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RESEARCH PAPER

Estimation of groundwater depth using ANN-PSO, kriging, and IDW models (case study: Salman Farsi Sugarcane Plantation)

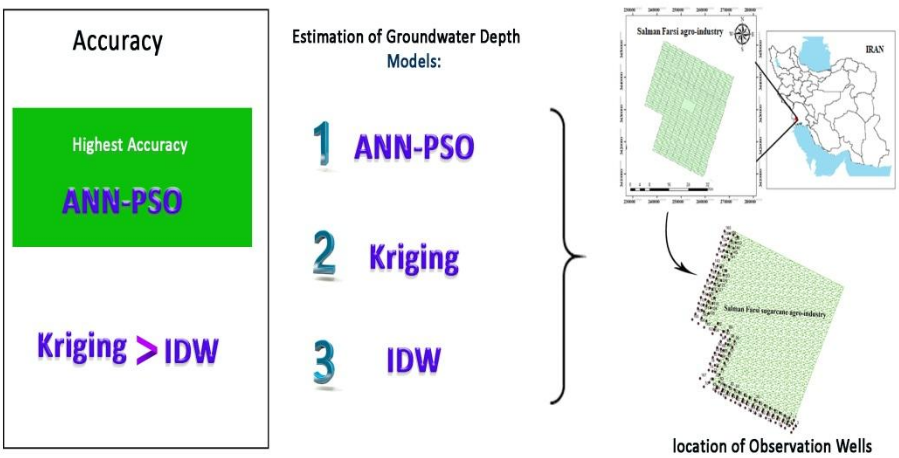
Atefeh Sayadi Shahraki, Saeed Boroomand Nasab, Abd Ali Naseri *, Amir Soltani Mohammadi

Department of Irrigation and Drainage, Shahid Chamran University of Ahvaz, Ahvaz, Iran

Highlights

- This research aims to simulate groundwater depth using IDW, kriging and neural network model integrated with particle swarm optimization algorithm in Salman Farsi Sugarcane Agro-Industry.
- Among the models used, the highest accuracy of groundwater depth estimation was related to the ANN-PSO model.
- Among the Kriging and IDW models used, the accuracy of the Kriging model was more than the IDW model.
- The purpose of this study, evaluate the accuracy of models for use when it is not possible to measure data or need to estimate data in the future.

Graphical Abstract



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Abstract

Appropriate management of groundwater resources requires accurate information about the characteristics of the groundwater table, spatial distribution of its characteristics, and the constant depth of the water table and its fluctuations. One of the most important issues in the quantitative management of groundwater resources is the estimation of water table using the data collected from the observation well network. In this study, to simulate the depth of groundwater Salman Farsi Sugarcane Plantation, three methods of Artificial neural network-integrated with particle swarm optimization algorithm, geostatistics (Kriging) and IDW was used. Inputs data include evapotranspiration, air temperature, precipitation and geographic location. The results showed that the highest simulation accuracy of groundwater depth in Salman Farsi Sugarcane Plantation was related to the ANN-PSO model with the highest R^2 (0.95) index and lowest RMSE and MAE (to 1.05 and 1.11) values. Also, among the Kriging and IDW models used, the accuracy of the Kriging model was more than the IDW model. Due to the acceptable accuracy of the results of the three models, the water resource planner and -maker in this field can apply this optimum interpolated groundwater depth to monitor the spatiotemporal fluctuation of groundwater depth in this area by updating its data.

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*Corresponding author: abaalinaseri@yahoo.com (A.A. Naseri)

1. Introduction

Groundwater resources are a significant source for agricultural, drinking, and industrial needs, especially in arid and semiarid regions (Nayak et al. 2006; Ahmadi and Sedghamiz, 2007). Surface resources are usually unstable and unsteady flows that are peaked after precipitation and gradually become inaccessible and costly to maintain. Appropriate management of groundwater resources requires accurate information about the characteristics of the groundwater table, the spatial distribution of its characteristics, and the constant depth of the water table and its fluctuations. Understanding the depth of the groundwater in each region is crucial and inevitable in sustainable irrigation and agricultural projects and planning (Gundogdu and Guney, 2007). Investigating the depth of groundwater as a spatio-temporal variable is very important in water resources planning. This requires a continuous and accurate estimate of groundwater depth. To date, many models have been used to predict groundwater depth, including intelligence and geostatistical models. Over the past years, extensive studies have been conducted to apply geostatistical and artificial intelligence models to groundwater modeling. Geostat was first founded by George Matron in the 1960s.

Building on local change and considering each point's dependence on neighboring points are features that have made extensive use of it (Lu et al., 2004). These features distinguish it from classical statistics and allow for more realistic modeling of environmental phenomena and parameters. In the other study, three methods of mediation of distance spacing weighting, radial basis functions, and kriging to predict temporal and spatial variations of groundwater depth was compared in the Minkin Desert in northern China (Yue et al., 2009). Comparison of the observed values with the interpolated values showed that the conventional kriging method is the optimal method for groundwater depth detection. Xiao et al., 2016 used data from 30 observation wells based on geostatistical theory to estimate groundwater level reduction in Beijing. The results showed that the simple kriging method is more suitable than other methods. In the other research the kriging method, radial functions, and IDW for interpolation of groundwater depth in the Minqinoasis region of China was evaluated, and the results shown concluded that the simple kriging method was more appropriate for this area (Sun et al., 2009). The capability of conventional kriging and neural-fuzzy inference networks was investigated for interpolating groundwater levels in a free aquifer in northern Iran (Kholghi and Hosseini, 2009; Kyoung-Jae et al., 2003).

The results showed that the neural-fuzzy inference model is more efficient in estimating groundwater level than conventional kriging. Jeihouni et al., 2015 used conventional kriging as a linear geostatistical estimator and two intelligent methods including artificial neural networks and adaptive fuzzy inference system for spatial analysis of groundwater electrical conductivity. The results showed that the adaptive fuzzy model has the highest accuracy among the models. Regarding the application of geostatistical methods can be mentioned the different researches (Varouchakis et al., 2019; Klein et al., 2017). The use of intelligence models for simulating groundwater depth is also rapidly increasing, due to the ease of application and high accuracy of these models in approximating nonlinear and complex mathematical equations. Artificial neural network is one of the intelligence models that come from the human brain. The results of using artificial neural networks as an intelligence model in studies show that this model has high ability to discover the relationship between data and pattern recognition (Asadollahfardi et al., 2012; Musavi-Jahromi and Golabi, 2008; Sreekanth et al., 2009). Study in Hyderabad, India showed that artificial neural network has a good capability for estimating groundwater level with ground mean square error of 4.5 m and explanation coefficient of 0.93.

From the forward and backward neural network methods with five different algorithms was used to predict groundwater level in an elevated tropical lagoon in India (Karthikeyan et al., 2013). They concluded that the forward neural network performed better with the Fletcher Reverse Conjunction Algorithm (GAFRC) than other simulation methods and algorithms. Also, the groundwater level using multiple linear regression and artificial neural network techniques was predicted at 17 sites in Japan (Sahoo and Jha, 2013). These results showed that in predicting the temporal-spatial distribution of groundwater level, ANN outperformed linear regression and presented better results. For the predict groundwater level in Lilakh plain used from artificial neural network and fuzzy-neural network (Rashidi et al., 2015). Results showed that the ANN model with three input parameters of average groundwater level, precipitation, temperature and monthly evaporation has the best results in the region.

Artificial neural network model due to back propagation training method sometimes reduce the accuracy of simulation and its main drawback is early convergence to local optimal. To solve this problem, the PSO algorithm is used to train the artificial neural network model. The application of neural network model optimization with evolutionary algorithms in groundwater discussion can be found in other studies (Shiri and Kisi, 2011; Traore and Guven, 2012; Moashrei et al., 2012; Balavalikar et al., 2018; Tapoglou et al., 2012). The present study aims to simulate groundwater depth using IDW, kriging and neural network model integrated with particle swarm optimization algorithm in Salman Farsi (West of Iran).

2. Materials and Methods

2.1. Case study

Salman Farsi Sugarcane Agro-Industry is located in 40 kilometers south of Ahvaz city, Khuzestan province, in Iran. Its agricultural area is 12,000 hectares, with 10,000 hectares annually harvested, and 2,000 hectares are grown and re-cultivated. Salman Farsi Agro-Industry from the north is limited to the Debal Khazaee sugarcane agro-industry and from the east to the Ahvaz-Abadan road and Karun River is west of it. The research area has a dry climatic with very hot summers and mild winters. The coldest month is in January and the warmest is July (The highest temperature is 47 °C and the lowest is 7.5 °C). The only source of irrigation in the farm is the large Karun River. The position of the Salman Farsi Sugarcane Agro-Industry is shown in Fig. 1.

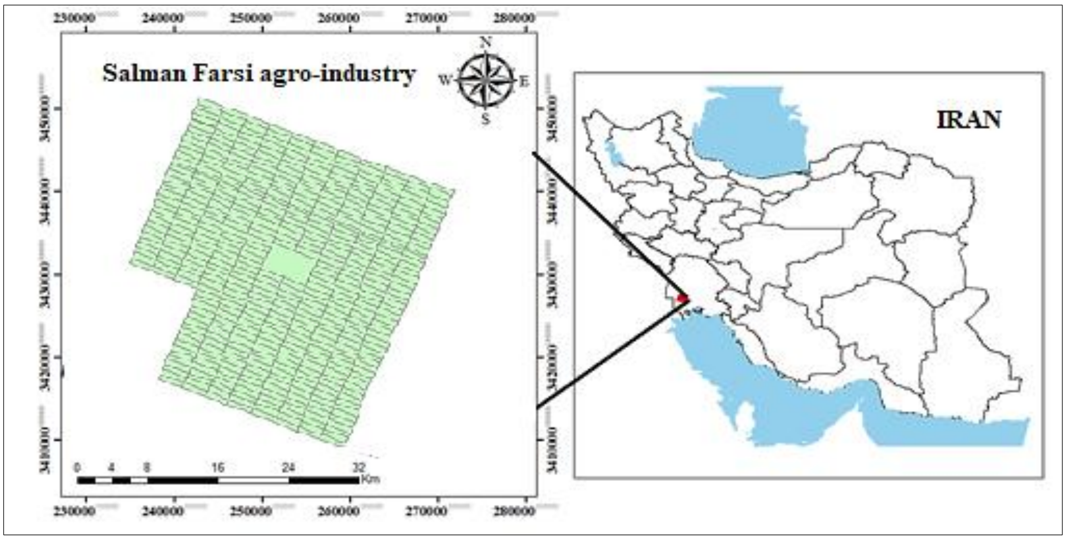

Fig. 1. Geolocation of the study area.

2.2. Required data

In this study, 160 observation wells were constructed in the study area and groundwater depth data were collected during two years from July, 2016 and twice each month. Evapotranspiration, air temperature and precipitation data were also collected during this time period and used as inputs for artificial neural network model and geographical location of wells for Kriging and IDW models. Fig. 2 shows the location of observation wells in the area.

2.3. Geostatistics

Geostatistics is a branch of statistics in which the unknown value of a quantity in points with known coordinates can be obtained by using the values of the same quantity in other points with known coordinates. This science consists of a series of studies examining the variations of a phenomenon in time and space, and is capable of modeling that phenomenon in a definite or uncertain temporal and spatial manner. Geostatistics, by providing a suitable model for describing these variables, while taking into account their structural and stochastic variability components, is able to determine the average value of these quantities in a range, estimate their value at a particular location, and map the distribution of variables. In this study, geostatistical ground-based mediation method called kriging was used to predict groundwater depth (Rajaee et al., 2019).

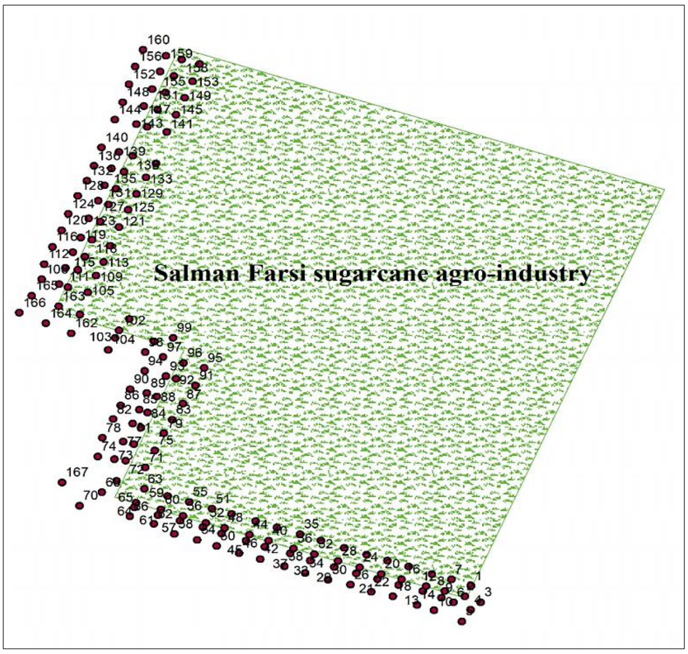

Fig. 2. Location of observation wells.

2.4. Kriging Method

Kriging is one of the most important and common methods of geostatistical estimation. This method relies on the weighted moving average logic and the best unbiased linear estimator, which in addition to estimating values, also determines the estimation error rate at each point (Goovaerts, 1997). The equation used for estimating the kriging method is in accordance with eq. (1).

2.5. Reverse Distance Weighting (IDW)

In this method, like kriging, the value of a variable at a point not sampled from its adjacent points is estimated using the relation. In this method, weights are determined with respect to the distance of each known point to the unknown point, and regardless of the position and how the points are scattered around the point of estimation. As a result, the nearer the points will be given more weight and the farther points will be given less weight. In fact, the shorter the distance, the greater the impact. This method assigns a weight to each of the measured samples for estimating the unknown point (equs. 2 and 3):

$$Z^* = \sum_{i=1}^{n} \lambda_i \,.\, Z(x_i) \tag{1}$$

$$Z^* = \sum_{i=1}^{n} \lambda_i \,.\, Z(x_i) \tag{2}$$

$$\lambda_i = \frac{1}{h_i^n} \tag{3}$$

Where Z^* is the estimated spatial variable value, $Z(x_i)$ is the spatial variable observed at the point, λ_i is the statistical weight assigned to the sample x_i and indicates the significance of the i-point estimate, h_i the distance between the points $x_i$and the point at which the variable is estimated and n is the distance power (Childs, 2004).

2.6. Artificial Neural Network Model (ANN)

The key element of this pattern is the new structure of the data processing system consisting of a large number of the data processing systems consisting of many elements (neurons) with strong internal communications that work harmoniously together to solve specific problems. Processing the experimental data, artificial neural networks transfer the knowledge or the law behind the data to the network structure; a training process. Using computer programming knowledge, data structures can be designed which act as a neuron. Then it can be trained by creating a network of interconnected artificial neurons, creating a training algorithm for network and applying the algorithm to the network. In general, a neural network is made up of three layers: The input layer only receives data and acts the same as independent variable. Thus the number of input layer neurons is determined based on the nature of the problem and depends on the number of independent variables. The output layer acts similar to a dependent variable and the number of its neurons depends on the number of dependent variables. But the hidden layer, unlike the input and output layers, represents nothing and is only an intermediate result in the process of calculating the output value. Fig. 3 shows the overview of an artificial neural network.

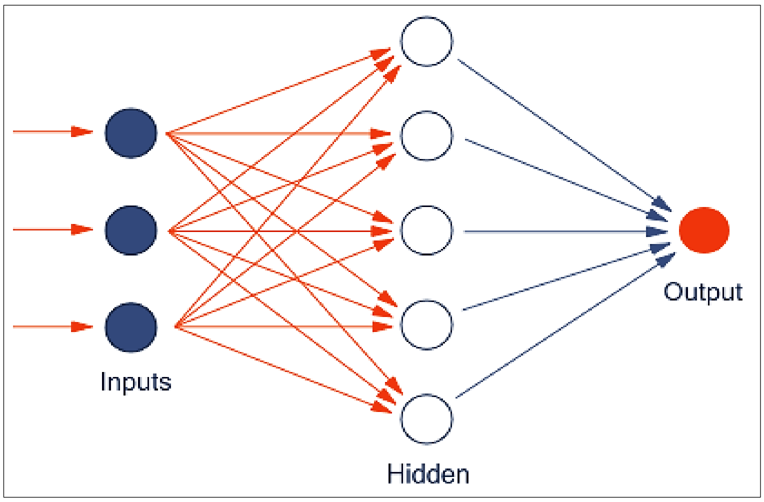

Fig. 3. Overview of an artificial neural network.

The design and implementation stages of neural network model include:

1. Measuring and standardization of neural network model input data.
2. The model designation, specifying the architecture, the number of layers (In this study, three-layer model is used) and determining the appropriate activation function for the intended neural network model (tangent sigmoid and logarithmic sigmoid is used as the activation function).
3. Training the network using a part of data (to determine the amount of weights and biases).
4. Testing and evaluating the network using the remaining data.
5. Displaying the output and simulation results of the model.

In this study, 80 percent and 20 percent of data were considered respectively for training and model validation. Training is a problem while using artificial neural network which is trained by backward error propagation method. In this study, using Particle Swarm Optimization Algorithm (PSO) method, this problem was attempted to be resolved.

2.7. Particle Swarm Optimization Algorithm (PSO)

The principle of this algorithm is based on the fact that swarm members in a search space are adopted towards the past successful regions and also are affected from the success of the neighboring members. This idea is explicitly stated as follows:

Each swarm member is called a "particle" which shows a potential solution, and in search space, changes the location and updates its velocity based on the flight experiences of itself and its neighboring particles, which help it to gain a better position. Particle i is shown as $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. The situation with the best fitting function will be recorded as the best current position. This position is considered as $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ and the corresponding fitting function is called and recorded as $Pbest_i$. The best general position in the swarm is related to the best fitting function, and called $Gbest_i$ and recorded as $P_g = (p_{g1}, p_{g2}, \dots, p_{gD})$. Velocity or the rate of position change of particle i, is shown as $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. During the replication process, velocity and position of the particle i will be updated in accordance with the following equation:

$$V_{id}(t+1) = K\left(V_{id}(t) + rand(0,\varphi_1).\left(P_{id}(t) - X_{id}(t)\right) + rand(0,\varphi_2).\left(P_{gd}(t) - X_{id}(t)\right)\right) \quad (4)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \qquad d = 1, 2, \dots, D \quad (5)$$

$$K = \frac{2}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}} \quad (6)$$

In where $\varphi = \varphi_1 + \varphi_2$:

K is the contraction factor and a function of φ_1 and φ_2 and constant acceleration values of φ_1 and φ_2 shows the weighting of particles random acceleration for tendency towards the personal and global best position. $\text{rand}(0,\varphi_1)$ and $\text{rand}(0,\varphi_2)$ functions, respectively produce random numbers in the range of $[0,\varphi_1]$ and $[0,\varphi_2]$. According to equation (5), particles current flight velocity includes three parts: The first part indicates the previous velocity of the particle, and the second and the third parts show single particle and swarm model. In single particle model, each member is separated and used personal thoughts and experiences independently; while in the swarm model, members move towards success based on the effective experiences of their neighbors (Eberhart and Shi, 2000). Although the PSO algorithm is able to quickly find the area of feasible solution, but the convergence rate will be severely reduced getting to this area. To solve this problem, equation (4) is amended as follows:

$$V_{id}(t+1) = \omega\left(V_{id}(t) + c_1 rand(0,\varphi_1).\left(P_{id}(t) - X_{id}(t)\right) + c_2 rand(0,\varphi_2).\left(P_{gd}(t) - X_{id}(t)\right)\right) \quad (7)$$

In the above equation, ω, c_1 and c_2 respectively represent inertia weight, a positive parameter called cognitive parameter, and a positive parameter called social parameter. Using inertia weight parameter leads to a compromise between global and local discovery capabilities of the category. A great inertia weight is a stimulus to enlarge the amount of velocity vector of particles throughout the solution spaces (moving towards solution spaces of the search space not experienced previously); while a smaller inertia weight narrows the solution spaces in the current small area. In fact, lower weight makes the search continue with higher accuracy in areas experienced in the past. A proper selection of ω ensures the establishment of the optimum balance between local and global solution spaces and consequently increases the efficiency of the algorithm. Thereby the amount of ω is determined equal to one at the beginning of the search, and gradually goes to zero.

2.8. Model evaluation criteria

To determine the accuracy of the models the values of Root Mean Square Error ($RMSE$), Mean Absolute Error (MAE) and Determination Coefficient (R^2) was used:

$$RMSE = \sqrt{\frac{1}{n}\sum(y_{observed} - y_{predicted})^2} \quad (8)$$

$$MAE = 100 * \frac{1}{n} \sum |y_{observed} - y_{predicted}| \quad (9)$$

$$R^2 = 1 - \frac{\sum (y_{predicted} - y_{observed})}{\sum y_{predicted}^2 - \frac{y_{observed}}{n}} \quad (10)$$

In the above equation, $y_{predicted}$, $y_{observed}$ and n are respectively the representatives of predicted values, observed values and the number of data. The more the values of $RMSE$ and MAE go to zero and the value of R^2 goes to one, the more accurate the model will be.

3. Results and Discussion

In this study, 160 observation wells were constructed in the study area and groundwater depth information was extracted twice a month from July 2016 to simulate the depth of groundwater in Salman Farsi Sugarcane Plantation**.** Evapotranspiration, air temperature and precipitation data were also collected during this time period and used as inputs for artificial neural network model and geographic location of wells for Kriging and IDW models. Table 1 shows the statistical characteristics of groundwater depth in the study area. According to Table 1, the skew coefficient is between -1 and +1, indicating that the depth of groundwater has normal distribution during the measurement period.

Table 1. Statistical specifications of groundwater depth in Salman Farsi Sugarcane Plantation**.**

Parameter	Unit	Maximum	Minimum	Average	Standard deviation	Skewness	Elongation
Depth of groundwater	cm	255	39.07	134.38	37.52	0.58	1.39

In this study, a ground-based statistical mediation method called kriging, inverse distance weighting (IDW) and artificial neural network modeling was used to simulate groundwater depth. Evapotranspiration data, air temperature and precipitation were used as inputs for the artificial neural network model and geographic location of wells were used as inputs for Kriging and IDW models. For the ANN model, 80% of the data (ie, data from 120 observation wells) for model training and 20% of data (data from 40 observation wells) for model testing Used. It is worth noting that the distribution of wells for training and testing has been trial and error. The results of the calculated statistics between the simulated and measured values are presented in Table 2.

Table 2. Results of statistics computed between simulated and measured values.

Statistical model / index	**RMSE**	**MAE**	**R^2**
ANN-PSO	1.05	1.11	0.95
Kiriging	1.72	2.01	0.83
IDW	3.54	4.02	0.77

Also the simulation accuracy of the kriging model is higher than the IDW model, which is consistent with the results of many studies (Yue et al., 2009; Ahmadi and Baghbanzadeh Dezfouli, 2012; Desbarats et al., 2002). Given that in IDW method all points are used to calculate the unknown value and in geostatistical methods by adjusting the variogram for all data it try to calculate the amount of variance over distance, one can expect that these methods, with all their advantages, have a major drawback. This weakness is the use of a general rule to calculate the unknown points.

Also, Figs. 4 and 5, show the diagram fit between the observed and simulated values in the GIS software environment for the two kriging and IDW models and the optimized artificial neural network model in the Excel software environment. Fig. 6 shows the comparison between the observed and simulated values for the two kriging and IDW models and the ANN model.

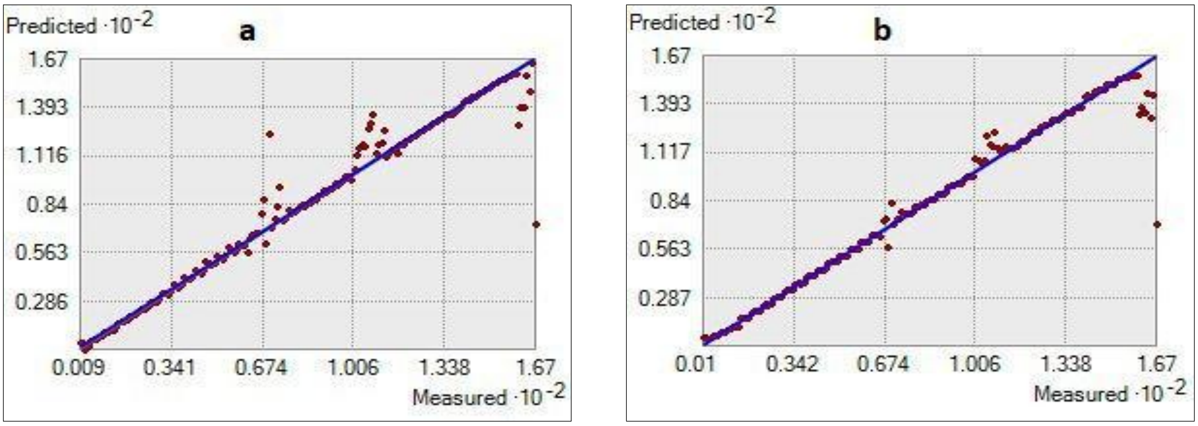

Fig. 4. Diagram fit between observed and simulated values using two models: a) kriging, b) IDW.

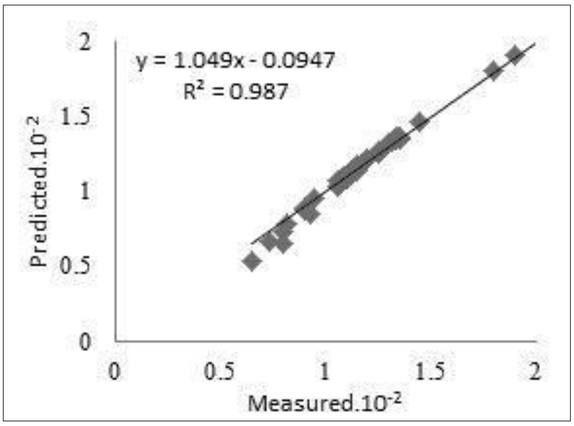

Fig. 5. Diagram fit between observed and simulated values using ANN-PSO model.

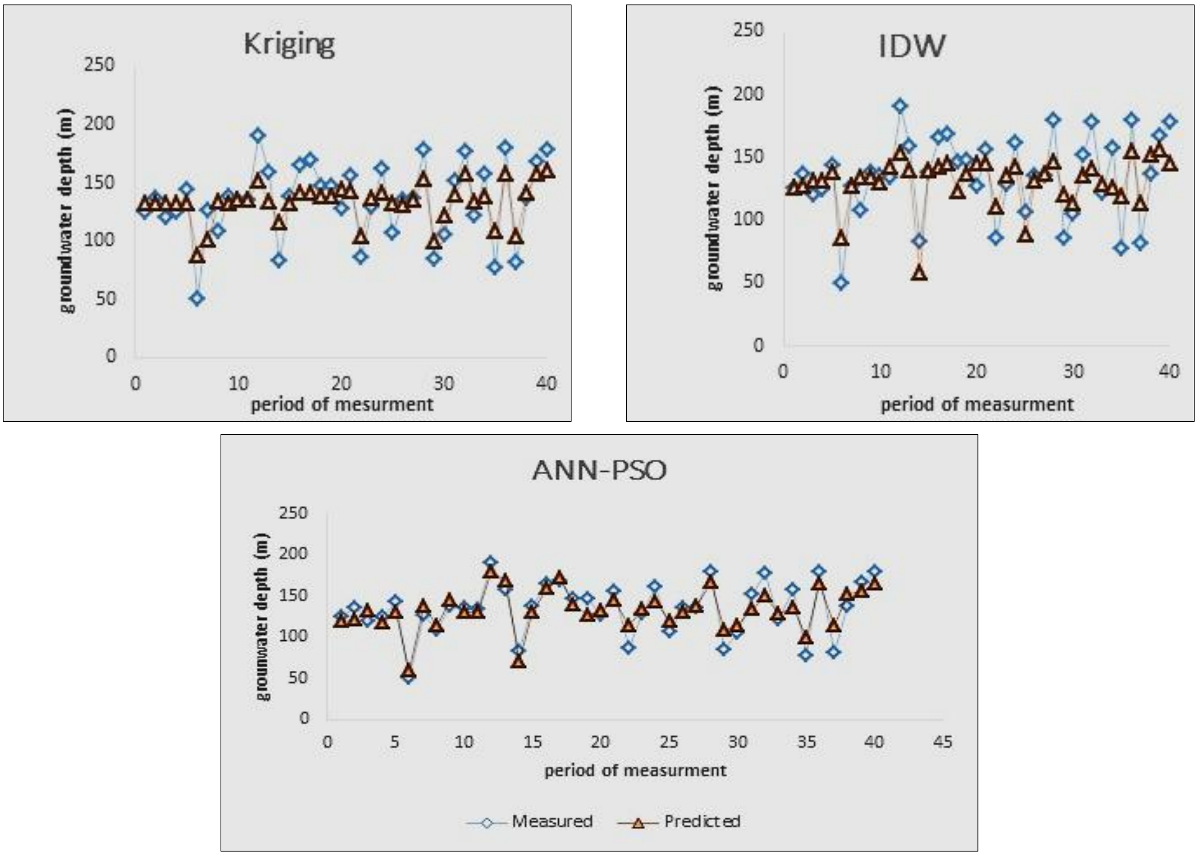

Fig. 6. Comparison between observed and simulated values.

Fig. 7 shows the groundwater zoning maps using both Kriging and IDW methods in the GIS software environment. According to the plotted maps, the highest depth of groundwater is in the northwest and north sections of Salman Farsi Sugarcane Plantation. Groundwater decreases gradually from north to south.

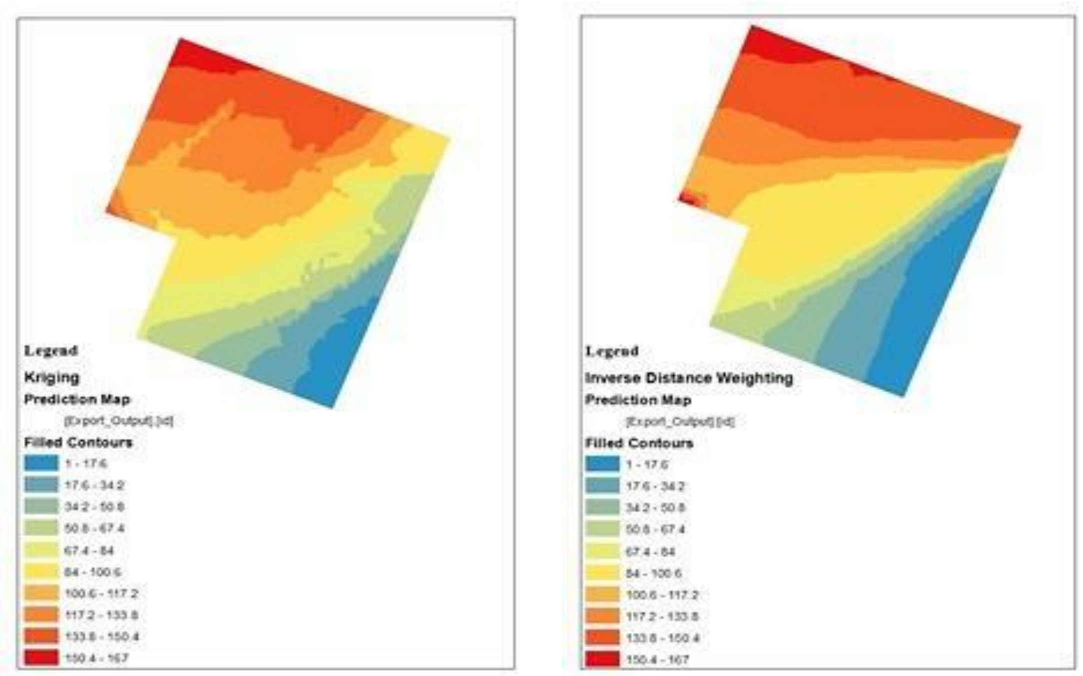

Fig. 7. Groundwater zoning map using both kriging and IDW methods.

Conclusion

Groundwater level data are particularly important in modeling the groundwater system, water resources management and drought. Since most of the groundwater flow models require water level data to simulate the behavior of the groundwater system, the number of wells observed in most study areas is limited and costly to construct. Therefore, there is a pressing need for different methods of simulation. In this study, the methods of artificial intelligence (ANN-PSO) and geostatistics (kriging) and IDW were used with evapotranspiration, air temperature, precipitation and geographic inputs for simulating the depth of Salman Farsi Sugarcane Plantation. The results showed that the highest accuracy of groundwater depth simulation was related to combined neural network model with particle aggregation optimization algorithm, with the highest R^2 index and the lowest value of RMSE and MAE. Also, in the case of the Kriging and IDW models, the simulation accuracy of the Kriging model was higher than the IDW model.

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