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INTERPOLATION OF SOIL INFILTRATION IN FURROW IRRIGATION: COMPARISON OF KRIGING, INVERSE DISTANCE WEIGHTING, MULTILAYER PERCEPTRON AND PRINCIPAL COMPONENT ANALYSIS METHODS

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Abstract. Study on soil infiltration rate as part of water cycle is essential for managing water resources and designing irrigation systems. The present study was conducted with the aim to compare Kriging, inverse distance weighting (IDW), multilayer perceptron (MLP) and principal component analysis (PCA) methods in the interpolation of soil infiltration in furrow irrigation, and determine the best interpolation method. To conduct infiltration tests, furrows were made on the farm in four triad groups. Infiltration through the blocked furrows method was measured 10, 20, 30, 40, 50, 60, 90, 120, 150, 160, 180 and 210 min after irrigation at a 10-meter distance in each furrow. Data were analyzed by GS+ and Neuro Solutions (NS) software packages. In this study, the maximum error (ME), mean bias error (MBE), mean absolute error (MAE), root mean square error (RMSE), relative error (RE) and correlation coefficient (r) were used to compare the interpolation methods. The results of analysis of variance (ANOVA) indicated that differences in methods based on RMSE, MBE, MAE and ME indices were not significant; however, this difference was significant based on r and RE indices. According to the ANOVA results, it can be said that the PCA method with r of 0.69 and RE of 31%, was predicted with a higher accuracy as compared to other methods.

Keywords: artificial neural network, geostatistical analysis, irrigation, soil infiltration

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INTRODUCTION

With increasing population and reducing water resources, water consumption efficiency improvement in agricultural production has attracted great attention in recent years. Surface irrigation, especially furrow irrigation, is one of the most common irrigation methods worldwide. The main problem with this method is low irrigation efficiency due to poor management of irrigation (Khatri and Smith 2006). Uniform distribution of water on the farm is essential for optimal exploitation of existing water resources. Many studies have reported the negative effects of non-uniform water distribution on product amount and wastes of cumulative infiltration (Sanchez *et al*. 2010, Salmeron *et al*. 2012, Perez Ortola *et al*. 2015). Infiltration is one of the most important soil parameters in designing, evaluating and planning surface irrigation methods (Elliott and Walker 1982), which directly affects its efficiency (Tabatabaei *et al*. 2005). Furthermore, water infiltration in soil is a function of time and location, and its measurement is difficult, time-consuming and costly. Therefore, finding an estimation method with the ability to provide the best results as compared to farm data seems necessary.

The process of estimating quantitative values for points with the lack of data using the neighboring points is called *interpolation*. Interpolation methods yield different accuracies depending on the type of variable (Tabatabaei and Ghazali 2011). Inverse distance weighting (IDW) and Kriging are the most commonly used interpolation methods in agriculture (Kravchenko and Bullock 1997). Artificial neural networks (ANNs) are other indirect methods used in estimating soil hydraulic properties in recent years. These networks are extensively used in various areas including classification, interpolation, estimation, detection, etc. (Das 2000).

In different studies carried out in recent years, geostatistical methods have been successfully used to estimate and predict different soil and water characteristics: the quality of groundwater (Bodrud-Doza *et al*. 2016), soil organic carbon content (Zauche *et al*. 2017), soil aggregate stability (Marashi *et al*. 2017) and soil electrical conductivity (Namdar-Khojasteh *et al*. 2010). Hodam *et al.* (2017) interpolated spatial variations of reference evapotranspiration in a region in India using Kriging and IDW methods. Better result was obtained through monthly evaluation by the Kriging method; however, the IDW method yielded good results in all the cases. Parchami Araghi *et al.* (2010) estimated the amount of water-to-soil cumulative infiltration in calcareous soils by the ANNs. In this study, two types of neural networks were used and the results indicated better performance of the first type of the neural network in estimating the amount of cumulative infiltration and also in estimating the cumulative infiltration curve. In this neural network type, the input variables included the hierarchical surface horizon characteristics. In 2010, Ekhmaj estimated soil infiltration using neural networks and multi-layered regression (MLR) methods. Ultimately, he introduced the neural network method as a better estimation method. In another study, ANNs were used to estimate soil moisture; the results of which demonstrated a high correlation between estimated and observed values (Arif *et al*. 2012). Beucher *et al*. (2017) and Garzia Bonelli *et al*. (2017) verified the efficiency of ANNs in prediction of soil drainage classes and evaluation of organic and mineral contaminations of agricultural soils, respectively.

The accuracy of geostatistical methods and neural networks has been compared in numerous studies. Pahlavan Rad *et al*. (2016) conducted a study on the prediction of spatial variations of soil salinity and clay using geostatistical methods and ANNs. The results indicated slightly higher accuracy of the ANNs method as compared to the geostatistical methods in the estimation of soil salinity and clay. Dai *et al*. (2014) examined spatial variations of soil organic matter content over time and on a regional scale using neural network, Kriging and IDW methods. After examining the accuracy of these methods, the ANN-Kriging method was proposed. In another study, the capability of ANNs in spatial interpolation was evaluated and compared with conventional interpolation methods like Kriging and IDW. The results indicated that despite the high value of RMSE in the MLP method, this method can be used in spatial interpolation (Nevtipilova *et al*. 2014). In an investigation Sitharam *et al*. (2008) compared on geostatistics, neural network and support vector machine methods; the results illustrated a better performance of the ANN method over the other methods. Misaghi and Mohammadi in 2007 zoned the rainfall data of a region using classical statistics and geostatistics and compared the results with those obtained by artificial neural networks.

Investigating the research background shows that, despite studies on the comparison between Kriging, IDW and ANNs interpolation methods, no concurrent comparisons have been conducted among these methods taking into account the cumulative infiltration. The present study was carried out to compare the aforementioned methods in the estimation of infiltration and determination of the best interpolation method.

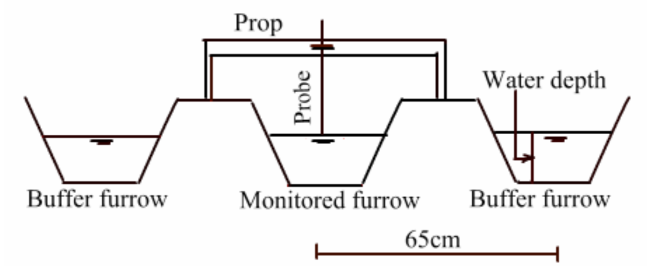
MATERIALS AND METHODS

The present research was conducted in East Azarbaijan Province, Iran, in the Agricultural Research Station of Tabriz University located in the geographical location of 46°17' eastern latitude and 38°5' northern altitude and 1,360 m above sea level. The dimension of the selected farm was 130 × 70 m, and the mean longitudinal slope was 1.56%; in addition, the soil consisted of loam up to 65 cm deep and was free from vegetation. The physical characteristics of the farm soil are presented in Table 1. In this farm, furrows with a length of 130 m and with spacing of 65 cm, were created in four groups of triad, the middle furrow as the main furrow and the lateral furrows were considered as protective furrows. Infiltration experiments were carried out at distances of 10 m and at a section of 85 cm in the furrow (Fig. 1). The experiments were carried out using the blocked furrows method. First, the blocked section was covered with a plastic plate and then the two plates with sharp edges were pounded into the ground in two sides of the furrow. In addition, the water level index with the holding base was placed in the perpendicular direction at the furrow cross section. A certain volume of water was poured inside each of the main and secondary furrows. Then, observations were made after removal of the plastic plate. The water was allowed to enter the soil and was regularly added to the furrow to replace the infiltrated water. The duration of the test was 210 min in each section and the final results were obtained as volume of water infiltrated in millimeters for the corresponding times.

Table 1. Soil physical properties

Depth (cm)	Texture	Gravel	Sand	Silt	Clay	BD ($g \cdot cm^{-3}$)	FC	TAW	TPS
		%					%		
0–25	Sandy loam	8.4	69.5	24.0	6.5	1.61	12.2	10.7	35.6
25–38	Sandy loam	14.3	55.5	29.7	14.8	1.37	18.2	12.9	46.5
38–65	Sandy loam	00.0	63.8	27.8	8.4	1.28	23.2	17.1	50.0
65–90	Loamy sand	12.0	80.4	16.2	3.4	1.57	17.1	16.7	37.2

BD – bulk density, FC – field capacity, TAW – total available water, TPS – total pore space



n.s – non-significant, * and ** indicate a significant difference at 5 and 1% levels, respectively

Fig. 1. A set of blocked furrows for infiltration tests

INTERPOLATION METHODS

Kriging

Basically, Kriging is a generalized name for all the geostatistical methods used for estimating spatial variables (Isaaks and Srivastava 1989). This method relies on the logic of weighted moving average (WMA) and the best unbiased linear estimator (BLUE), which determines the estimation error in each point in addition to the estimates (Goovaerts 1997). The Kriging function is defined as relation 1 (Delbari *et al*. 2013, Webster and Oliver 2000):

$$\hat{z}(x) = \sum_{i=1}^{n} \lambda_i z\,(\mathrm{x_i}) \tag{1}$$

Where: $z\ (x)$ is the estimated value of z at the point with the coordinates x, $z(x_i)$ is the observed value of z at the point with the coordinates x_i, λ_i is the weight attributed to the variable z at the point x_i and n is the number of samples. The success of this method in the interpolation of variables is entirely dependent on the accuracy of selection of the semivariogram empirical model. The variogram function is defined according to relation (2) (Nanos and Montero 2002, Isaaks and Srivastava 1989, Mohammadi 2001); such that $\gamma\hat{}(h)$ is the semivariogram value for N number of sample pairs separated from each other by a distance (h). $Z(x)$ is also the value of the variable x in point i.

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \tag{2}$$

Inverse distance weighting (IDW)

The IDW method is a geostatistical method with a vast application in calculation of problems in sciences regarding water resources. This method, unlike the Kriging method, is not dependent on model, rather depends on the inverse distance weighting to the estimation point. In this method, the value of the variable in the non-sampled points was determined by relation (3) (Jahani and Delbari 2009).

$$Z = \frac{\sum_{i=1}^{n} \frac{z_i}{d_i^m}}{\sum_{i=1}^{n} \frac{1}{d_i^m}} \tag{3}$$

In this relation, Z, d_i and n are the estimated value of the variable in the non-sampled region, distance of the sampled point to the estimation point, and the total number of the sample, respectively. The parameter m is the distance power, changes of which results in the flexibility of the IDW method. Calculations for the Kriging and IDW methods were performed by GS+ software version 5.1.

Artificial neural networks (ANNs)

ANNs are powerful mathematical tools created by imitation of the biological nervous system (Fulop *et al*. 1998). Each artificial neural network is generally composed of three layers: input, hidden and output; and in each layer, there

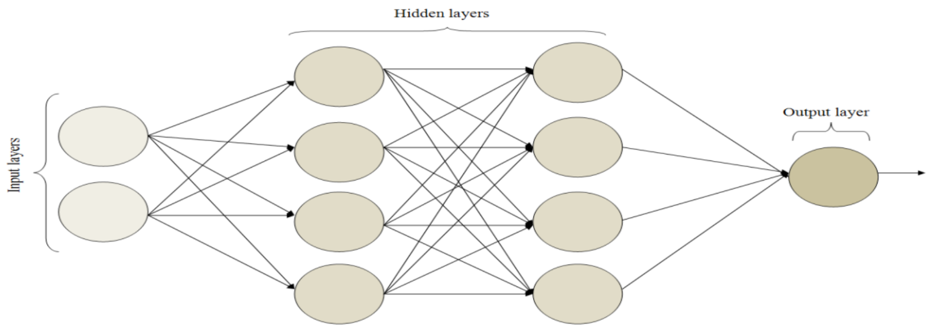


Fig. 2. View of an artificial neural network

are a number of processors called *neurons* (Fig. 2). The most important issue in making a network is determining the number of hidden layers and the number of neurons in each of them (Menhaj 2009). The general method for achieving them is the trial and error method, and of course, the use of knowledge obtained from other studies. In general, it can be said that the structure of a neural network consists of the number of layers, the number of neurons in each layer, how the layers are interlinked, the network training method and how to distribute the parameters. In the present study, NeuroSolutions software version 5 was used for modeling. Some of the most commonly used neural network architectures in this program include MLP, RBF, PCA, SVM, GFF and MNN. Data normalization must be performed before they are entered into the software in order to increase the accuracy and speed of implementation of ANNs, and in order to equalize the value of the data. A concept of normalization, which is also known as standardization and is also used in the analysis of ANNs and data envelopment analysis (DEA), is as relation (4) in which X_n, X, X_{min} and X_{max} are the standardized, unstandardized, minimum and maximum data, respectively.

$$Xn = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

After normalizing, input and output data were entered into the software. Then, data were randomized and divided into three classes: training, validation and test to avoid slant of errors. MLP and PCA methods were used to train the data in this study. The design and network architecture begins from this stage; the network architecture involves determination of the number of hidden layers, number of elements and various activation functions. After constructing different models, evaluation and comparison of models was performed to determine the optimal model. In both methods, the error criteria for selection of the final model were determined from the network test section, since a model may respond well in the training section; however, it failed to perform well in the test section. Therefore, the network must be tested. In the present study, MLP and

PCA methods were exploited as interpolation methods to estimate and predict the infiltration rate in irrigation furrows.

Comparison of interpolation methods

In this study, the maximum error (ME), mean bias error (MBE), mean absolute error (MAE), relative error (RE), root mean square error (RMSE) and correlation coefficient (r) were used to evaluate the accuracy and efficiency of the models and methods used in accordance with the following relations:

$$\mathrm{ME} = \max\left|p_i - o_i\right|_{i=1}^{n} \tag{5}$$

$$\mathrm{MBE} = \sum_{i=1}^{n}\left[{(p_i - o_i)}/{n}\right] \tag{6}$$

$$\mathrm{MAE} = \sum_{i=1}^{n}\left[{|p_i - o_i|}/{n}\right] \tag{7}$$

$$\mathrm{RE} = \left(\frac{\mathrm{MAE}}{\bar{O}}\right) \times 100 \tag{8}$$

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n}(P_i - o_i)^2}{n}\right]^{1/2} \tag{9}$$

$$r = \frac{n\sum_{i=1}^{n} o_i p_i - \left(\sum_{i=1}^{n} o_i\right)\left(\sum_{i=1}^{n} p_i\right)}{\sqrt{\left[n\sum_{i=1}^{n} o_i^2 - \left(\sum_{i=1}^{n} o_i\right)^2\right] \times \left[n\sum_{i=1}^{n} p_i^2 - \left(\sum_{i=1}^{n} p_i\right)^2\right]}} \tag{10}$$

In these relations, P_i, O_i, $\bar{O}$ and n are the estimated values, observed (measured) values, mean of the measured values and the number of samples, respectively. Low error rates (RMSE, MBE, RE, MAE and ME) and high correlation coefficient indicate acceptable accuracy and superiority criterion.

RESULTS AND DISCUSSION

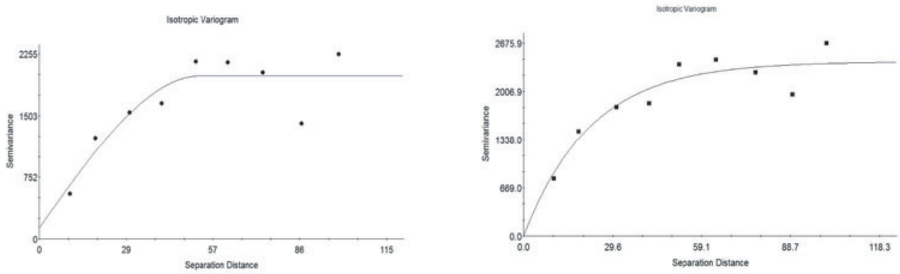
The normal distribution of data was first studied after entering the coordinates X and Y of the measurement points and cumulative infiltration values at 10, 20, 30, 40, 50, 60, 90, 120, 150, 160, 180 and 210 min in GS+ software. The values of skewness and shape of the graphs were evaluated in order to determine the normal distribution of the data. The values of skewness close to zero and the bell-shaped form of the graph both represent the normal distribution of the data. In this study, the cumulative infiltration values were normalized in all the studied periods by the square root method before performing the geostatistical calculations. A statistic summary of the cumulative infiltration data is presented in Table 2. To achieve an appropriate interpolation in the Kriging method, the most important problem is the fitting of a suitable model to the semivariogram. The best model was determined on the basis of the behavior of the semivariogram near the origin of the coordinates, the residual sum of squares (RSS), the coefficient of determination (r^2), and the ratio of $\frac{C}{C.+C}$. In this study, the spherical model was determined as the best model at all times under investigation except for 40 and 210 min (Table 3). The exponential model was obtained at times of 40 and 210. Figure 3 provides the semivariogram diagrams at 180 (spherical) and 210 (exponential) minutes for the sample. Failure to properly determine the selected model to be interpolated will lead to the occurrence of any mistakes in the executive issues. The proportional effect of $\frac{C}{C.+C}$ was used as an index for evaluating the percent spatial structure of the data. If this ratio is less than 0.25, it indicates a weak spatial correlation, if this ratio is between 0.25 and 0.75, it indicates a moderate spatial correlation, and if this ratio is greater than 0.75, it indicates a strong spatial correlation. The results indicated that the spatial correlation of the variable (infiltration) on the farm surface increases with increase in the irrigation time, thus, this correlation reaches 100% at the time of 210 min. The next step is to develop the zoning maps of infiltration. Soil infiltration patterns at t = 210 min were presented in Figures 4 and 5 for Kriging and IDW methods, for instance. The variations and the non-uniformity of infiltration in the furrows is well illustrated by the Kriging and IDW methods.

Table 2. Descriptive statistics of cumulative infiltration

Time	n	Mean	Max	Min	SD	Skewness	Kurtosis
10	51	3689.37	8495.43	679.41	188.87	-0.29	0.41
20	51	5878.57	14259.40	1495.39	254.71	-0.04	0.39
30	51	7917.76	19747.80	2600.25	330.31	0.21	0.33
40	51	9703.23	23391.30	3109.40	415.76	0.11	0.21
50	51	11309.09	28286.20	3679.65	505.11	0.15	0.17
60	51	13237.59	31995.90	4293.7	626.47	0.15	-0.01
90	51	17908.20	43163.50	5699.08	902.38	0.19	-0.13
120	51	22190.72	53756.80	6829.44	1144.33	0.17	-0.29
150	50	26042.09	61767.90	8189.55	1380.73	0.22	-0.32
160	49	27123.21	65456.40	8499.26	1475.03	0.26	-0.31
180	45	30334.49	69964.80	9437.62	1844.73	0.19	-0.65
210	43	33514.55	77891.10	10836.20	2139.68	0.21	-0.71

n – number of samples, SD – standard deviation.

In the ANNs method, to estimate the amount of cumulative infiltration, after standardizing the data, the coordinates (X and Y) of the measured points were considered as inputs; in addition, the amount of the cumulative infiltration at these points at 10, 20, 30, 40, 50, 60, 90, 120, 150, 160, 180 and 210 min each was considered as the output layer separately. Therefore, each network included two input layers and one output layer. Then, the data were randomized and 60, 15 and 25% of the whole data were allocated to training, validation and test,



(a) (b)

Fig. 3. The experimental semivariogram diagram of cumulative infiltration at a) 180 minutes (spherical) and b) 210 minutes (exponential)

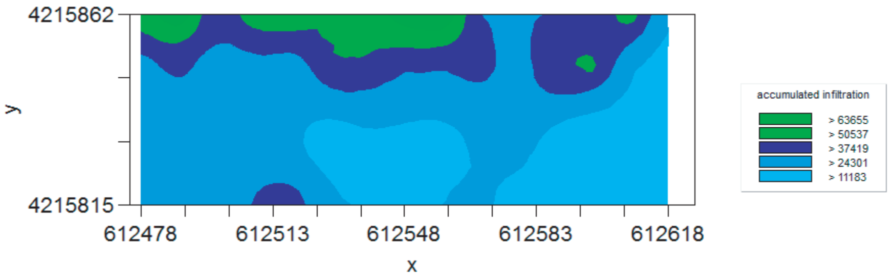


Fig. 4. Infiltration zoning map by Kriging (210 min)

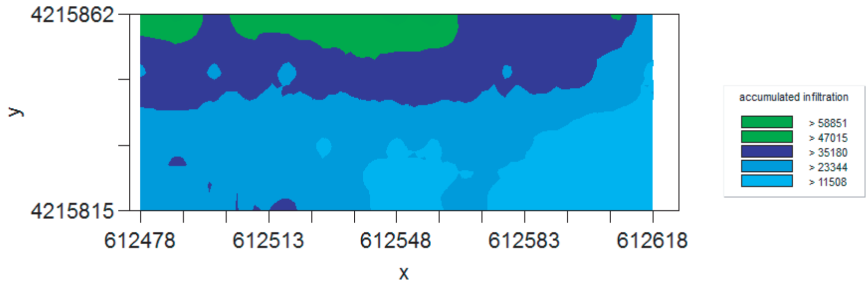


Fig. 5. Infiltration zoning map by IDW (210 min)

respectively. In this study, the MLP and PCA were used once for training the neural networks. The next step was to determine the number of hidden layers. It has been proven that each function is trained with a maximum of three hidden layers, as the network is first trained with a hidden layer and the number of hidden layers is increased in the case of inappropriate performance; 2 hidden layers were selected in the present study. The trial and error method was used to find the optimal network state and eventually, the optimal architecture for the desired neural networks was selected taking into account the values of the statistical indicators MSE and MAE and the value correlation coefficient which were calculated by the software at the test stage. Obviously, the greater the correlation coefficient (closer to one) and the lower MAE and MSE values (closer to zero), the greater the prediction accuracy of the model. Figure 6 shows the error trend diagram along with the epoch cycle for achievement of sustainability in optimal network selection at 210 min for the PCA method. According to this diagram, the minimum squared error (MSE) in the training stage was equal to 0.03 and in the validation step it was equal to 0.2. Then, a comparison was made between the evaluation stage, the measured infiltration values, and the values predicted by the model for selection of the optimal network. For selection of the optimal network using the PCA method, the values of MSE = 0.03, MAE = 0.15 and r = 0.87 were obtained by the software in 210 minutes (Fig. 7) (PCA method and the time of 210 min are presented as an example). All the above steps were performed and repeated to obtain the cumulative infiltration values for all study periods and two educational PCA and MLP algorithms, and eventually, the results of the trial and error among different types of neural network models in this study indicated that the optimal network for the two training algorithms used was the same. This model consisted of 2 hidden layers, 4 elements, Tanh Axon activation function, and the momentum learning rule in the hidden layer and the output layer, with step 1 and coefficient 0.7, step 0.1 and coefficient 0.7, and step 0.01 and coefficient 0.7 in the first hidden layer, the second hidden layer and the output layer, respectively, and the number of computational iterations of the network of at most 1,000 (Table 4).

Table 3. Parameters of the models fitted to the semivariograms for cumulative infiltration

Time	Model	R2	C/(C.+C)	RSS
10	Spherical	0.93	0.71	703
20	Spherical	0.85	0.60	2230
30	Spherical	0.71	0.64	9949
40	Exponential	0.70	0.99	17278
50	Spherical	0.69	0.67	27074
60	Spherical	0.57	0.50	35582
90	Spherical	0.69	0.50	52229
120	Spherical	0.78	0.62	84963
150	Spherical	0.85	0.70	104967
160	Spherical	0.90	0.87	118469
180	Spherical	0.78	0.93	540906
210	Exponential	0.85	1.0	377611

Table 4. Optimal training parameters used in neural network models

Network model	Hidden layers	Processing elements	Transfer	Learning rule	Epoch
MLP	2	4	Tanh Axon	Momentum	1000
PCA	2	4	Tanh Axon	Momentum	1000

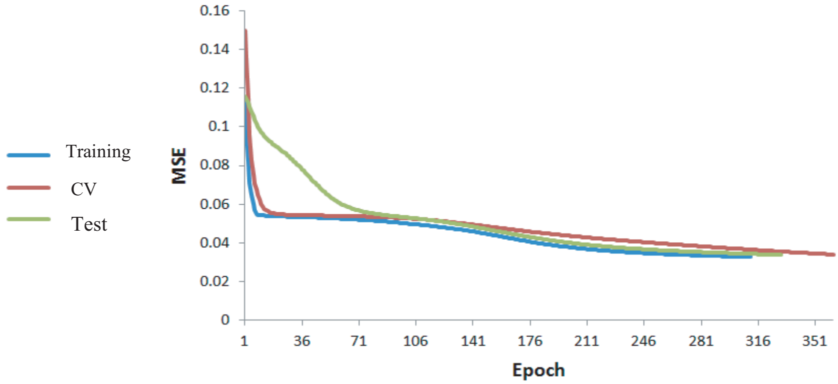


Fig. 6. Epoch cycle error chart for optimal network (PCA method and the time of 210 min)

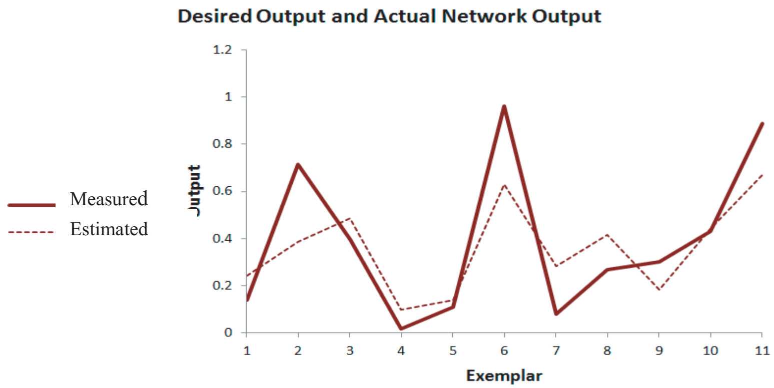


Fig. 7. Comparison between the values of the measured cumulative infiltration and the infiltration obtained by neural network (PCA method and the time of 210 min)

Comparison of methods

Table 5 shows the mean values of the statistical parameters of RMSE, MBE, RE, MAE, ME and *r*, which were calculated for evaluation of Kriging, IDW and neural networks methods. MBE values, which were reported to be negative while using Kriging and IDW methods, and positive while using MLP and PCA methods, is considered as an indicator for the comparison of digits and numbers with base values. So that the values close to zero indicate that the estimated and measured values are similar and the positive sign represents the overestimation of the model, while the negative sign represents the low estimation of the model. Analysis of the values of statistical parameters did not show a significant difference between methods. Hence, analysis of variance (ANOVA) was performed on these methods for more accurate analysis of the calculations (Table 6). According to the results, these methods did not show a significant difference based on RMSE, MBE, MAE and ME indices and all put into one group. However, these methods were statistically significant at less than 1 and 5% level based on the correlation coefficient index and relative error index RE, respectively. The PCA method with the mean values of ME = 13.88, MAE = 5.83, MBE = 0.05, RMSE = 6.94, RE = 31.06% and r = 0.69, due to less relative error rate and high correlation coefficient, was chosen as the most accurate interpolation method in this study. In fact, this model of neural networks in the present study was able to estimate and predict the amount of cumulative infiltration in points with lack of statistics with a more acceptable accuracy.

Table 5. The results of statistical methods

Methods	ME	MAE	RE (%)	MBE	RMSE	r
Kr	19.12	4.92	26.71	-0.42	6.33	0.61
IDW	20.49	5.35	28.38	-0.8	6.92	0.54
MLP	13.66	5.97	32.68	0.7	7.18	0.66
PCA	13.88	5.83	31.06	0.05	6.94	0.69

Table 6. Variance analysis of methods based on the indices.

Source of variation	Degree of freedom	MBE		MAE		RMSE		RE		ME		r	
		mean squares	p- value	mean squares	p- value	mean squares	p- value	mean squares	p- value	mean squares	p- value	mean squares	p- value
between indices	3	5.03	$0.26^{n.s}$	2.75	$0.89^{n.s}$	1.56	$0.16^{n.s}$	85.83	0.05^{*}	149.69	$0.16^{n.s}$	0.05	0.01^{**}
within indices	44	3.63		12.24		17.29		30.76		82.21		0.011	
total	47												

This result is similar to the result of the study by Pahlavan Rad *et al.* (2016), in which the spatial variation of salinity and clay soil was predicted by geostatistics and neural networks methods in a similar study. They also used the coordinates of X and Y as inputs of neural networks and the calculations of RMSE and R^2 parameters did not show much difference between methods, and with a small difference, they identified neural networks method as a better method. Similar results were obtained in a study conducted by Ekhmaj (2010) on the estimation of soil infiltration rates using neural networks and MLR methods. Agreement index (D) and correlation coefficient (r) had the same values in both methods. But despite a small difference, due to lower values of MAE and RMSE in neural networks method, this method was chosen as a better method. This result is consistent with that of Sitharam *et al*. (2008) and Nevtipilova *et al*. (2014). They also examined the superiority of ANNs over other methods.

Misaghi and Mohammadi (2007) used MSE, MAE and R^2 indices to compare the results obtained by classical statistics and geostatistical methods with those of neural networks method. They stated that considering the error values and low-determination coefficient in artificial neural networks method, geostatistical method is a better estimation method but considering the high ease and speed of post-training calculations, neural networks method can still be considered as one of the preferred methods in predicting variables. Similar to the study by Dai *et al*. (2014), they proposed using a combination of geostatistical estimators and neural networks method.

Moreover, the results of the present study (application of the neural network in estimating water-to-soil infiltration) confirmed the effectiveness of ANNs in water and soil sciences, as Garzia Bonelli *et al*. (2017), Beucher *et al*. (2017) and Arif *et al*. (2012) also confirmed the effectiveness of neural networks in estimating soil contamination, soil drainage and soil moisture, respectively.

CONCLUSIONS

The characteristic of soil infiltration is a function of time and place, and it is difficult to measure it. Using geostatistical models or ANNs is justifiable and cost effective. Therefore, in the present study, the efficiency of Kriging, IDW and neural networks with MLP and PCA models in estimating and interpolating the rate of soil infiltration was determined. Comparison of the methods showed that accuracy of the PCA method with RE = 31% and r = 0.69 was better in comparison with other methods and better results were obtained on the site of the study. What is more, selecting a proper method for interpolating and estimating a variable depends on the nature of the variable and the regional factors influencing it. Furthermore, given the proximity of the results of the methods used, it is suggested that it is valuable to have large local soil database from many sites, in order to have a stronger assessment of models. Since the spatial and temporal variation of infiltration problem reduces access to suitable levels of uniform irrigation and hence, causes increase in wastes and reduction of water efficiency in farm conditions, the results of this study can be useful in water resource planning and management and improvement of irrigation efficiency.

REFERENCES

[1] Arif, C., Mizoguchi, M., Setiawan, B.I., Doi, R., 2012. *Estimation of soil moisture in paddy field using artificial neural networks*. International Journal of Advanced Research in Artificial Intelligence, 1(1): 17–21.

[2] Beucher, A., Moller, A.B., Greve, M.H., 2017. *Artificial neural networks and decision tree classification for predicting soil drainage classes in Denmark*. Geoderma (in press).

[3] Bodrud-Doza, M.D., Towfiqul Islam, A.R.M., Ahmed, F., Das, S., Saha, N., Safiur Rahman, M., 2016. *Characterization of groundwater quality using water evaluation indices, multivariate statistics and geostatistics in central Bangladesh*. Water Science, 30: 19–40.

[4] Dai, F., Zhou, Q., Lv, Z., Wang, X., Liu, G., 2014. *Spatial prediction of soil organic matter content integrating artificial neural network and ordinary kriging in Tibetan Plateau*. Ecological Indicators, 45: 184–194.

[5] Das, G., 2000. *Hydrology and Soil Conservation Engineering*. Asoke K. Ghosh, Prentice Hall of India, 489 pp.

[6] Delbari, M., Bahraini Motlagh, M., Kiani, M., Amiri, M., 2013. *Investigating spatio-temporal variability of groundwater quality parameters using geostatistics and GIS*. International Research Journal of Applied and Basic Sciences, 4(12): 3623–3632.

[7] Ekhmaj, A.I., 2010. *Predicting soil infiltration rate using artificial neural network*. International Conference on Environmental Engineering and Applications.

[8] Elliott, R.L., Walker, W.R., 1989. *Field evaluation of furrow infiltration and advance functions*. Transactions of the ASAE (American Society of Agricultural Engineers), 25(2): 396–400.

[9] Fulop, I.A., Jozsa, J., Karamer, T., 1998. *A neural network application in estimating wind induced shallow lake motion*. Hydro Informatics, 98(2): 753–757.

[10] Garzia Bonelli, M., Ferrini, M., Manni, A., 2017. *Artificial neural networks to evaluate organic and inorganic contamination in agricultural soils*. Chemosphere, 186: 124–131.

[11] Goovaerts, P., 1997. *Geostatistics for Natural Resources Evaluation*. Oxford University Press, New York.

[12] Hodam, S., Sarkar, S., Marak, A.G.R., Bandyopadhyay, A. 2017. *Spatial interpolation of reference evapotranspiration in India: Comparison of IDW and Kriging method*. Journal of the Institution of Engineers (India), 98(4): 511–524.

[13] Isaaks, E.H., Srivastava, R.M., 1989. *An Introduction to Applied Geostatistics*. Oxford University Press, New York, 561 pp.

[14] Jahani, S., Delbari, M., 2009. *Evaluation and estimation of the 24-hour maximum rainfall in the province of Golestan* (in Persian). Journal of Water Engineering, 2(4): 13–22.

[15] Khatri, L., Smith, R., 2006. *Read-time prediction of soil infiltration characteristics for the management of furrow irrigation*. Irrigation Science, 25(1): 33–43.

[16] Kravchenko, A., Bullock, D.G., 1997. *A comparative study of interpolation methods for mapping soil properties*. Agronomy Journal, 91: 393–400.

[17] Marashi, M., Mohammadi Torkashvand, A., Ahmadi, A., Esfandiari, M. 2017. *Estimation of soil aggregate stability indices using artificial neural network and multiple linear regression models*. Spanish Journal of Soil Science, 7(2): 89–99.

[18] Menhaj, M.B., 2009. *Fundamentals of Neural Networks, Computational Intelligence* (in Persian). Vol., 1, 8th edition, Amirkabir University of Technology, Tehran, Iran, 715 pp.

[19] Misaghi, F., Mohammadi, K., 2007. *Estimating spatial distribution of rainfall using statistical and geostatistical methods and comparison with artificial networks*. The Scientific Journal of Agriculture (SJA), 29(4): 1–13.

[20] Mohammadi, J., 2001. *Review on fundamentals of geostatistics and its application to soil science* (in Persian). Journal of Soil and Water Sciences, 15(1): 99–121.

[21] Namdar-Khojasteh, D., Shorafa, M., Omid, M., Fazeli-Shaghani, M., 2010. *Application of artificial neural networks in modeling soil solution electrical conductivity*. Soil Science, 175(9): 432–437.

[22] Nanos, N., Montero, G., 2002. *Spatial prediction of diameter distribution models*. Forest Ecology and Management, 161: 147–158.

[23] Nevtipilova, V., Pastwa, J., Boori, M.S., Vozenilek, V., 2014. *Testing artificial neural network (ANN) for spatial interpolation*. Journal of Geology & Geophysics, 3(2): 01–09.

[24] Pahlavan Rad, M.R., Dehghani, A.A., Shahriari, A., Akbari Moghaddam, A.R., Dahmardeh, K., 2016. *Predicting spatial variability of soil salinity and clay content using geostatistics and artificial neural networks methods* (in Persian). Journal of Soil Management and Sustainable Production, 6(1), http://ejsms.gau.ac.ir

[25] Parchami Araghi, F., Mirlatifi, S.M., Ghorbani Dashtaki, S., Mahdian, M.H., 2010. *Estimating cumulative infiltration using artificial neural networks in calcareous soils* (in Persian). Journal of Water and Soil, 24(3): 512–526.

[26] Perez Ortola, M., Daccache, A., Hess, T.M., Knox, J.W., 2015. *Simulating impacts of irrigation heterogeneity on onion (Allium cepa L.) yield in a humid climate*. Irrigation Science, 33: 1–14.

[27] Salmeron, M., Urrego, Y.F., Cavero, J., 2012. *Effect of non-uniform sprinkler irrigation and plant density on simulated maize yield*. Agricultural Water Management, 113: 1–9.

[28] Sanchez, I., Zapata, N., Faci, J.M., 2010. *Combined effect of technical, meteorological and agronomical factors on solid-set sprinkler irrigation: I. Irrigation Performance and soil water recharge in alfalfa and maize*. Agricultural Water Management, 97: 1571–1581.

[29] Sitharam, T.G., Samui, P., Anbazhagan P., 2008. *Spatial variability of rock depth in temperate forests*. Geotechnical and Geological Engineering, 26: 503–517.

[30] Tabatabaei, S.J., Nayshabori, M.R., Fardad, H., Liaghat, A., 2005. *Agricultural management effect on soil basic infiltration rate in furrow irrigation of corn* (in Persian). Journal of Soil and Water Sciences, 19(2): 255–262.

[31] Tabatabaei, S.H., Ghazali, M., 2011. *Accuracy of interpolation methods in estimating the groundwater level (Case study: Farsan-Jooneghan and Sefiddasht Aquifers)* (in Persian). Water and Soil Science (Journal of Science and Technology of Agriculture and Natural Resources), 15(57): 11–22.

[32] Webster, R., Oliver, M.A., 2000. *Geostatistics for Environmental Scientists*. Wiley Press, 271 pp.

[33] Zauche, M., Bel, L., Vandour, E., 2017. *Geostatistical mapping of topsoil organic carbon and uncertainty assessment in western Paris croplands (France)*. Geoderma Regional, 10: 126–137.