h) \right]^2 \right\}}{2n} \tag{8}$$

Where n is the number of data pairs within a given class of distance and direction. If the values of $z(x_i)$ and $z(x_{i+h})$ are auto correlated the results of Equation (8) will be small, relative to an uncorrelated pair of points. From analysis of the experimented Variogram, a suitable model (e.g., spherical, exponential) is then fitted, usually by weighted least squares and the parameters (e.g., range, nugget and sill) are then used in the Kriging procedure (Isaaks and Srivastava, 1989).

The "co-regionalization" (expressed as correlation) between two variables, i.e. the variable of interest, groundwater salinity in this case and another easily obtained and inexpensive variable, can be exploited to advantage for estimation purposes by the Cokriging technique. In this sense, the advantages of Cokriging are realized through reductions in costs or sampling effort. The cross semivariogram is used to quantify cross-spatial auto-covariance between the original variable and the covariate. The cross-semivariance is computed through the equation:

$$\gamma_{uv}(h) = E[\{Z_u(x) - Z_u(x+h)\}\{Z_v(x) - Z_v(x+h)\}] \tag{9}$$

Where $\gamma_{uv}(h)$ is cross-semivariance between u and v variable, $Z_u(x)$ is primary variable and $Z_v(x)$ is secondary variable.

5. Proposed conjugated model and results

By combining the artificial neural network capability in modeling complicated and non-linear systems and geostatistical ability in linear estimation with low estimation error, a new hybrid model (MANNG) of spatiotemporal groundwater level and salinity forecasting in coastal aquifers has been proposed in this paper which uses both of mentioned models in unique framework. Figure 3 shows the proposed model scheme.

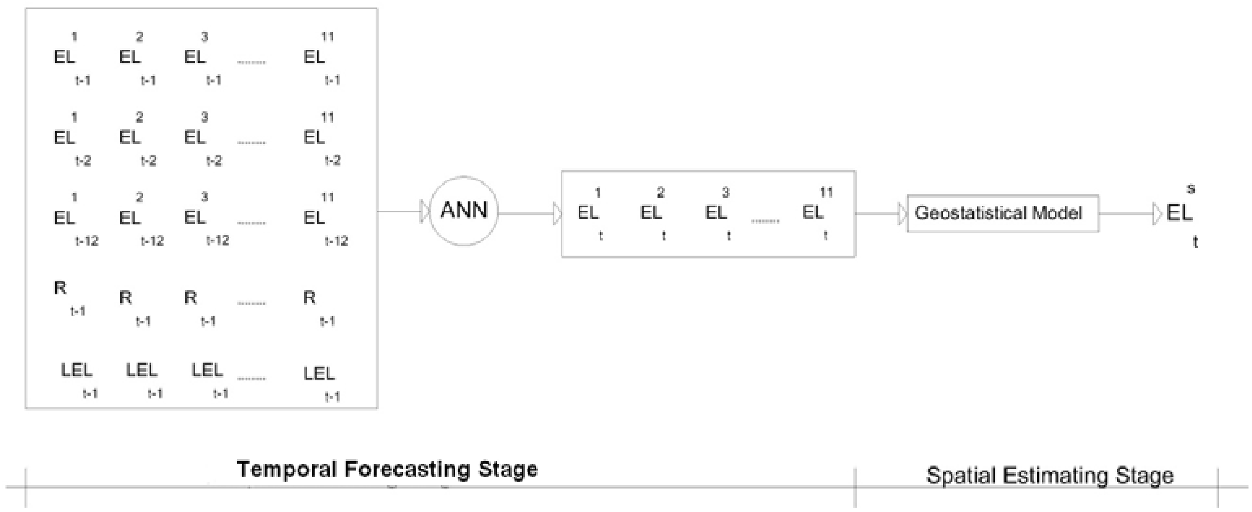


Fig. 3. Diagram of new modified proposed hybrid model (MANNG)

The proposed model contains two separated stages. At the first stage, an ANN is trained for all of the piezometers (P1, P2, …, and P11) for time series modeling of the water level. The model predicts the preceding month ground water level of the piezometers based on quantity of present month rainfall in study area (R_{t-1}), Urmieh Lake water surface level at that month (LEL_{t-1}) and groundwater levels in present, first and twelfth previous months (EL_{t-1}, EL_{t-2},EL_{t-12}) in order to handle the seasonality of the process as well as the auto regressive characteristics. A sensitivity analysis was employed in order to select the mentioned input parameters from the all available data, as it will be discussed in the next section.

At the second stage, the predicted values of water levels at different piezometers are imposed to a calibrated geostatistics model in order to estimate groundwater level and salinity at any desired point in the plain. Finally, as a cross-validation process the proposed spatio-temporal model is evaluated by the data of piezometers TP1,TP2, and TP3 which are not contributed in the calibration step of the model. The details and results of the stages are presented in the following sections.

5.1 Temporal forecasting stage

In order to ensure good generalization ability by an ANN model, some empirical relationships between the number of training samples and the number of connection weights have been suggested in the literature. However, network geometry is generally highly problem dependent and these guidelines do not ensure optimal network geometry, where optimality is defined as the smallest network that adequately captures the relationships in the training data (principle of parsimony). In addition, there is quite a high variability in the number of input and hidden nodes suggested by the various rules. While research is being conducted in this direction by the scientists working in ANNs, it may be noted that traditionally, optimal network geometries have been found by trial and error (Maier and Dandy, 2000). Consequently, in the current application the number of hidden neurons in the network, which is responsible for capturing the dynamic and complex relationship between various input and output variables, was identified by several trials. Also, this trial and error procedure with domain knowledge was explored for general guidance in the number of inputs selected.

The trial and error procedure started initially with two hidden neurons, and the number of hidden neurons was increased up to fifty with a step size of one in each trial. For each set of input and hidden neurons, the network was trained in batch mode to minimize the mean square error at the output layer. In order to check any over-fitting during training, a validation was performed by keeping track of the efficiency of the fitted model. The training was stopped when there was no significant improvement in the efficiency. The parsimonious structure that resulted in minimum root mean squared error (Equation 10), and maximum efficiency coefficient (Equation 11) during training as well as testing was selected as the final form of the ANN model for all piezometers.

The variables are scaled to a limit between zero and one as the activation function warrants. The total available data were divided into two sets, calibration and validation sets. In the training step the models were trained using data of ten years (1994-2003) and then validated on the rest of the data (2004-2006).

The Root Mean Squared Error (RMSE) and coefficient of efficiency (CE) were used in order to assess the effectiveness of each model and its ability to make precise predictions. The RMSE calculated by

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{N}} \tag{10}$$

Where y_i and $\hat{y}_i$ are the observed and predicted data respectively and N is the number of observations. RMSE indicates the discrepancy between the observed and calculated values. The lowest the RMSE, the more accurate the prediction is. Nash and Sutcliffe (1970) proposed the non-dimensional coefficient of efficiency (CE) criterion on the basis of standardization of the residual variance with initial variance, which provides a measure for the proportion of the variance explained by the model. It can be used to compare the relative performances of the models which are developed by different methods. It is estimated as (Nash and Sutcliffe, 1970).

$$CE = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \overline{y}_i\right)^2} \tag{11}$$

Where $\overline{y}_i$ is the average of observed values and the CE represents the initial uncertainty explained by the model. The CE is varying between -∞, 1 and the best fit between observed and calculated values would have CE=1. The quality of the fit statistics is measured by RMSE and CE between the computed and observed data. The sensitivity analysis showed that present month rainfall, lake water surface level at that month and groundwater levels in first, second and twelfth previous months are the most dominant parameters in forecasting the groundwater level in the most of piezometers and these parameters were considered as the input neurons for ANNs (Nourani et al.,2010).

The results of temporal modeling of groundwater levels in piezometers P1,P2,…,P11 ,as the first stage of the hybrid modeling have been briefly shown in table 2.

Piezometer	UTM		Networks Parameters		Calibration		Validation	
	x	y	Structure	Epoch	CE	RMSE(m)	CE	RMSE(m)
P1	586050	4238025	(5,6 ,1)	40	0.85	0.08	0.78	0.11
P2	562800	4230450	(5, 6,1)	40	0.95	0.07	0.89	0.10
P3	561450	4217350	(5,6 ,1)	40	0.95	0.06	0.88	0.09
P4	562250	4221350	(5,6,1)	40	0.96	0.07	0.86	0.10
P5	576925	4223350	(5,6,1)	40	0.89	0.05	0.83	0.11
P6	577600	4222950	(5, 6,1)	40	0.90	0.05	0.83	0.10
P7	584800	4229250	(5,6 ,1)	40	0.88	0.06	0.81	0.09
P8	546600	4223900	(5,6,1)	40	0.96	0.02	0.88	0.04
P9	551700	4220350	(5,6 ,1)	40	0.96	0.03	0.89	0.05
P10	554550	4220050	(5,6 ,1)	40	0.95	0.04	0.92	0.06
P11	555050	4220250	(5,6 ,1)	40	0.97	0.03	0.89	0.06

Table 2. ANN results for temporal forecasting stage

5.2 Spatial estimation stage

Groundwater has become one of the important sources of water for meeting the requirements of various sectors in the world in the last few decades. It plays a vital role in countries economic, development and in ensuring them food security. The rapid pace of agriculture development, industrialization and urbanization has resulted in the over exploitation and contamination of groundwater resources in the world, resulting in various adverse environmental impacts and threatening its long-term sustainability.

Salinity is the saltiness or dissolved salt contents of a water body. Salt content is an important factor in water use. Salinity can be technically defined as the total mass in grams of all the dissolved substances per kilogram of water (TDS). Different substances dissolve in water giving it taste and odor.

Salinity always exists in groundwater but in variable amounts (100<TDS<50000 mg/lit). It is mostly influenced by aquifer material, solubility of minerals, duration of contact and factors such as the permeability of soil, drainage facilities, quantity of rainfall and above all, the climate of the area.

The salinity of groundwater in coastal areas may be due to air borne salts originating from air water interface over the sea and also due to over pumping of fresh water which overlays saline water in coastal aquifer system.

Unlike Ordinary Kriging dealing with the primary variable alone, Cokriging utilized not only the primary variable (e.g,, salinity) but also cross-correlated secondary variables (e.g., groundwater level). Cokriging is thus a linear interpolator of both primary and secondary data values. If only a limited number of observations are available for the primary variable in concern, knowledge of secondary variables that are correlated with the primary variable can be used to reduce the estimation error and to improve the estimation. The estimation error is thereby reduced since more information is being used for the estimation of the primary parameter; a twofold reduction in error of estimation would be typical. Improvement of Cokriging over Ordinary Kriging with the primary variable alone is greatest when the primary variable is under sampled, as we often encounter in salinity sampling.

In this study we apply the common geostatistical method of Cokriging to estimate groundwater salinity in the study area.

The Variogram measures dissimilarity, or increasing variance between points (decreasing correlation) as a function of distance. In addition to helping us assess how values at different location vary over distance, the Variogram provide a way to study the influence of other factors which may affect whether the spatial correlation varies only with distance (the isotropic case) or with direction and distance (the anisotropic case).Variogram map provides a visual picture of semivariance in every compass direction. If there is anisotropy, this allows one to easily find the appropriate principal axis for defining the anisotropic Variogram model. In this map, the surface (z-axis) is semivariance, and the x and y axes are separation distances in E-W and N-S directions, respectively. The center of the map corresponds to the origin of the Variogram $\gamma(h)=0$ for every direction.

At stage two of the current modeling which deals with spatial prediction of groundwater level, estimated groundwater level of following month at the location of each piezometer was firstly corrected via bedrock elevation at the same location because of termination of existing trend (see Figure 4). Afterward, the Variogram map of the study area was plotted using the temporally averaged values of the groundwater levels at different piezometers.

Figure 5 shows that, the isotropic spatial modeling of the groundwater levels could be taken in use.

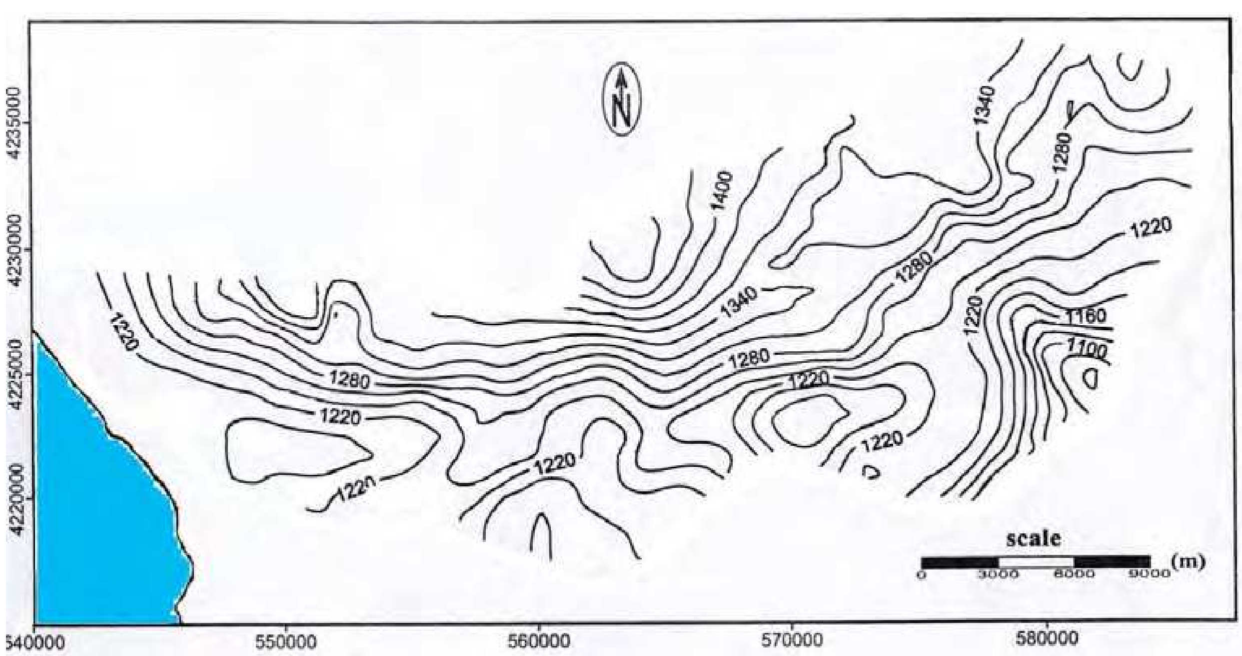
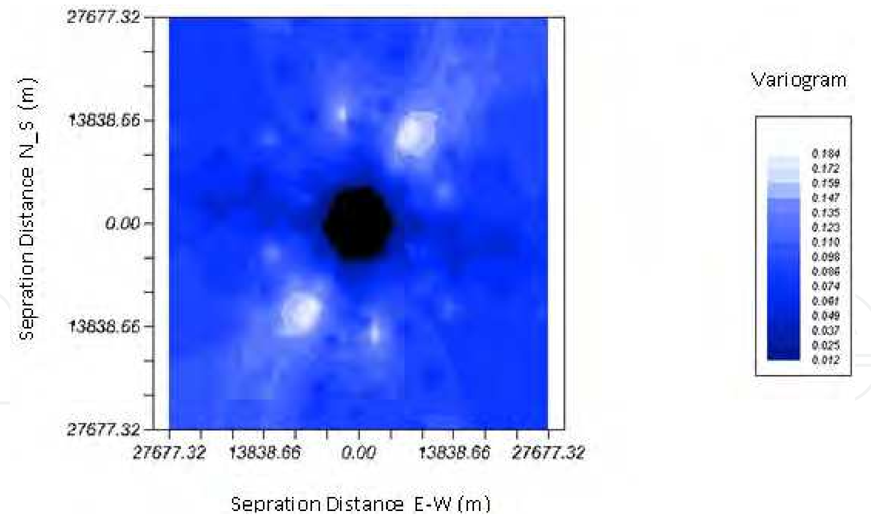
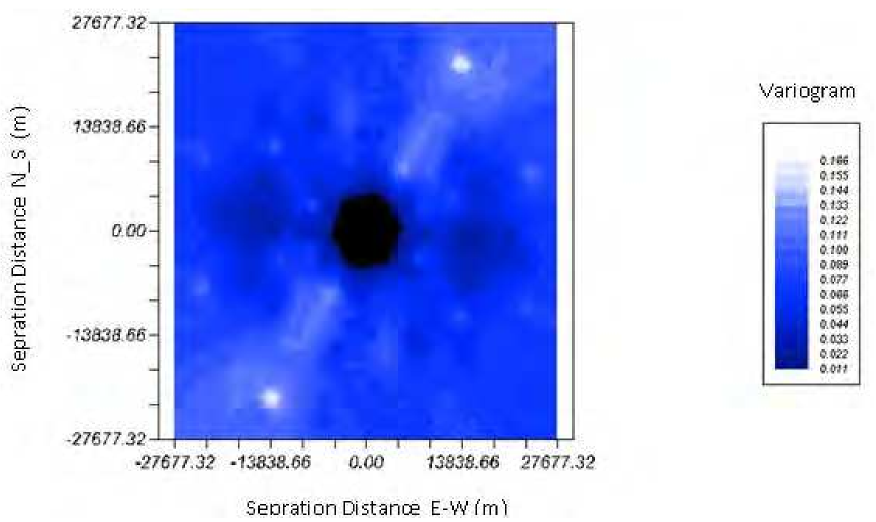


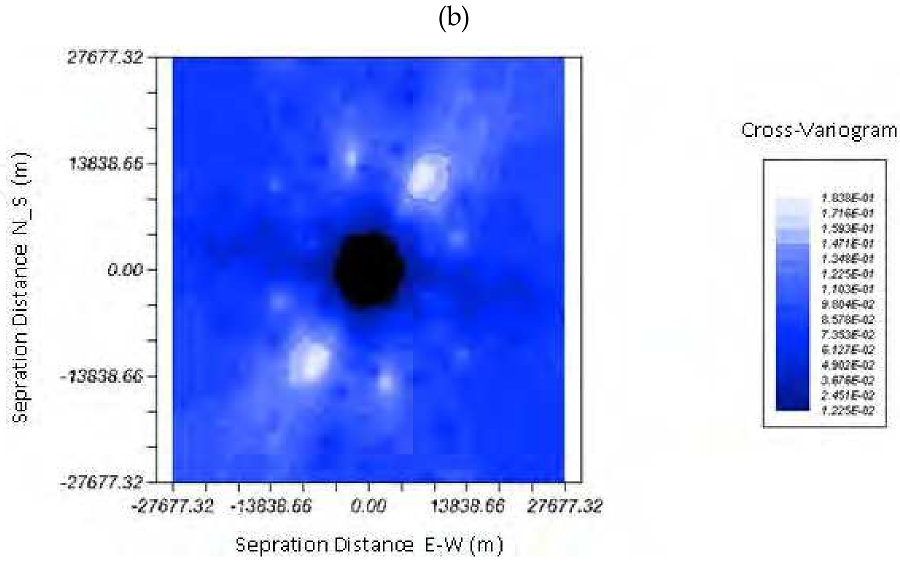
Fig. 4. Bedrock elevations in study area (units in meters)



(a)



(b)



(c)

Fig. 5. Variogram maps : (a) Primary variogram (TDS); (b) Covariate variogram (EL) and (c) Cross variogram (TDS and EL)

Thereafter, a suitable Variogram model was determined by fitting some well-known Variogram models (i.e., spherical, exponential, Gaussian) to the experimental Variogram using weighted least squares method (Myers, 1982).

The geostatistical model having the least error was selected by comparing the observed water-table and salinity values with the values estimated by Variogram models. (Gundogdu and Guney,2007).

According to table 3 the best fitted models were Spherical, Gaussian and Spherical models for first, second and co-variables respectively, and their parameters (i.e., range, nugget and sill) were then used in the CoKriging procedure.

The results of the modeling have been presented in Figure 6.

RSS	Variogram for TDS	Variogram for Elevation	Cross Variogram
Gaussian model	9.22E-03	**5.09E-03**	5.98E-03
Exponential model	8.32E-03	9.20E-03	7.80E-03
Spherical model	**7.41E-03**	6.41E-03	**5.93E-03**

Table 3. Results of the different Variogram models

Based on the mentioned Variogram models spatial ground water level and salinity estimation of the area has been carried out using CoKriging method. The calibrated CoKriging method was then verified via a cross validation technique. Cross validation is a process for checking the compatibility between a set of data, the spatial model and neighborhood design. In cross validation, each point in the spatial model is individually removed from the model, and then its value is estimated by a covariance model. In this way, it is possible to complete estimated versus actual values. Figure 7 shows the results of cross validation procedure as a scatter plot, which denotes to the reliability of the proposed geostatistical modeling.

At this moment both stages of the hybrid model have been completed and the model can be used for spatio-temporal modeling of groundwater level within the Shabestar plain.

Finally, the proposed new modified hybrid model was validated using the verification data set (2004-2006, 3 years) of piezometers TP1, TP2, and TP3 which have not been utilized neither for training the ANNs nor for the calibration of the geostatistices model. For this purpose, the forecasted values of the water level time series at different piezometers (P1, P2,…, and P11) via the trained ANNs models for the verification data set (2003 to 2006) were imposed to the calibrated geostatistical model in order to estimate the water level and salinity of piezometers TP1,TP2, and TP3, time step by time step.

The results of the modeling have been presented and compared with the previous model results (ANNG) in Figure 8 which demonstrates the capability of the new proposed time-space hybrid model (MANNG).

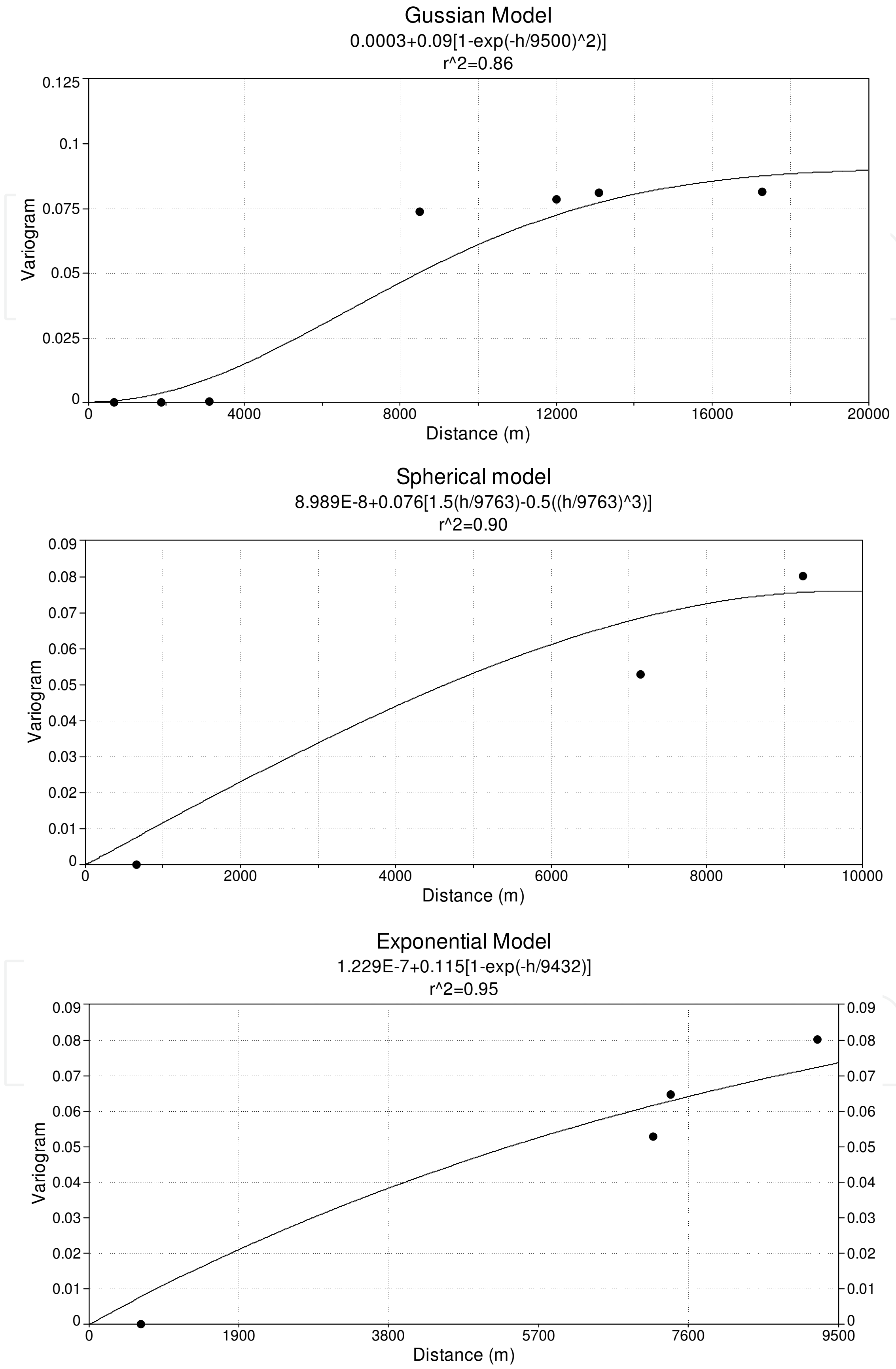


Fig. 6a. Variogram models for TDS.

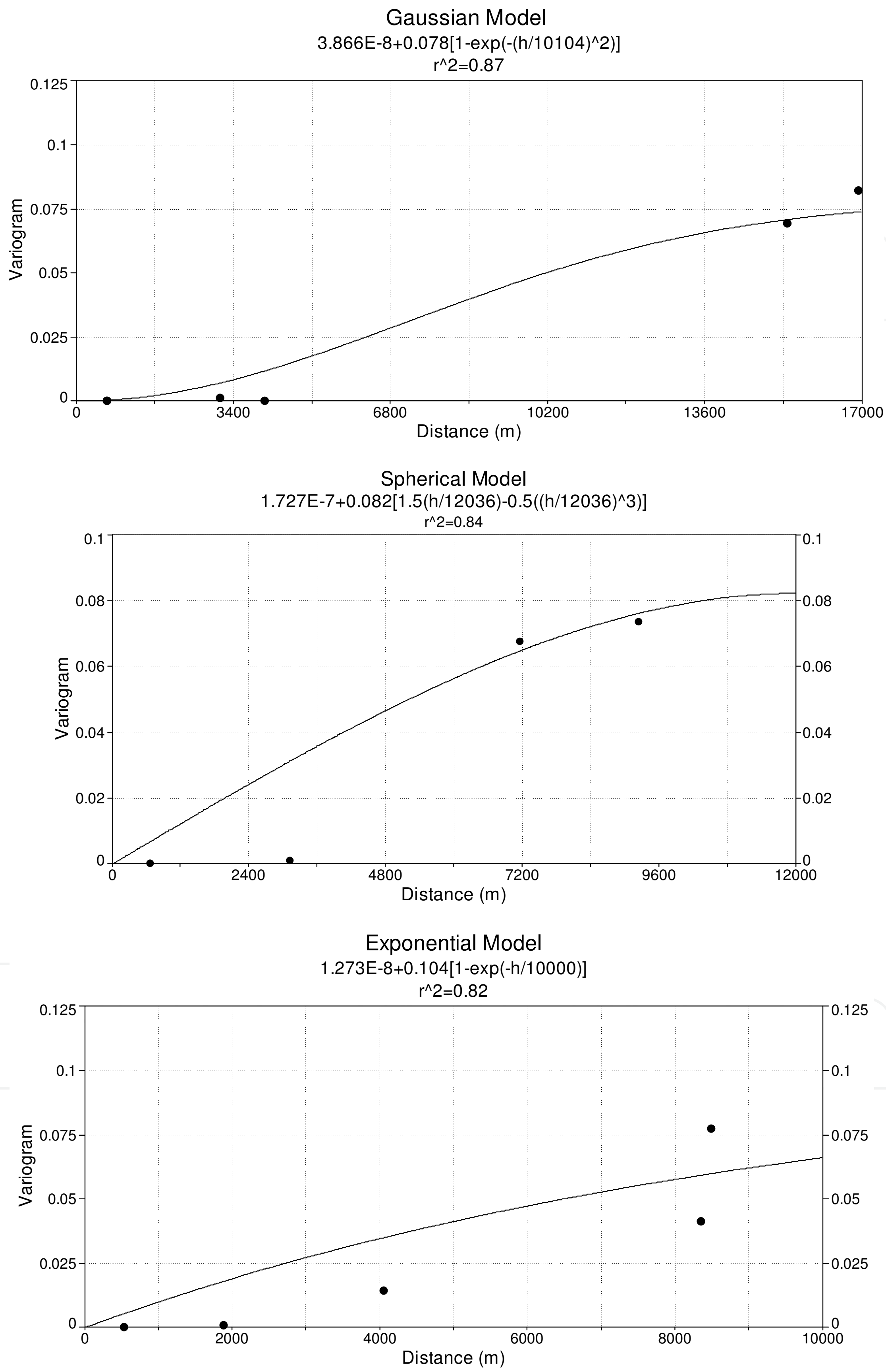


Fig. 6b. Variogram models for groundwater level.

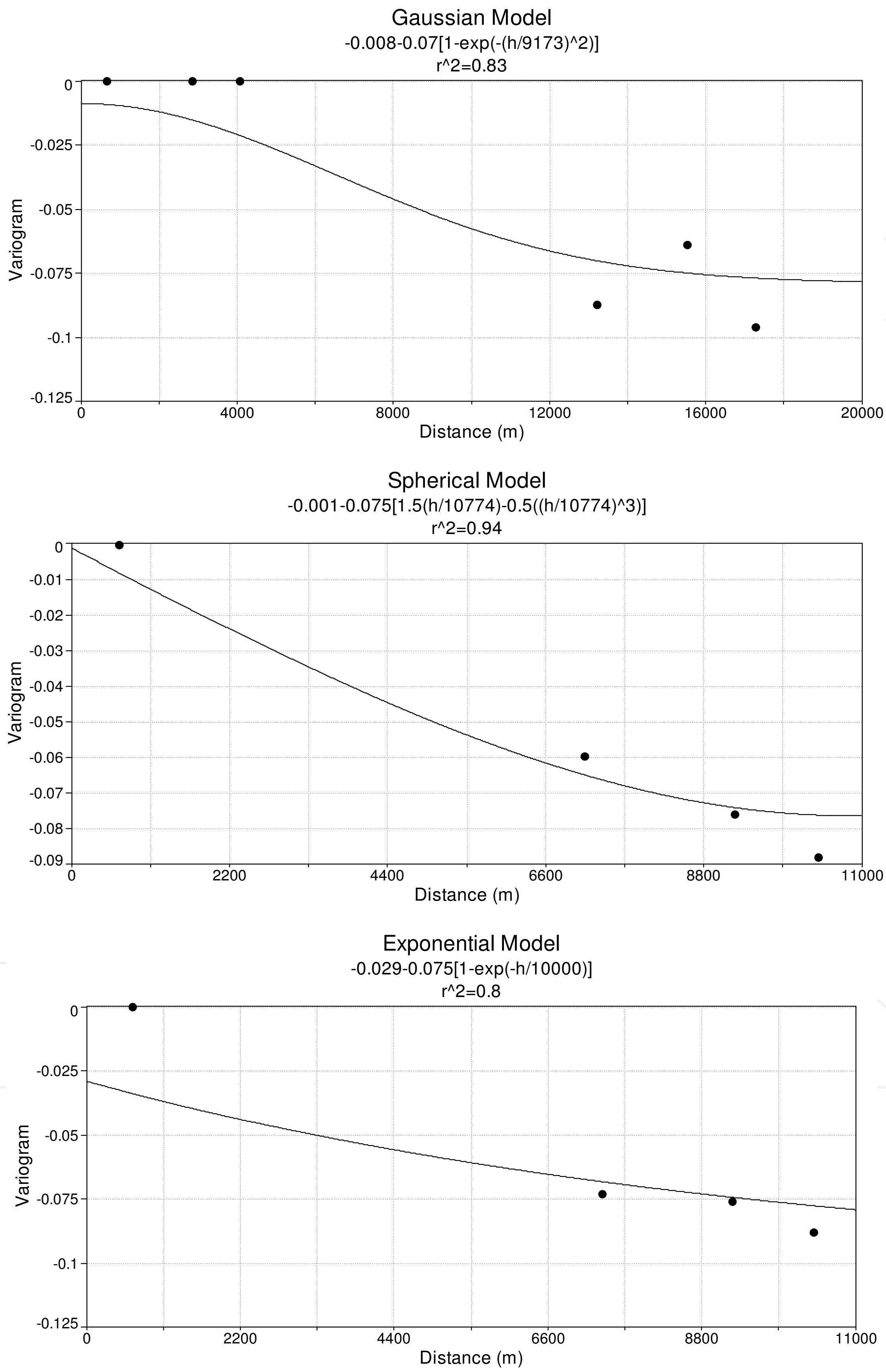
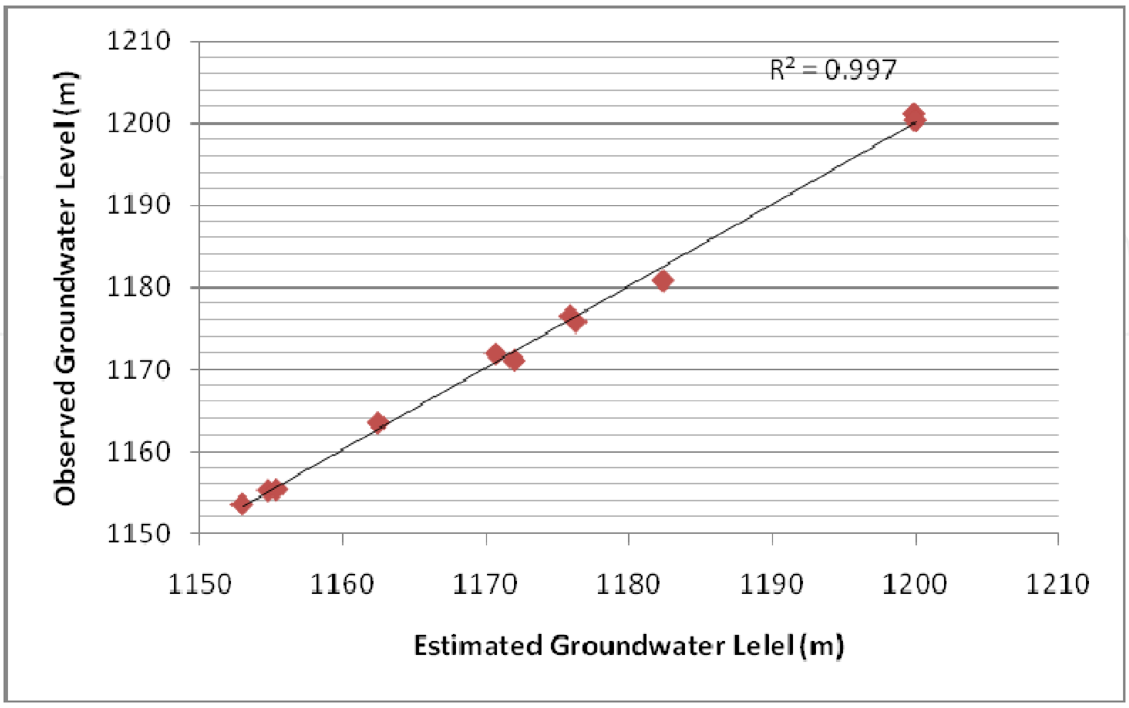
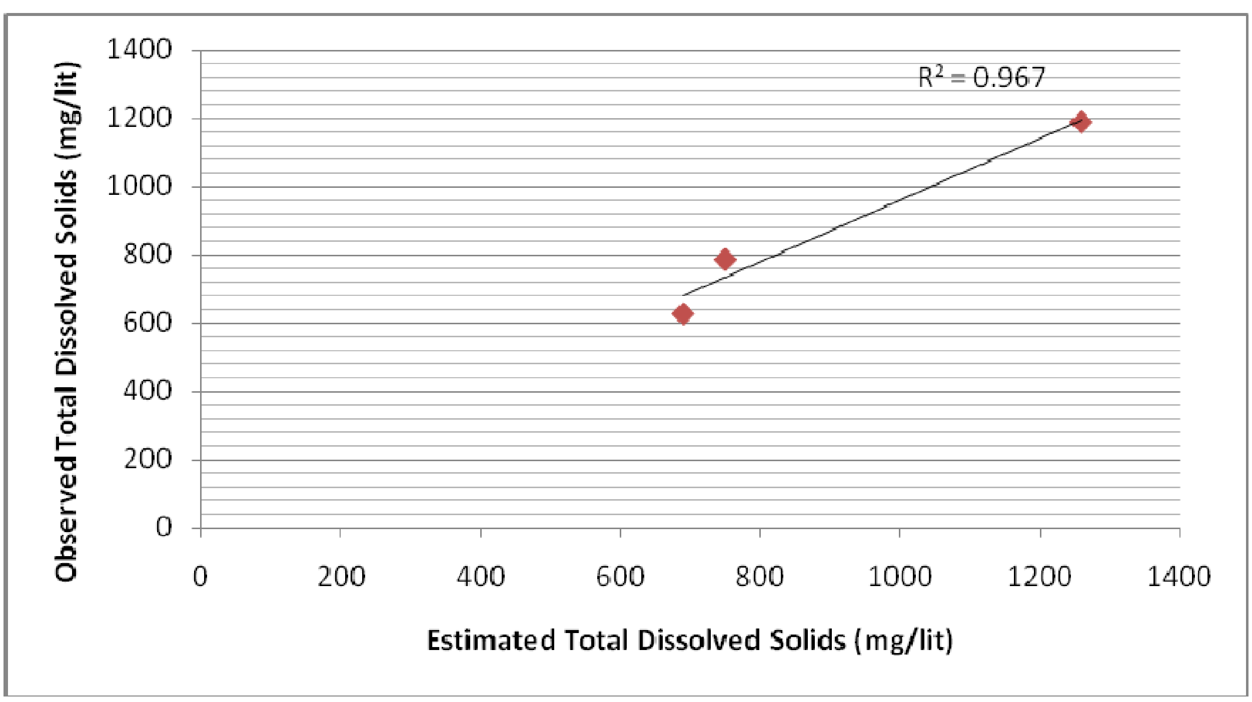


Fig. 6c. Variogram models for Cross.

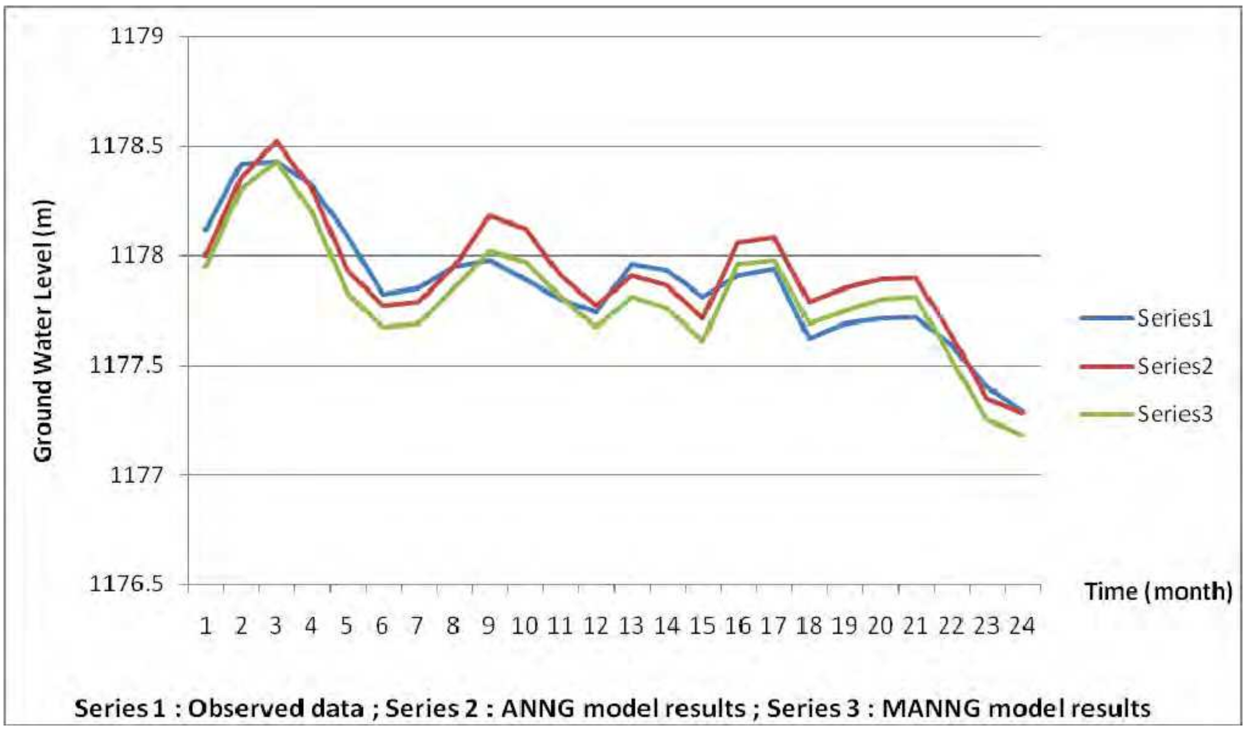


(a)

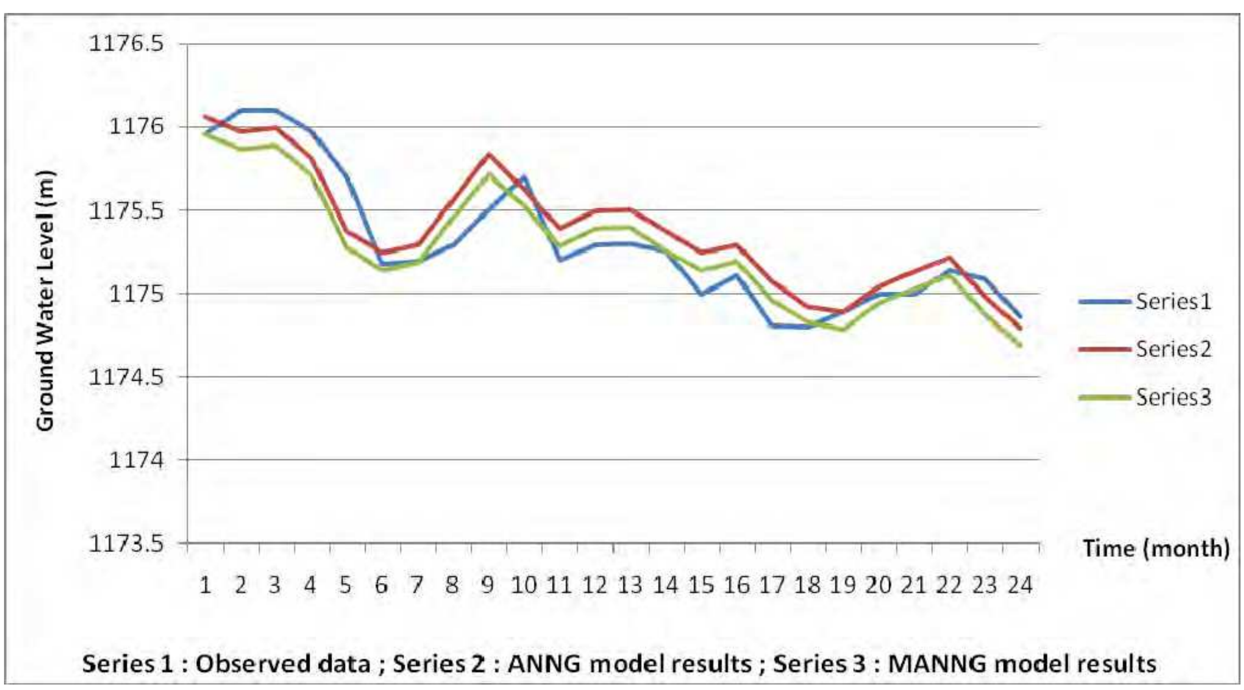


(b)

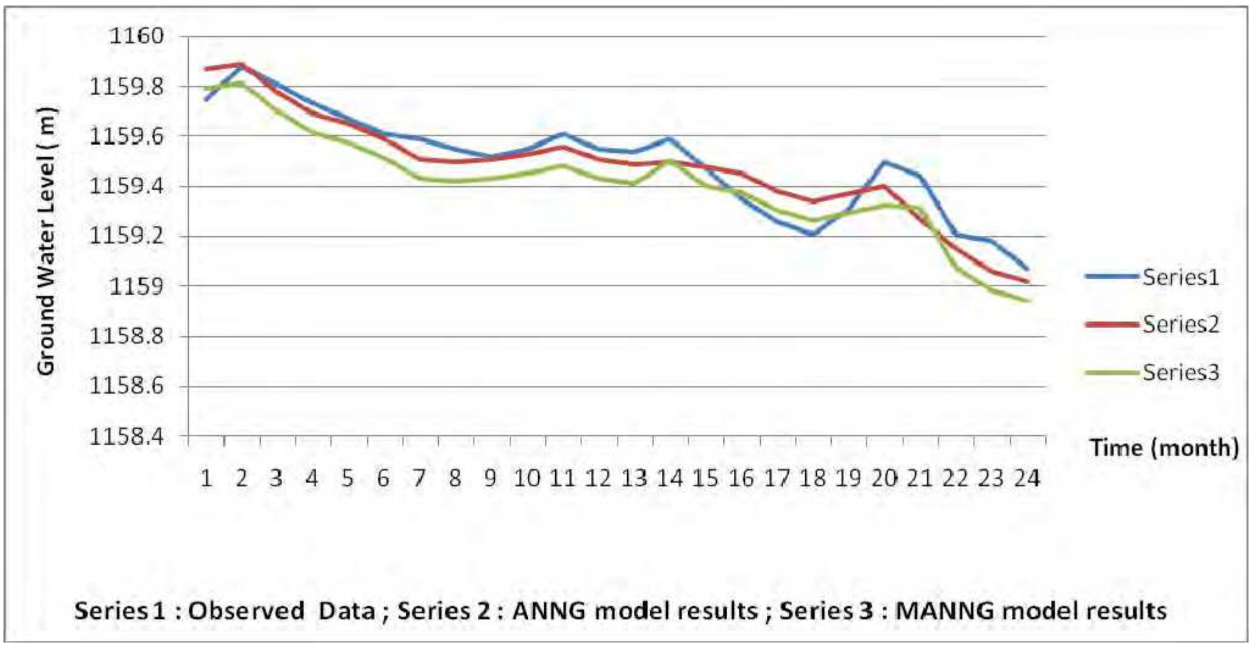
Fig. 7. Cross validation results: (a) for Groundwater level and (b) for TDS.



(a)
[R^2=0.75 for ANNG & R^2=0.83 for MANNG]



(b)
[R^2=0.78 for ANNG & R^2=0.84 for MANNG]



(c)
[R^2=0.87 for ANNG & R^2=0.91 for MANNG]

Fig. 8. Results of spatiotemporal modeling for piezometers; a) TP1, b) TP2 and c) TP3.

According to the obtained results it can be clearly seen that the model is more capable to estimate the groundwater levels and salinity where are close to the lake. Since the water depth of lake is considered as a input variable to the ANNs, the proposed model could simulate the groundwater level of the near region to the lake were accurate than the far points.

7. Concluding remarks

There are many hydrological variables that can be viewed as spatiotemporal phenomena. For example, monthly rainfalls or piezometric readings exhibit random aspects both with respect to time and space. The estimation of such variables at un-sampled spatial locations or un-sampled times requires the adequate techniques into space-time domain. In this study, according to inherent capability of artificial neural networks in temporal forecasting and geostatistics in spatial estimating, the potential of the proposed hybrid empirical model (MANNG) was evaluated for the purpose of spatio-temporal prediction of groundwater levels and salinity in a coastal aquifer in Iran.

Monthly groundwater levels data from eleven piezometer (P1, P2,… P11), rainfall and lake water surface elevations in the 13 years are the inputs of multilayer feedforward neural network. CoKriging was applied to the outputs from ANN model to estimate groundwater levels and salinity in un-sampled locations such as coordinates of three selected piezometers (TP1, TP2, and TP3).

This modeling framework is applied for the Shabestar plain which is located in northwest Iran at Azerbaijan province. The major results of the study are summarized as follows:

- The results of the research reported in the paper shows high efficiency of three-layer back propagation artificial neural network (BPANN) with Levenberg-Marquardt (LM) training algorithm for groundwater elevation prediction in the case study for coastal aquifer.
- Because of spatial structure between groundwater levels and salinity in adjacent points of this coastal aquifer, application of CoKriging with isotropic adequate Variogram geostatistical models have been led to appropriate results.
- In general, the results of the case study are satisfactory and demonstrate that the proposed hybrid model (MANNG) is a promising spatio-temporal prediction tool for groundwater modeling and may be also employed to fill the temporally and/or spatially missed data.
- According to Fig 8, application of the new modified hybrid model (MANNG) respect to previous model (ANNG) presented by Nourani et al. (2010), was led to exact results. In the other word, the results of cross validation procedure of the new model were 3 percent better than the old model. Generally, the proposed modified hybrid empirical model (MANNG) was used for the purpose of spatio-temporal prediction of groundwater levels and salinity in a coastal aquifer in Iran, efficiently.

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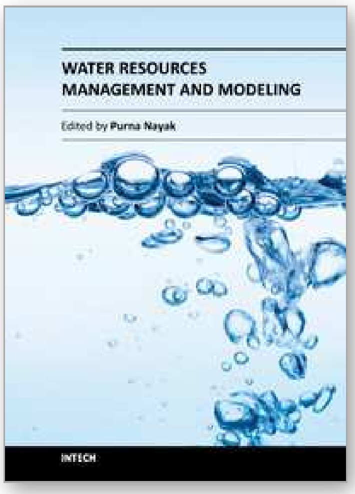

Water Resources Management and Modeling

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Hydrology is the science that deals with the processes governing the depletion and replenishment of water resources of the earth's land areas. The purpose of this book is to put together recent developments on hydrology and water resources engineering. First section covers surface water modeling and second section deals with groundwater modeling. The aim of this book is to focus attention on the management of surface water and groundwater resources. Meeting the challenges and the impact of climate change on water resources is also discussed in the book. Most chapters give insights into the interpretation of field information, development of models, the use of computational models based on analytical and numerical techniques, assessment of model performance and the use of these models for predictive purposes. It is written for the practicing professionals and students, mathematical modelers, hydrogeologists and water resources specialists.

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