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Evaluation of Interpolation Techniques for Estimating Groundwater Level and Groundwater Salinity in the Salman Farsi Sugarcane Plantation

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Abstract

Due to the essential role of groundwater resources as useable and depleting water resources, the study and management of groundwater exploitation are of great importance. Proper management of groundwater resources needs knowledge of the spatial variability of groundwater level and groundwater salinity over the study area. To obtain such information, appropriate interpolation and mapping of groundwater level and groundwater salinity based on a limited number of observations is needed. The purpose of the present study is to evaluate Ordinary Kriging and IDW interpolation techniques for estimating groundwater level and groundwater salinity in Salman Farsi Sugarcane Plantation (West of Iran). The results showed that the prediction accuracy of the Ordinary Kriging model for groundwater level and groundwater salinity parameters was higher than the IDW model. To this aim, the Root Mean Square Error (RMSE) value was calculated to simulate the groundwater level in Ordinary Kriging and IDW method by 1.02 and 2.14, respectively, and to simulate the salinity of groundwater by 1.45 and 2.79. Due to the acceptable accuracy of the results of the Kriging model, planners can, by updating the data of this model, use it to predict the quantity and quality of groundwater parameters.

Introduction

Groundwater is the primary source, especially in arid and semiarid regions (Ahmadi & Sedghamiz 2007; Ta'any et al. 2009). Appropriate management of groundwater resources requires accurate information about the groundwater characteristics, the spatial distribution, and the constant groundwater and its fluctuations (Kumar & Remadevi, 2006). Understanding groundwater level and groundwater salinity in each region are crucial and inevitable in sustainable irrigation and agricultural projects and planning (Sulhi Gundogdu & Guney, 2007). Investigating groundwater level and groundwater salinity as a Spatio-temporal variable is very important in water resources planning. It requires a continuous and accurate estimate of groundwater level and groundwater salinity. Geostatistics focuses on spatial and temporal varying phenomena. It can be considered a collection of numerical techniques dealing with the description of spatial properties, employing chiefly random models like how time series analysis characterizes temporal data. It offers a way of describing the spatial continuity of natural phenomena and provides adaptations of classical regression techniques to take advantage of this continuity (Bohling, 2005). Over the past years, extensive studies have been conducted to apply Geostatistical to groundwater modeling. Yu et al. (2009) compared three mediation methods of distance spacing weighting, radial basis functions, and Kriging to predict temporal and spatial variations of groundwater depth in the Minkin Desert in northern China. Comparing the observed values with the interpolated values showed that the conventional Kriging method is optimal 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. Sun et al. (2009) evaluated the Kriging method, radial functions, and IDW for interpolation of groundwater depth in the Minqinoasis region of China. They concluded that the simple Kriging method was more appropriate for this area. Kholghi and Hosseini (2009) investigated the capability of conventional Kriging and Neural-Fuzzy inference networks for interpolating groundwater levels in a free aquifer in northern Iran. The results showed that the Neural-Fuzzy inference model is more efficient in estimating groundwater level than conventional Kriging. Moslemzadeh et al. (2011) investigated the efficiency of the Kriging and Cokriging models for estimating groundwater levels. Their results showed that the Cokriging method's accuracy is higher than Kriging in calculating groundwater level.

Also, the arithmetic averaging method (which has lower accuracy) led to the higher level estimation of groundwater. Jeihouni et al. (2015) used traditional Kriging as a linear Geostatistical estimator and two intelligent methods, including Artificial Neural Networks and the Fuzzy adaptive inference system for spatial analysis of groundwater electrical conductivity. The results showed that the adaptive Fuzzy model has the highest accuracy among the models. Ansarifar et al. (2019) used a combination of borehole data interpretation and inverse solution method to estimate the spatial distribution of hydraulic conductivity (K) and specific yield (Sy) for the Bandar-e Gaz unconfined aquifer located in Northern Iran, considering no access to pumping test data. Their results showed that estimated K and Sy are in the ranges of 5–15 and 0.024–0.036 m/day. Their spatial distribution pattern shows a decreasing trend in the south-to-north direction, which is well suited to the spatial design of aquifer sediment's type and size. Varouchakis et al. (2019) used Spatiotemporal Geostatistical modeling of groundwater levels under a Bayesian framework using physical background. The results showed that the model used has better results than Space-time Ordinary kriging. Regarding the application of Geostatistical methods can be mentioned the researches of Varouchakis et al. (2019), Klein et al. (2016), Rajai et al. (2018).

The essential parameters of irrigation and drainage that affect sugarcane yield are groundwater level and groundwater salinity. By examining these parameters and determining the effect of each, it is possible to provide solutions that achieve the maximum yield in sugarcane fields by using the existing facilities and conditions (Mansouri, 2004).

The present study aims to evaluate interpolation techniques for estimating groundwater level and groundwater salinity in Salman Farsi Sugarcane Plantation (West of Iran).

Materials and Methods

Case Study

Salman Farsi Sugarcane Agro-Industry is located 40 km south of Ahvaz city, Khouzestan province, Iran. Its agricultural area is about 12,000 hectares, 10,000 hectares annually harvested, and the remaining 2,000 hectares are grown and re-cultivated. Salman Farsi Agro-Industry is limited to the Debal Khazaee sugarcane agro-industry from the north, Ahvaz-Abadan road from the east, and Karoon River from the west. The research area has a dry climate with scorching summers and mild winters. The coldest and warmest months are January (with the lowest temperature of 7.5 ° C) and July (with the highest temperature of 47 ° C).

Moreover, the average precipitation of the study area is 266 mm, and the annual evaporation is reported as 2788 mm. The only irrigation source of the farms is the large Karoon River. The position of the Salman Farsi Sugarcane Agro-Industry is shown in Figure (1).

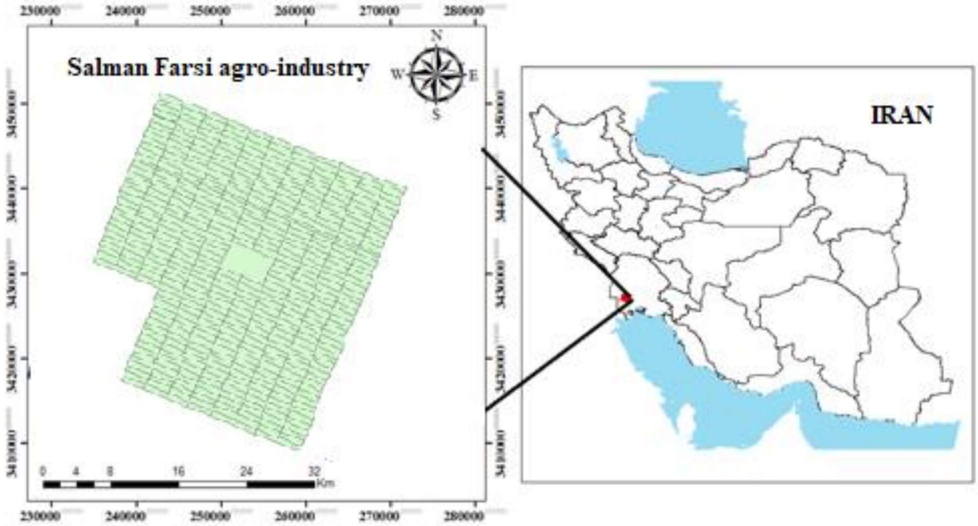

Fig. 1- Location of Salman Farsi Agro Industry unit in Southwest Iran

Required Data

In the present study, 166 observation wells were constructed in the study area, and groundwater level and groundwater salinity information were extracted twice a month from July 2018. Wells have been constructed in 100-m apart strips on both sides of the land border (inside and outside). The wells were 3 m deep with a radius of 4 in. Figure (2) shows the location of observation wells in the area.

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 can model that phenomenon in a definite or uncertain temporal and spatial manner. By providing a suitable model for describing these variables, while taking into account their structural and stochastic variability components, Geostatistics can determine the average value of these quantities in a range, estimate their value at a particular location, map the distribution of variables, and so on (Isaaks & Srivastava, 1989).

Kriging Method

Kriging is one of the most essential and standard methods of Geostatistical estimation. This method relies on the weighted moving average logic and the best unbiased linear estimator, which estimates values and determines the estimation error rate at each point (Goovaerts, 1997). This method does not necessarily require observation networks where data are typically distributed. Estimating the structure of the regionalized variables considers only the neighboring points of estimation data (De Marsily, 1986). The procedure facilitates the estimation at unsampled locations. Kriging estimates are calculated as weighted sums of the adjacent sampled concentrations. That is, if data appears to be highly continuous in the spatial domain, the values closer to those estimated receive higher weights than those farther away (Ersoy et al., 2004). One of the main advantages of Kriging is that it presents the interpolation error of the values of the regionalized variable where there are no initial measurements. This feature offers a measure of the estimation accuracy and reliability of the spatial distribution of the variable (Theodossiou and Latinopoulos, 2006). The equation used for estimating the Kriging method is the following Eq. (1).

$$Z^{*} = \sum_{i=1}^{n} \lambda_i \cdot Z(x_i) \qquad (1)$$

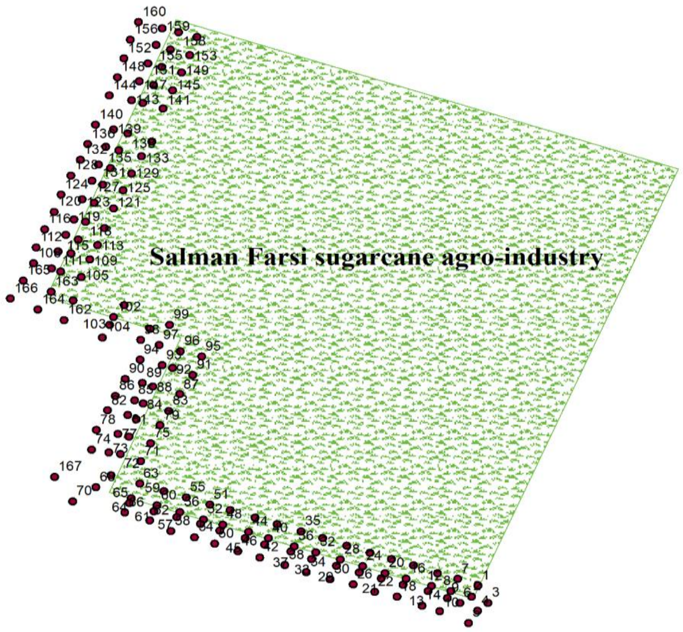

Fig. 2- location of observation wells

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 concerning the distance of each known point to the unknown one, regardless of the position and how the points are scattered around the estimation point. As a result, the nearer points will be given more weight, and the farther points will be given less weight. The shorter the distance, the greater the impact. This method assigns a weight to each of the measured samples for estimating the unknown point (Eqs. (2) and (3)):

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

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

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 & Colin, 2004).

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:

$$RMSE = \sqrt{\frac{1}{n}\sum\left(y_{observed} - y_{predicted}\right)^2} \tag{4}$$

$$MAE = 100 * \frac{1}{n}\sum\left|y_{observed} - y_{predicted}\right| \tag{5}$$

$$R^2 = 1- \frac{\sum(y_{predicted} - y_{observed})}{\sum y_{predicted}{}^2 - \frac{y_{observed}}{n}} \tag{6}$$

In the above equation, $y_{predicted}$, $y_{observed}$, and n represent predicted values, observed values, and the number of data, respectively. 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.

Results and Discussion

In the present study, 166 observation wells were constructed in the study area, and groundwater level and groundwater salinity information were extracted twice a month from July 2018. Table (1) shows the statistical characteristics of groundwater level and groundwater salinity in the study area. According to Table (1), the skew coefficient is between -1 and +1, indicating that the groundwater level and groundwater salinity are normally distributed during the measurement period.

To ensure the normality of the output data, a histogram and a Q-Q plot diagram were drawn. The results are shown in Figs. (3) to (6) for groundwater level and groundwater salinity. Given that in Figs. (3) and (4), the median and average values of the data are very close to each other and as shown in Figs. (5) and (6), all points are along a line, the assumption that the data is normal is confirmed.

Table 1 - Statistical Specifications of groundwater level and groundwater salinity in Salman Farsi Sugarcane Plantation

Parameter	Unit	Maximum	Minimum	Average	Standard deviation	Skewness	Elongation
groundwater level	cm	255	39.07	134.38	37.52	0.58	1.39
groundwater salinity	ds/m	85.54	3.61	25.7	20.38	0.95	-0.35

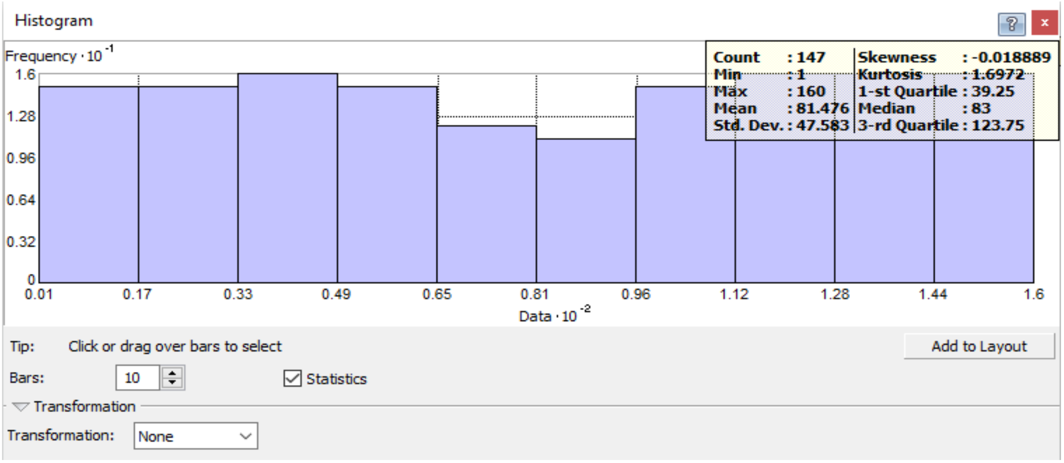

Fig. 3- histogram of groundwater level data

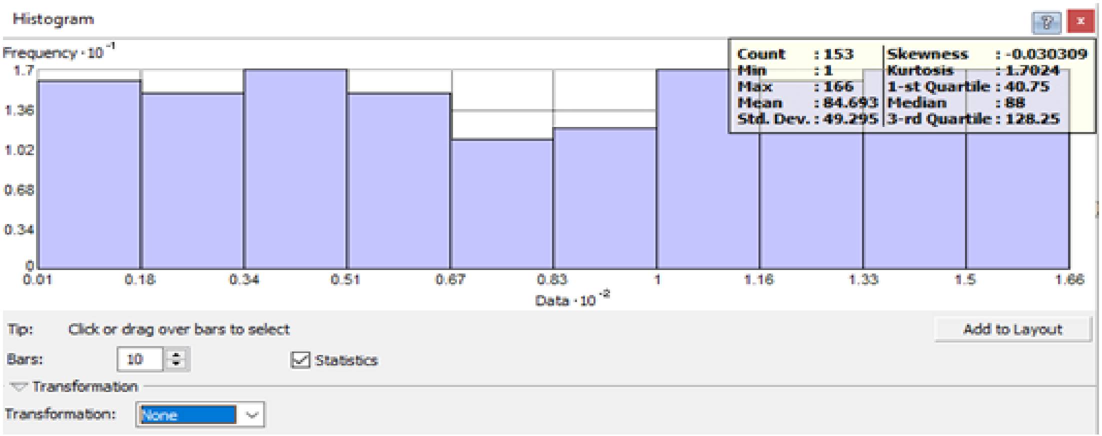

Fig. 4- histogram of groundwater salinity data

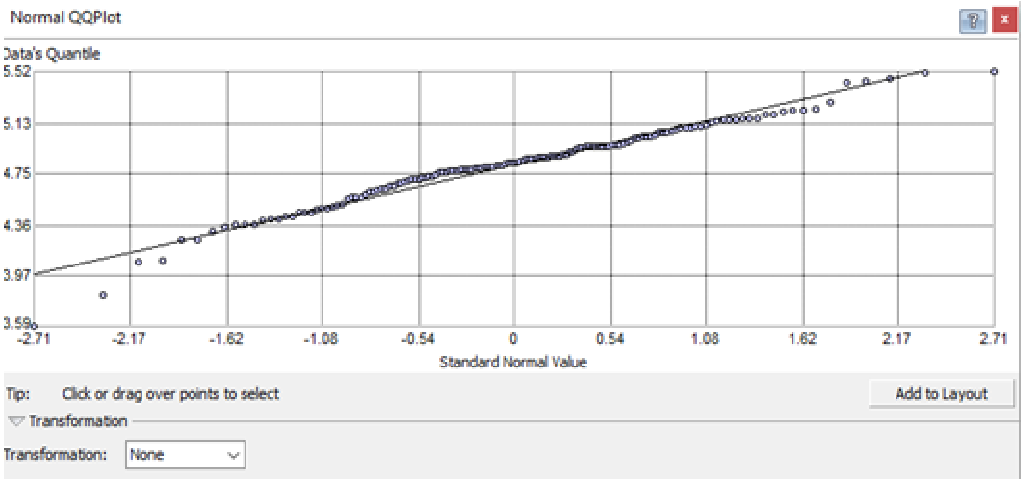

Fig. 5- Q-Q plot of groundwater level data

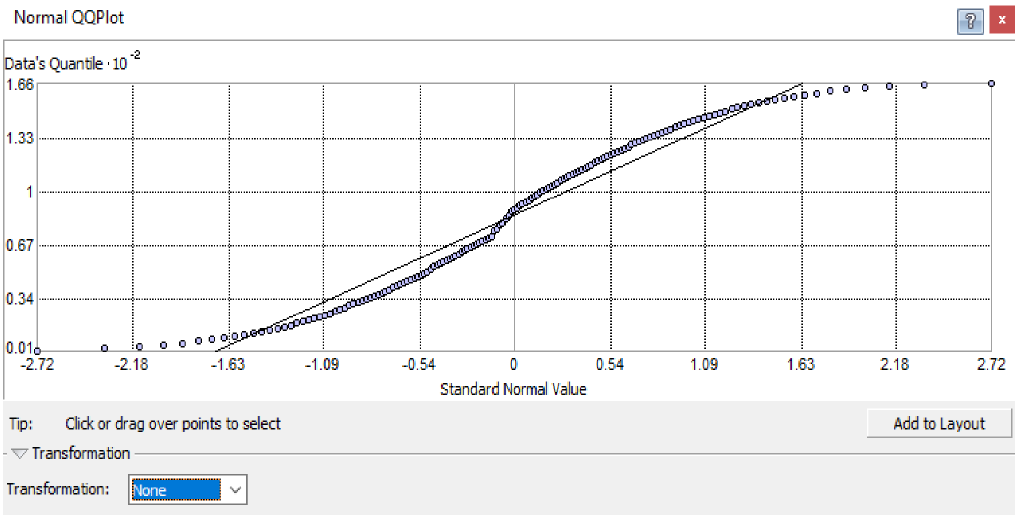

Fig. 6- Q-Q plot of groundwater salinity data

As mentioned in this study, the Ordinary Kriging and IDW method were used to estimate the groundwater level and groundwater salinity. The performance of the models (Ordinary Kriging and IDW) is calculated with ArcGIS 10.3 software. Ordinary Kriging is robust and straightforward and, therefore probably, the most widely used Kriging technique (Heuvelink & Pebesma, 2002). In the Ordinary Kriging method, the intermediate process As a general average plus independent variations followed the average. Therefore, large variations add up to the average, and as a result, the prediction values are never very skewed. Groundwater level and groundwater salinity prediction maps using Ordinary Kriging and IDW methods are shown in Figs. (7) and (8).

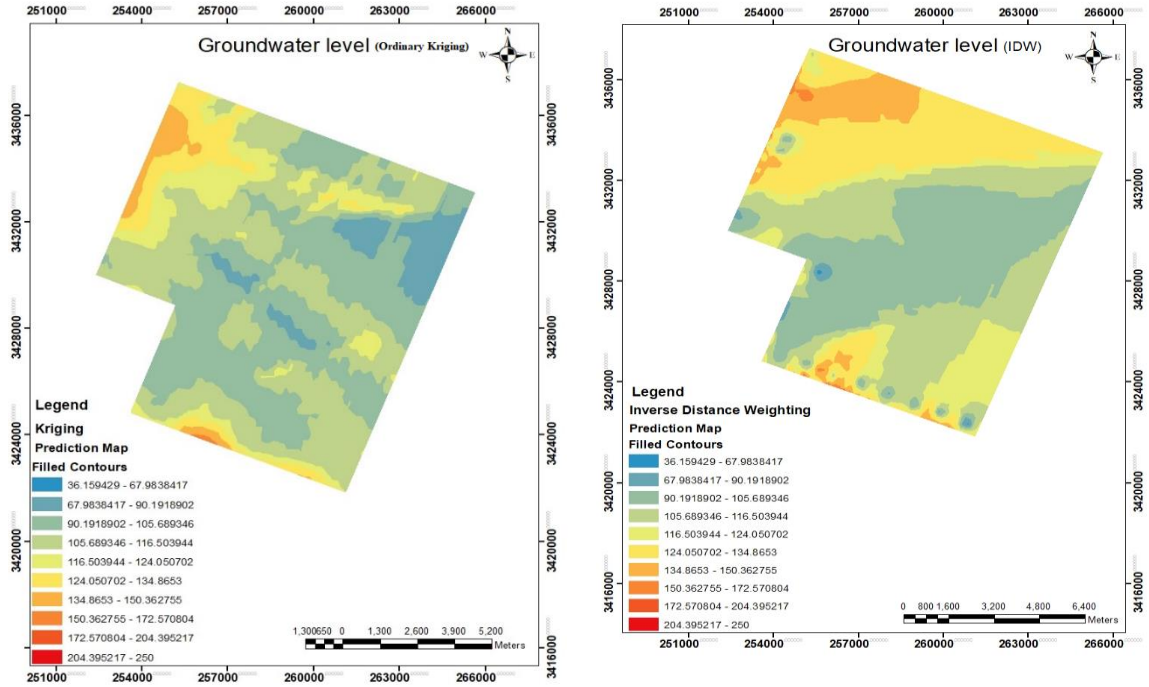

Fig. 7- Groundwater level prediction maps using Ordinary Kriging and IDW methods

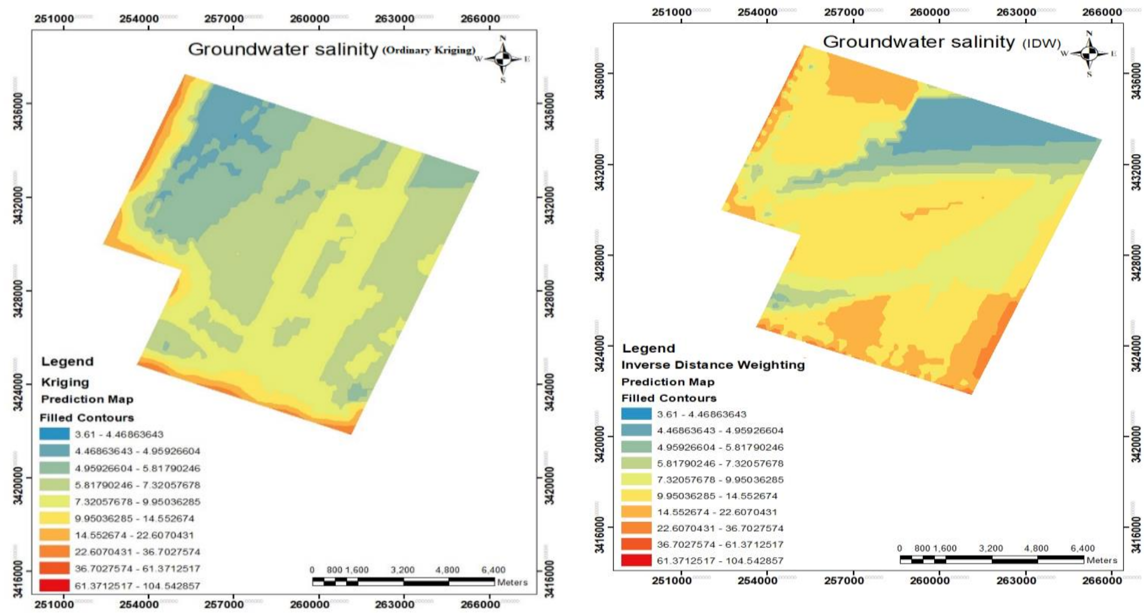

Fig. 8- Groundwater salinity prediction maps using Ordinary Kriging and IDW methods

The deviations in the observed and simulated values are calculated with cross-validation to test the validity of the variogram. Figures (9) and (10) show the regression line between the observed and estimated values of groundwater level and groundwater salinity. Also, the best-fitted line between the measured and estimated decrease in the groundwater level and the 1:1 line is showed in Figs. (9) and (10).

One of the main advantages of the Kriging method is the ability to draw a standard error map of the prediction, which can be used to check the accuracy of the prediction in different places. The maps of Standard Error of Prediction were created using the Ordinary Kriging method for both groundwater level and groundwater salinity parameters are shown in Fig. (11). Since the wells in the study area are located in the south, southwest, west, and northwest, the amount of prediction error in these areas is small. In other areas, due to the lack of available information, the prediction error values increase.

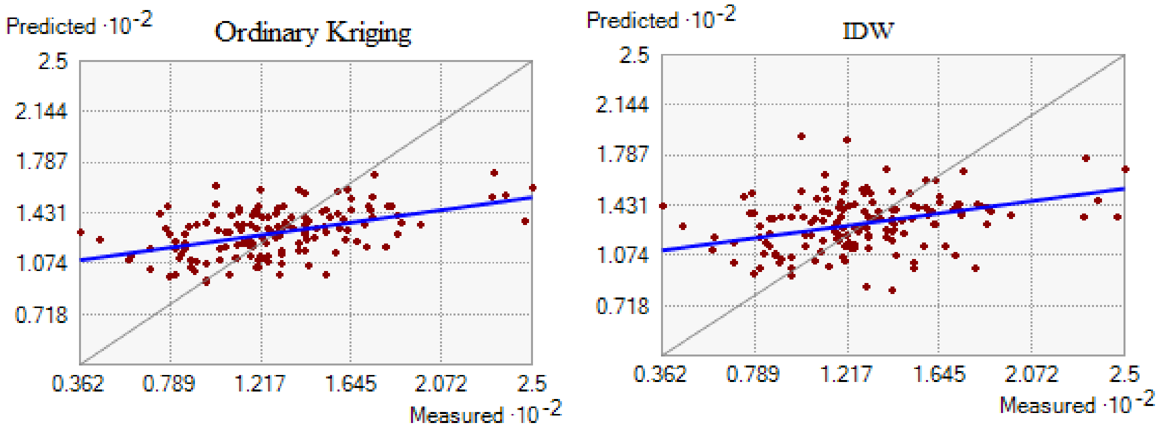

Fig. 9- Results of cross-validation for groundwater level parameter

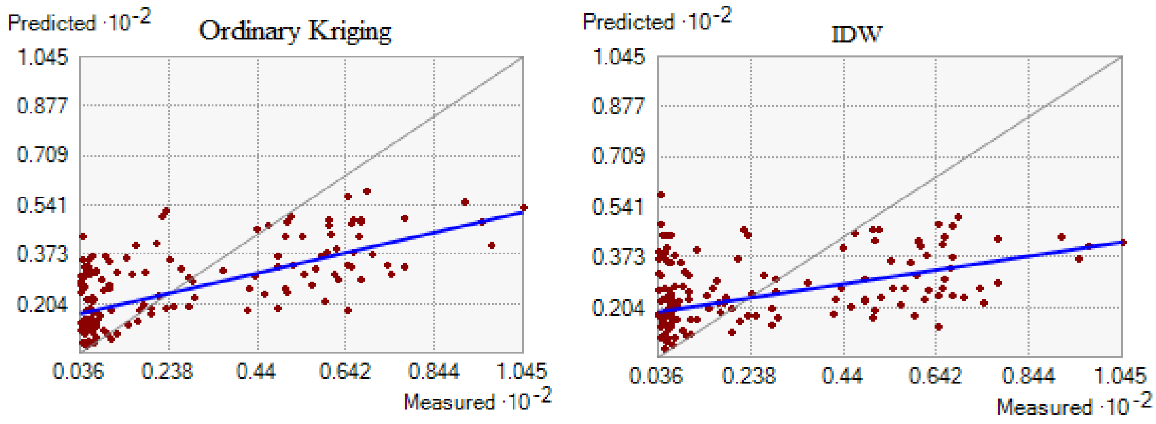

Fig. 10- Results of cross-validation for groundwater salinity parameter

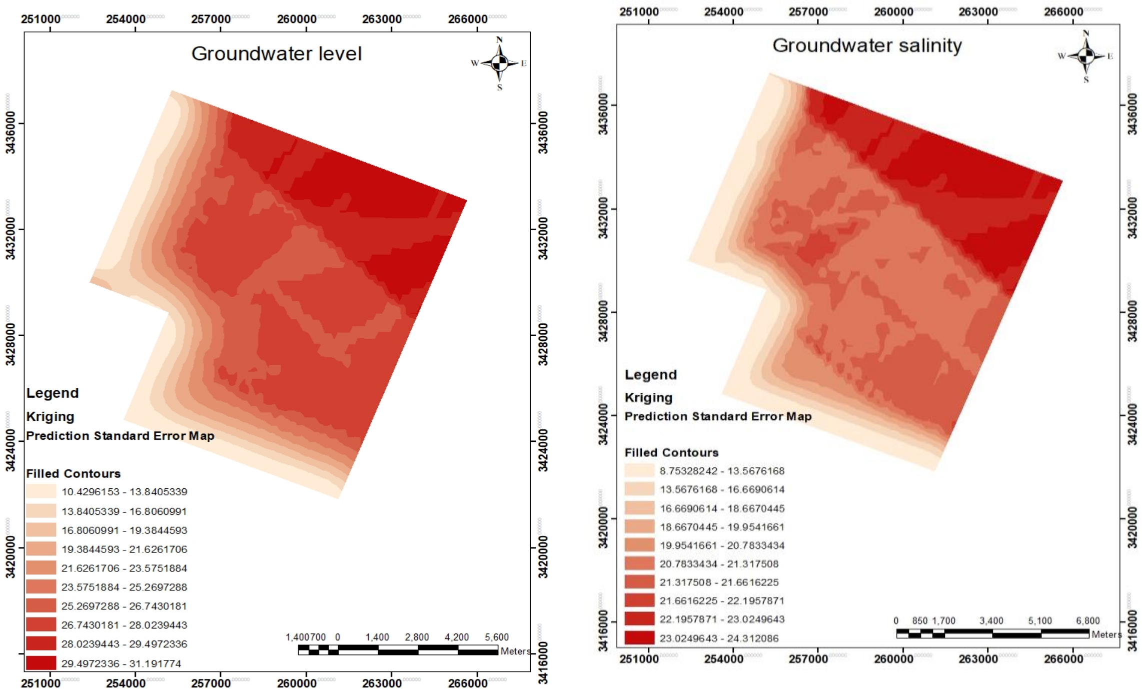

Fig. 11- The map of prediction standard error the differences of the groundwater level and groundwater salinity

To compare the accuracy of the models, groundwater level and groundwater salinity interpolation was performed using Deterministic (Inverse Distance Weighting (IDW), Global Polynomial Interpolation (GPI), Local Polynomial Interpolation (LPI), Radial Basis Function (RBF)), and Kriging Geostatistical (Ordinary, Simple, Universal, Disjunctive) interpolation methods in GIS software. The results showed that among Geostatistical methods, the Ordinary Kriging, and among Deterministic methods, the Inverse Distance Weighting had the highest accuracy in estimating groundwater level and groundwater salinity parameters. The results of the calculated statistics between the simulated and measured values are presented in Table (2).

The results showed that among Geostatistical methods, the Ordinary Kriging (Hamad, 2009; Rostami Fathabadi, 2017) and among Deterministic methods, the Inverse Distance Weighting (Lee et al. 2003; Einlo et al. 2017) had the highest accuracy in estimating groundwater level and groundwater salinity parameters. Also, in general, the results showed that the accuracy of Geostatistical methods is higher than Deterministic methods (Charkhkarzadeh et al. 2015; Hu et al. 2005; Yu et al. 2009; Ahmadi & Baghbanzadeh Dezfouli, 2012; Vijay & Remadevi, 2006; Desbarats et al. 2002). In the IDW method, all points are used to calculate the unknown value. In Geostatistical methods, adjusting the variogram for all data aims to figure the amount of variance over a distance; therefore, one can expect that these methods demonstrate a major drawback with all their advantages. This weakness is the use of a general rule to calculate the unknown points.

On the other hand, Ordinary Kriging is the most widely used Geostatistical method. This method is based on the logic of weighted moving average and the best linear unbiased estimator that determines the amount of estimation at any point (Goovaerts, 1997; Kumar et al., 2011). This property can help delineate the sampling network and determine the additional points to decrease the estimation error (Mehrjardi et al., 2010).

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

Parameters	Statistical model / index	RMSE	MAE	R^2
groundwater level	Kriging (Ordinary)	1.02	1.91	0.91
	Kriging (Simple)	1.25	1.28	0.9
	Kriging (Universal)	1.9	1.84	0.88
	Kriging (Disjunctive)	3.1	2.89	0.54
	IDW	2.14	2.52	0.79
	GPI	4.52	4.72	0.49
	LPI	2.99	3.7	0.75
	RBF	2.78	3.3	0.68
groundwater salinity	Kriging (Ordinary)	1.45	2.1	0.89
	Kriging (Simple)	1.89	2.45	0.81
	Kriging (Universal)	1.64	2.44	0.88
	Kriging (Disjunctive)	2.99	3.25	0.6
	IDW	2.79	2.9	0.75
	GPI	4.25	4.1	0.51
	LPI	3.11	3.15	0.7
	RBF	3.19	3.27	0.68

Conclusion

Groundwater is one of the valuable water resources that has always been of interest to researchers. Groundwater level data are fundamental in modeling the groundwater system, water resources management, and drought. Since most 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. The purpose of the present study is to evaluate Ordinary Kriging and IDW interpolation techniques for estimating groundwater level and groundwater salinity in Salman Farsi Sugarcane Plantation (West of Iran). The results showed that the Ordinary Kriging model's prediction accuracy for groundwater level and groundwater salinity parameters was higher than the IDW model. Also, in general, the results showed that the accuracy of Geostatistical methods is higher than Deterministic methods. Therefore, the Kriging method can be used to interpolate quantitative and qualitative parameters of groundwater.

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