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Prediction of Unsaturated Hydraulic Conductivity of Agricultural Soils Using Artificial Neural Network and c#

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Authors' contributions

This work was carried out in collaboration between the two authors. Author MAAS managed the required instrumentations, supervised on the experimental work, contributed in writing the first draft of the manuscript and discussed the conclusion. Author AMA wrote the protocol, managed the literature searches, analyzed data, carried out the analysis of artificial neural network model and wrote the first draft of the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

Aims: The objective of this study was to develop an artificial neural network model and interactive application using C# application to predict unsaturated hydraulic conductivity of soil.
Study Design: The actual measurements of unsaturated hydraulic conductivity of soil were obtained using the Mini Disk Infiltrometer (Decagon Devices, Inc.).
Place and Duration of Study: The study was conducted in laboratory located in Community College, Huraimla, Shaqra University, Saudi Arabia during March-April 2015.
Methodology: The experiments were conducted using water having electric conductivity of 2.26 dS/m and sodium adsorption ratio of 4.8. Unsaturated hydraulic conductivity of different soil textures (sand, sandy loam, loam and loamy sand) was determined at suction of -6 cm using Mini Disk Infiltrometer. The soil samples were taken from depth of 0-20 cm and repacked in a plastic 1000 cm^3 container.

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Results: The predicted unsaturated hydraulic conductivity of soils compared favorably with the actual measurements in testing stage, however, mean relative error was 4.184% and coefficient of determination (R^2) was 0.9979. In general, artificial neural network model gave considerable results but more data is still necessary. The main equations for C# application were obtained from the trained artificial neural network model.

Conclusion: It could be concluded that the developed interactive application is recommended for estimating unsaturated hydraulic conductivity of agricultural soils within the range of the studied variables to provide data for water management in Saudi Arabia.

Keywords: Artificial neural network; C#; mini disk infiltrometer; unsaturated hydraulic conductivity of soil.

1. INTRODUCTION

In the field of irrigation agricultural, water management is required to improve the efficiency and sustainability of agricultural systems when water is scarce [1]. One of the tasks of water management is to quantify, to predict and in the end to control water and solute transport into soil. Consequentially, these processes are dependent on soil hydraulic conductivity which needs to be determined in the field or in the laboratory. On the other hand, direct measurement of hydraulic conductivity of soil is difficult, tedious, relatively costly, labour intensive and time-consuming [2-5]. Thus, indirect methods using predictive approaches have been developed for estimation of hydraulic properties of a soil from easily measurable soil properties [6-8]. However, predictive approaches of the soil hydraulic conductivity have gained considerable attention and efforts have been made by researchers to improve the power of predictability [9]. The predictive approaches of the soil hydraulic conductivity may be developed by different methods such as multiple linear regression, adaptive neuro-fuzzy inference systems and artificial neural network models. These methods have been recommended in the field of hydraulic conductivity as encourage results of different research papers [10-11] were reported.

Hydraulic conductivity is defined as “the meters per day of water seeping into the soil under the pull of gravity or under a unit hydraulic gradient” [12]. Additionally, hydraulic properties of a soil and their applications in the soil water flow models play an important role on solving many water management issues [13].

Hydraulic conductivity is useful to soil and water scientists, land managers, and growers, in knowing how quickly water will infiltrate when applied to a given field or soil type [14]. The selection and determination of soil hydraulic parameters are the basis of predicting water movement and solute transfer in soils [15]. The measurements show that the value of unsaturated hydraulic conductivity varies considerably from soil to soil with different water content [16]. Soil hydraulic conductivity includes two items, the first is saturated hydraulic conductivity and the second is unsaturated hydraulic conductivity [17]. Of all hydraulic properties, the unsaturated hydraulic conductivity is the most difficult to measure. It is considered to be the most important parameter for modelling flow process in unsaturated soil. Furthermore, unsaturated soil hydraulic conductivity is essential to many agriculture and environmental applications [18]. It is considered the most important variable in soil water flow models [13]. It is a function of soil moisture content [19]. It is also one of hydraulic characteristics needed for numerical modelling of water flow and solute transport [20]. It is also often necessary for solving unsaturated flow problems [21].

Measurement of unsaturated soil hydraulic conductivity is a challenging task and requires costly and skilled experimentation [22]. Therefore, the use of indirect methods has become common to estimate the unsaturated hydraulic conductivity from more easily measured soil properties [23]. Additionally, unsaturated soil hydraulic conductivity could be estimated from air permeability [24], from soil electrical conductivity [25] and from moisture retention data [26].

Vereecken et al. [7] measured hydraulic conductivity (saturated and unsaturated) on 127 soil cores, which were taken in different horizons of a wide variety of Belgian soil series. The textural composition in nine fractions, the organic carbon content and the dry bulk density were determined for each of the sample horizons as well. Four different empirical models were evaluated on their performance in describing the measured hydraulic conductivity.

Zhuang et al. [17] estimated the unsaturated hydraulic conductivity of soil based on some physical properties of the soil which were soil texture, the hydraulic conductivity of soil, soil water properties and amounts of gypsum and lime precent, actual and apparent the distribution of particle sizes.

Neshat and Farhad [19] carried out an experiment and made calculations for estimating the unsaturated hydraulic conductivity of a soil to get suitable relationship between the unsaturated hydraulic conductivity of the soil and the soil physical properties.

Malaya and Sreedeep [22] investigated the correlation between grain size distribution curve of a soil and unsaturated hydraulic conductivity of soil. They reported that unsaturated hydraulic conductivity of soil could be estimated from grain size distribution curve of a soil.

Amer et al. [27] proposed an equation to predict unsaturated hydraulic conductivity based on water viscosity, acceleration due to gravity, and density of water, ratio of total volume pores and radius of equivalent cylindrical pore size.

Neyshabouri et al. [28] proposed a simplify method to predict unsaturated soil hydraulic conductivity using readily accessible soil. Tests with 51 soils with estimated electrical properties were confirmed good agreement of the developed model for coarse–medium-textured soils (<35–40% clay).

Direct measurement of soil properties is easier and much rapid than unsaturated hydraulic conductivity of soil [29]. There are several studies that have attempted to use artificial neural networks (ANN) for estimating hydraulic conductivity of soil from its physical parameters due to ANN is becoming a common tool for modeling complex input–output dependencies [30]. Ghanbarian-Alavijeh et al. [31] developed ANN model to predict saturated hydraulic conductivity of soil using calculated fractal dimensions, air entry values, bulk density and effective porosity. In the training and testing steps of ANN, 114 and 28 measured soil samples were used, respectively. Coefficient of determination and mean squared error were 0.76 and 0.0028, respectively. Erzin et al. [32] developed ANN model for determining hydraulic conductivity of fine-grained soils. The ANN model exhibits higher prediction performance based on their performance indices. It has been demonstrated that the developed ANN model could be employed for determining hydraulic conductivity of compacted fine-grained soils quite efficiently. Ghanbarian-Alavijeh et al. [33] developed an ANN model with back propagation algorithm to estimate saturated hydraulic conductivity from available parameters such as sand and clay contents, bulk density, van Genuchten retention model parameters as well as effective porosity functions. The results showed that ANN model estimated saturated hydraulic conductivity in a good way. Moosavi and Sepaskhah [34] used sand, silt, clay, bulk density, soil organic matter and initial and saturated volumetric water content to predict the unsaturated hydraulic conductivity by the help of ANN. They showed that silt, clay, sand, bulk density and soil organic matter were the most basic influential input variables for prediction of unsaturated hydraulic conductivity.

In semi-arid regions like Saudi Arabia, water management is vital goal to improve the efficiency and sustainability of agricultural systems as water is scarce. So, the objective of this study was to use artificial neural network technique to create a model for unsaturated soil hydraulic conductivity predictions based on sand, silt, clay contents, soil electric conductivity, soil adsorption ratio, soil organic matter, initial soil moisture content and soil bulk density to be used as a tool for creating a database collection about soil hydraulic conductivity for agricultural soils in Saudi Arabia.

2. MATERIALS AND METHODS

2.1 Soil and Water Samples Characteristics

Experiments were conducted in laboratory located in Community College, Huraimla, Shaqra University, Saudi Arabia during March-April 2015. Three samples of each soil were taken from the top 20 cm of the selected sites. Textural analyses showed that the soils were classified as sand, sandy loam, loam and loamy sand. The initial soil water content (dry base) of the samples was measured by the help of electric oven for 24 hr at 105℃. The soil was carefully repacked in a plastic container with capacity of 1000 cm^3 with almost volume of 600 cm^3.

Sodium adsorption ratio (SAR) is a measure of the sodicity of soil, as determined from analysis of water extracted from the soil. The formula for calculating sodium adsorption ratio is as follows [35]:

$$SAR = \frac{Na^{+}}{\sqrt{\frac{1}{2}\left(Ca^{++} + Mg^{++}\right)}} \quad (1)$$

Where Na^{+}, Ca^{++}, and Mg^{++} represent concentrations of sodium, calcium and magnesium, respectively expressed in milliequivalents per litre (meq/L). The characteristics of water used in the laboratory experiments are shown in Table 1.

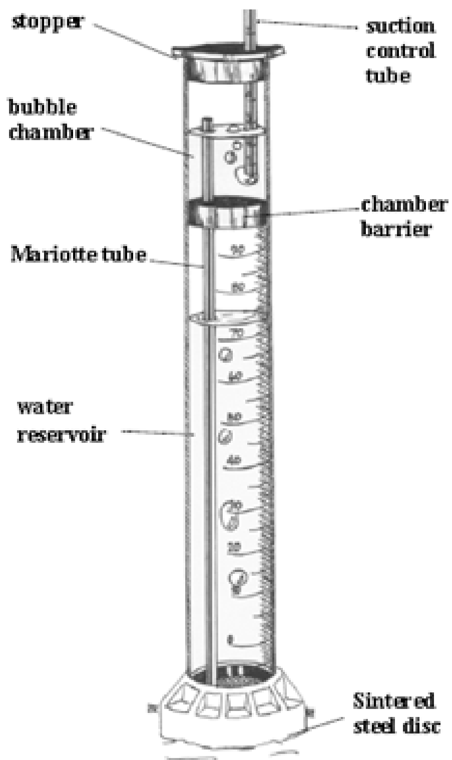

Fig. 1. Mini disk infiltrometer (Decagon devices, Inc.)

2.2 Mini Disk Infiltrometer

Mini disc infiltrometer (Decagon Devices, Inc.) measures soil hydraulic conductivity quickly and easily in any soil type. The infiltrometer (Fig. 1, above) is constructed of a polycarbonate tube with a semi-permeable stainless steel sintered disk on the bottom. An adjustable steel tube above the sample chamber regulates the discharge rate. The top and bottom chambers are both filled with water. The top chamber controls the infiltrometer's suction. The lower chamber contains the water that will infiltrate into the soil and is marked like a graduated. It can measure the hydraulic conductivity in the unsaturated medium (close to near saturation) for adjustable suction ranging from -0.5 cm to -7 cm. At time zero, the infiltrometer is placed on the soil surface. The volume of water that infiltrate into the ground has been recorded as a function of time, based on which infiltration and permeability characteristics is determined.

2.3 Calculating Hydraulic Conductivity

A number of methods are available for determining soil hydraulic conductivity [36]. The method proposed by Zhang [37] is quite simple and works well for measurements of infiltration into dry soil from the recorded data by mini disk infiltrometer. The method requires measuring cumulative infiltration vs. time and fitting the results with the function:

$$I = C_1 t + C_2\sqrt{t} \quad (2)$$

Where I is the cumulative infiltration (cm), t is the time (sec), and C_1 (cm/sec) and C_2 (cm/sec$^{-0.5}$) are parameters. C_1 is related to hydraulic conductivity and C_2 is related to soil sorptivity. The hydraulic conductivity (*Ki*) of the soil is then computed from

$$Ki = \frac{C_1}{A} \quad (3)$$

Where C_1 is the slope of the curve of the cumulative infiltration vs. the square root of time (Fig. 2) and (A) is a value relating the van Genuchten parameters for a given soil type to the suction rate and radius of the infiltrometer disk. (A) is computed from:

$$A = \frac{11.65\left(n^{0.1} - 1\right)\exp\left[2.92(n - 1.9)\alpha h_0\right]}{\left(\alpha r_0\right)^{0.91}} \qquad n \geq 1.9 \quad (4)$$

$$A = \frac{11.65\left(n^{0.1}-1\right)\exp\left[7.5(n-1.9)\alpha h_0\right]}{\left(\alpha r_0\right)^{0.91}} \qquad n < 1.9 \tag{5}$$

Where n and α are the van Genuchten parameters for the soil, r_0 is the disk radius and h_o is the suction at the disk surface. The van Genuchten parameters for the 12 texture classes were obtained from Carsel and Parrish [38].

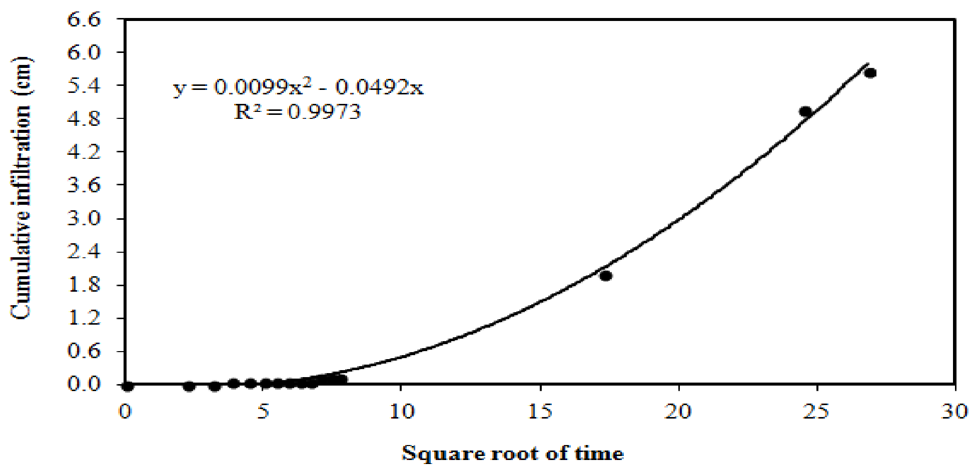

Fig. 2. Cumulative iinfiltration versus square root of time for a soil

Table 1. The characteristics of water used in the laboratory experiments

pH	EC_{water}	SAR_{water}	HCO_3	SO_4	Cl	Na	K	Ca	Mg
(---)	(dS/m)		(meq/L)						
7.7	2.26	4.81	8	5.8	22	15.3	0.3	15	5.2

2.4 Measurement of Soil Hydraulic Conductivity

The unsaturated hydraulic conductivity was measured using a mini disk infiltrometer (Decagon Devices Inc.). The mini disk infiltrometer consists of two chambers (water reservoir and bubble chamber), which are connected via a Mariotte tube to provide a constant water pressure head (suction) of -0.5 to -7 cm as depicted in Fig. (1). The bottom of the mini disk infiltrometer contains a porous sintered steel disk. The water filled tube is placed upon the soil surface (Fig. 3) resulting in water infiltrating into the soil, with the volume of water and speed of infiltration depending on the sorptivity and hydraulic conductivity of the soil. A pressure head (suction) of -6 cm was chosen in this study as the recommended suction for sandy soil [14]. All measurements within one sample test were taken on the same day. The mini disk infiltrometer measurements were taken three times for every soil sample. During the measurement, the volume of the water in the reservoir chamber was documented in regular intervals.

2.5 Artificial Neural Networks

For predicting soil properties, artificial neural networks (ANN) models have become an alternative method as described in different studies [39-40]. The ANN tool is a computational approach that simulates biological neuron function. The performance of an ANN model is sensitive to its architecture, such as the number of input nodes, hidden layer nodes and output nodes. The appropriate an ANN model architecture is, therefore, highly problem dependent [41]. The ANN model is trained to reproduce the input–output relation used to find the optimal weights. The training process consists of calculating the output variables from the input variables; comparing the measured output with the calculated output form ANN model; and then adjusting the weights and bias for each node to minimize the difference between the measured and calculated values.

Fig. 3. Mini disk infiltrometer used for laboratory infiltration measurements

Commercially available QNET 2000 was employed in this study [42]. This software is a Windows-based package, which supports standard back-propagation algorithm for training purposes. QNET 2000 operates via a graphical user interface (GUI) that enables the user to load the data of training and testing sets, design the network architecture and feed values for the training parameters. The ANN type used in this study was a standard back-propagation neural network. The neurons in the ANN layers are connected by weights. The weights connecting input neuron i to hidden neuron j are denoted by w_{ji}^{h}, while the weights connecting hidden neuron j to output neuron are denoted by w_j^o. The input of each neuron is the weighted sum of the network inputs, and the output of the neuron is a transfer function value based on its inputs. More specially, for the j th hidden neuron [43].

$$\begin{cases} net_j^h = \sum_{i=1}^{P} w_{ji}^h x_{t-1} + b_j \quad , \\ y_j = f\left(net_j^h\right) \end{cases} \tag{6}$$

While for the output neuron

$$\begin{cases} net^o = \sum_{j=1}^{m} w_j^o y_j + c \quad , \\ \tilde{x}_t = f\left(net^o\right) \end{cases} \tag{7}$$

Where b_j and c are thresholds (bias), this network has P neurons in the input layer and m neurons in the hidden layer, f is typically taken to be an transfer function and in this study, it was changed to be sigmoid function as shown in equation (8) or hyperbolic tangent (tanh) as shown in equation (9).

$$f(x) = \frac{1}{1+e^{-x}} \tag{8}$$

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{9}$$

It must be noted that because the variables (input or output) presented were of different orders of magnitude, all of the original inputs or output variables were normalized between 0.15 and 0.85 before entering into the network structure using the following equation:

$$T = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \tag{10}$$

Where t is the original values of input and output parameters, T is the normalized value; t_{max} and t_{min} are the maximum and minimum values of the input and the output parameters in the training data set, respectively. The training data set was used to compute the network parameters. The testing data set was used to ensure robustness of the network parameters. Table 2 illustrates minimum and maximum values of input and output variables in training date set for ANN model.

In the study, trial and error approach [44] was used to determine the optimum neurons in the hidden layers of the network. Transfer function was also varied; however, they were sigmoid and hyperbolic tangent (tanh) in the hidden layers. The training data set was consisted of 9 laboratory-measured patterns. Electric conductivity of soil, soil sodium adsorption ratio, initial soil water contents, sand, silt and clay contents, soil bulk density and soil organic matter were measured. However, these variables were considered as input variables. The output variable in this study was consisted of 9 laboratory measured unsaturated hydraulic conductivity of soil at suction of -6 cm. Preliminary trails indicated that two hidden layers network performed better results to predict unsaturated hydraulic conductivity of soil from the studied parameters. To determine the optimal number of the neurons in the hidden layers, the training network was performed using 8-n1-n2-1 architectures. The number of neurons in the first hidden layer (n1) was varied from 1 – 12. The number of neurons in the second hidden layer (n2) was varied from 2 – 20. The results showed that among the various structures, the best training performance to predict unsaturated hydraulic conductivity of soil was belong to the 8-8-14-1 structure. However, the best ANN model was elected based on the highest correlation coefficient and the lowest training error. Fig. (4) illustrates the best ANN structure in the study. Meanwhile, final training error after 10000 iterations was 0.001277 as shown in Fig. (5) and the details of network definitions to predict unsaturated hydraulic conductivity of agricultural soils is depicted in Table 3. Additionally, Table 4 illustrates network statistics after training process.

2.6 Evaluation of ANN Model Predictability

In order to perform a supervised training, a way in which the ANN output error between the actual and the predicted output could be evaluated is therefore required. A popular measure is the mean absolute error (MAE), root mean square error (RMSE) and mean relative error (MRE) as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| K_{v\,iobs} - K_{v\,ipre} \right| \tag{11}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left(K_{vi\,obs} - K_{vi\,pre} \right)^2}{N}} \tag{12}$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left(\frac{K_{vipre} - K_{viobs}}{K_{iobs}} \right) \tag{13}$$

Where $K_{v\,iobs}$ and $K_{v\,ipre}$ are experimental and predicted unsaturated hydraulic conductivity of soil, N is number of observations. In addition, the coefficient of determination (R^2) was selected to measure the linear correlation between the calculated and the predicted values. However, R^2 reflects the degree of fit for the mathematical model [45]. The closer the R^2 value is to 1, the better the model fits to the actual data [46].

2.7 C# Application

C# (C-Sharp) programming language available under.NET programming environment has been used for developing an application to predict unsaturated hydraulic conductivity of agricultural soils. This application has been developed keeping in view of its user friendliness and easily operable. Moreover, C# was chosen because it is a generic portable language and will run on other operating systems [47]. In addition, C# is also a clean, well-designed and implemented object-oriented language. Additionally, Sharma and Lal [48] reported that by using C# language, a fast development of MS-Windows based applications could be implemented for easy analysis of agricultural data. The current C# application was developed based on the weights obtained from the developed ANN model during training stage. These weights were formulated into equations in C# for easy prediction of unsaturated hydraulic conductivity of agricultural soils. The developed C# application was validated with experimental data to ascertain its suitability for unsaturated hydraulic conductivity of agricultural soils predictions. However, Fig. (6) depicts the starting screen of the developed C# application.

Table 2. Statistical values of input and output variables in training data set for ANN model

	Input variables								Output variable
	Sand	**Silt**	**Clay**	**EC**	**SAR**	**Organic matter**	**Initial soil water content**	**Soil bulk density**	**Unsaturated hydraulic conductivity**
	(%)	**(%)**	**(%)**	**(dS/m)**	**(---)**	**(%)**	**(%,db)**	**(g/cm^3)**	**(cm/sec)**
Minimum	52	2	1	1.06	2.00	0.26	3.60	1.30	0.00017
Maximum	95	28	39.	91.10	57.60	2.62	7.54	1.54	0.02037
Average	76.22	11.11	12.67	13.93	11.42	1.68	5.65	1.46	0.00624
Standard deviation	15.18	9.57	13.71	29.09	17.46	0.82	1.16	0.07	0.00813
Coefficient of variation (%)	5.02	1.16	0.92	0.48	0.65	2.05	4.86	19.49	0.7678

SAR= soil sodium adsorption ratio, EC =soil electric conductivity

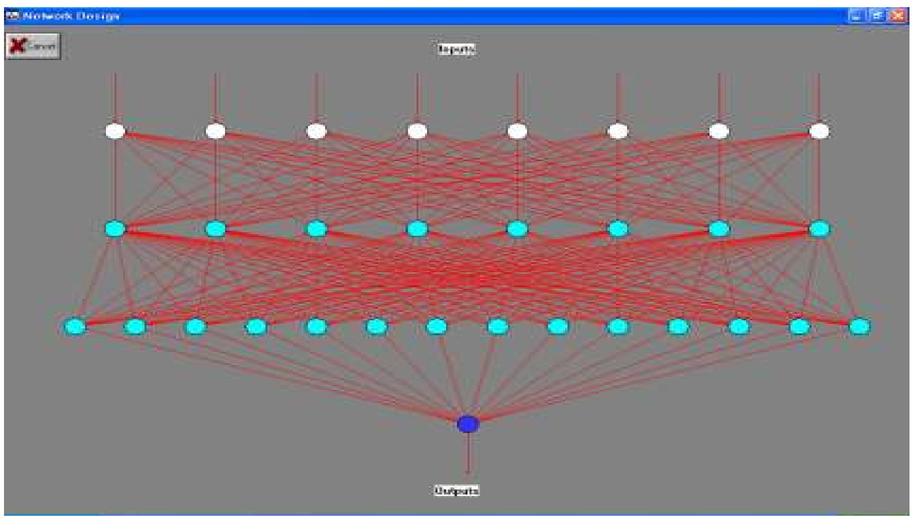

Fig. 4. Structure of the best ANN used in the study

Table 3. Network definitions to predict unsaturated hydraulic conductivity of agricultural soils

Network definitions	Value
Number of layers	4
Input layer nodes	8
Hidden Layer 1 Nodes	8
Transfer function	Sigmoid
Hidden Layer 2 nodes	14
Transfer function	Sigmoid
Iterations	10000
training error	0.001277
learn rate	0.095193
momentum factor	0.8
training patterns	9

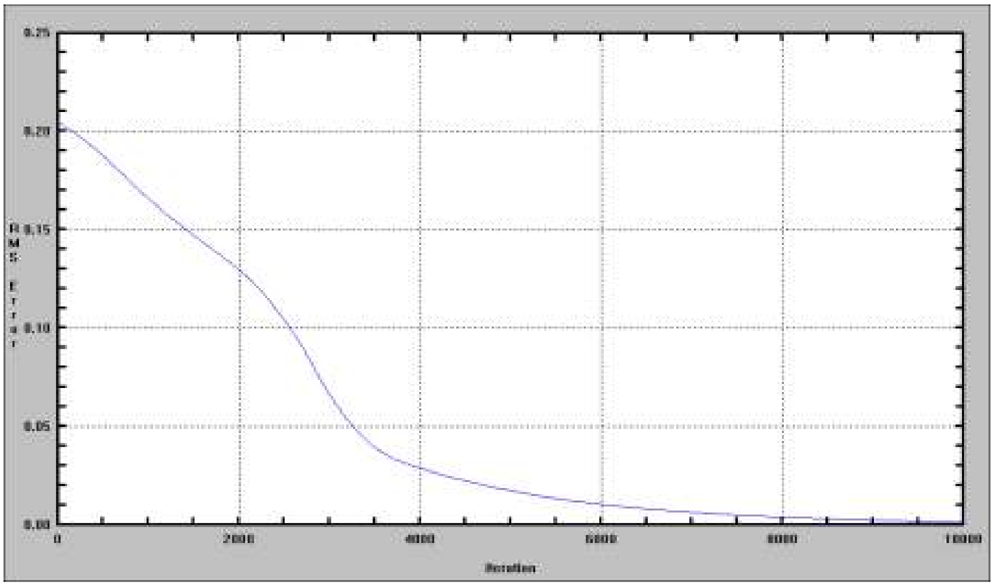

Fig. 5. Error curve during training proces

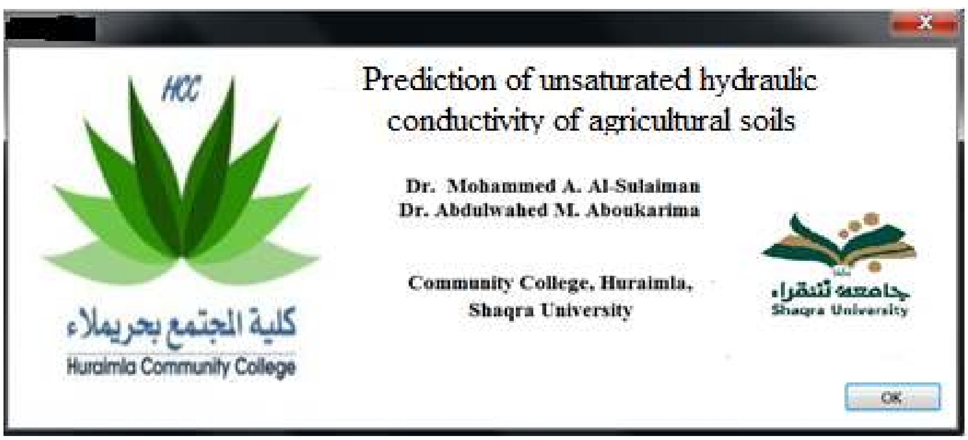

Fig. 6. The starting screen of the developed C# application

Table 4. Network statistics from Qnet software after training process to predict unsaturated hydraulic conductivity of agricultural soils

Standard deviation (cm/s)	Bias (cm/s)	Maximum error (cm/s)	Correlation coefficient
0.0000369	-0.000000395	0.0000728	0.99999

3. RESULTS AND DISCUSSION

3.1 Analysis of Unsaturated Hydraulic Conductivity Data

From Table 2, it is clear that the lowest and the highest unsaturated hydraulic conductivity of the soils were 0.00017 and 0.02037 cm/sec, respectively with coefficient of variation of 0.7678 % which indicates that no big variations between measured unsaturated hydraulic conductivity of soil. However, Gulser and Candemir [49] reported that hydraulic conductivity gave significant positive correlations with silt, sand contents and bulk density values of soils. Besides, hydraulic conductivity gave negative correlations with clay content and soil moisture constant. Schaap et al. [40] reported that if clay content increases so hydraulic conductivity of soil decreases. Additionally, Hudson [50] stated that increased soil organic matter generally produced a soil with increased water holding capacity and conductivity, largely as a result of its influence on soil aggregation and associated pore space distribution. Furthermore, Olourunfemi and Fasinmirin [51] indicated that hydraulic conductivity of soil increases with increase in soil organic matter content. Neshat and Farhad [19] showed that increases in volume soil moisture content and apparent density results increase in unsaturated hydraulic conductivity of soil.

3.2 Performance of ANN Model

In this study, ANN technique was employed to predict unsaturated hydraulic conductivity of agricultural soils based on physical and chemical properties of soil. The results showed that structure of ANN model with two hidden layers gave best result compared to other structures; however, Moosavi and Sepaskhah [34] also employed ANN with two hidden layers for estimating unsaturated hydraulic conductivity from soil properties.

After training process, the developed ANN model was tested by 3 patterns of data which were not use in training process. The error criteria during testing process of ANN model for prediction of unsaturated hydraulic conductivity of agricultural soils were shown in Table 5. In general, the RMSE, MRE and MAE (0.000333251 cm/sec, 4.184% and 0.000284699 cm/sec) measure showed a small error between the measured the predicted values for unsaturated hydraulic conductivity of agricultural soils (Table 5), suggesting that the employed ANN model was very accurate in predicting the values of it. The results suggest that the ANN model could be used as a reliable tool that can be employed for estimating unsaturated hydraulic conductivity of agricultural soils at any values of independent variables, falling within the range of values in the study.

Table 5. Error criteria during testing process of ANN model for prediction of unsaturated hydraulic conductivity of agricultural soils

Error criteria	Unit	Value
RMSE	(cm/sec)	0.000333251
MAE	(cm/sec)	0.000284699
MRE	(%)	4.184
R^2	(---)	0.9979

Fig. (7) shows the relationship between the measured and the predicted unsaturated hydraulic conductivity of soil during testing phase using the developed ANN model. The figure clearly shows that the points, during the testing process, are uniformly scattered around the regression line with high correlation represented by values of coefficients of determination (R^2) that were 0.9979.

3.3 Contribution of Inputs on Predicted Unsaturated Hydraulic Conductivity of Agricultural Soils

The Qnet provides a contribution calculation for how the change in each input, changes the output prediction. The contribution percentage of the eight input variables to the output (unsaturated hydraulic conductivity of agricultural soils) was calculated using the developed ANN model and the results are illustrated in Table 6. It can be deduced from Table 6 that the major contribution to the unsaturated hydraulic conductivity of agricultural soils was attributed to the clay content in the soil with a contribution percentage of 22.2%. Hence, clay content in a soil should be obtained accurately as it greatly influence the resulting predicted the unsaturated hydraulic conductivity of agricultural soils within the boundaries of the training data set used in the study. This result is in agreement with the finding by Chiu and Shackelford [52] who reported that the major factor to predict the unsaturated hydraulic conductivity of the sand-clay mixture was the amount of clay in the mixture. In addition, Al-Shayea [53] reported that the hydraulic conductivity sharply decreases with increasing clay content up to 40%.

The other variables, i.e initial soil water content and soil bulk density were also found to have high influence on the predicted the unsaturated hydraulic conductivity of agricultural soils with a contribution percentage of 20.63 and 19.12%, respectively. Meanwhile, silt content, soil organic matter were also found to have moderate influence on the predicted the unsaturated hydraulic conductivity of agricultural soils with a contribution percentage of 13.6 and 12.62%, respectively. Finally, soil electric conductivity, soil sodium adsorption ratio and sand content in a soil were found to have lower influence on the predicted unsaturated hydraulic conductivity of agricultural soils with a contribution percentage of 6.88, 3.17 and 2.5%, respectively. However, McNeal and Coleman [54] reported that saturated hydraulic conductivity of soil decreased with decreasing total electrolyte concentration and increasing SAR values.

Table 6. Contribution percentage of eight independent variables used in the 8-8-14-1 ANN model for prediction of unsaturated hydraulic conductivity of agricultural soils

Input variables	Contribution (%)
Sand	2.5
Silt	13.06
Clay	22.02
EC	6.88
SAR	3.17
Organic matter	12.62
Initial soil water content	20.63
Soil bulk density	19.12

3.4 Performance of C# Application

To valid the C# application to predict unsaturated hydraulic conductivity of agricultural soils, an interface for input required data was developed as shown in Fig. (8). When the inputs were 82.9%, 13.08%, 4.02%, 4.6 dS/m, 2.08, 0.98%, 4.71% db and 1.36 g/cm^3 for sand, silt, clay, electric conductivity of soil, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density, respectively, the unsaturated hydraulic conductivity of soil obtained by the C# application was 0.001815 cm/sec (Fig. 9), meanwhile, the measured unsaturated hydraulic conductivity of soil was 0.001756 cm/sec. Also when the inputs were 86.92%, 6.04%, 7.04%, 2.9 dS/m, 2.15,0.62%,

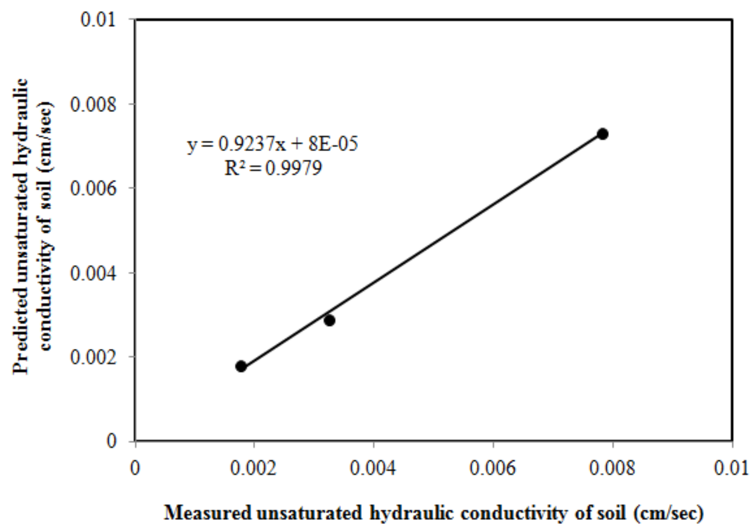

Fig. 7. Relationship between the measured and the predicted unsaturated hydraulic conductivity of soil during testing phase using the developed ANN model

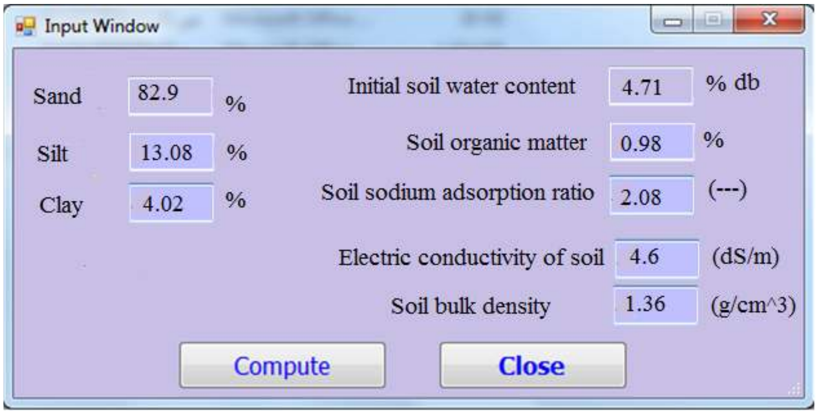

Fig. 8. Screenshot of interface for input required data for unsaturated hydraulic conductivity of soil prediction

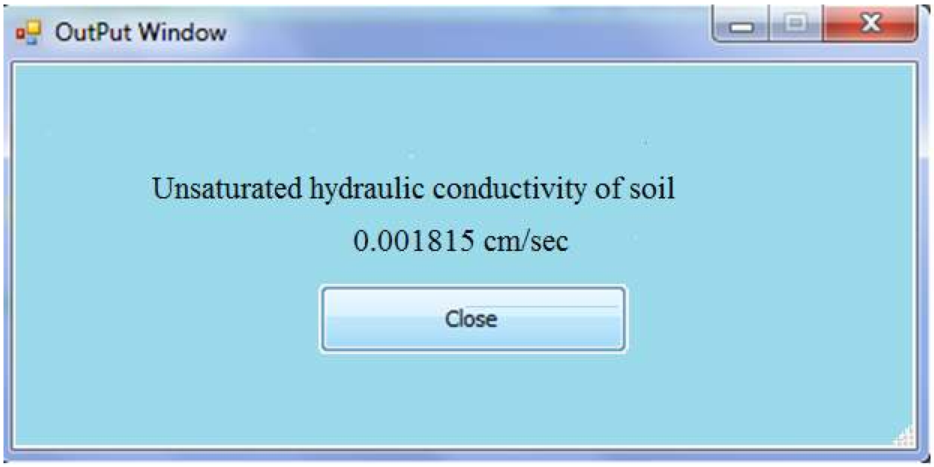

Fig. 9. Screenshot of computer interface for predicting unsaturated hydraulic conductivity of soil at specific input data

6.26% db and 1.41 g/cm^3 for sand, silt, clay, electric conductivity of soil, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density, respectively, the unsaturated hydraulic conductivity of soil obtained by the C# application was 0.002913 cm/sec, meanwhile, the measured unsaturated hydraulic conductivity of soil was 0.003228 cm/sec. Additionally, When the inputs were 90.95%, 6.04%, 3.02%, 0.69 dS/m, 3.73,1.14%, 4.87%db and 1.54 g/cm^3 for sand, silt, clay, electric conductivity of soil, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density, respectively, the unsaturated hydraulic conductivity of soil obtained by the C# application was 0.007336 cm/sec, meanwhile, the measured unsaturated hydraulic conductivity of soil was 0.007816 cm/sec.

4. CONCLUSION

As Saudi Arabia is semi-arid country, an applied model for prediction of unsaturated hydraulic conductivity of soil is needed for studying the moving of water in the unsaturated soil in order to prevent of water waste. The higher performance, higher prediction accuracy and ability to re-learn are important to create a powerful model. The results obtained from the study show that the ANN model learned the relationship between the eight input factors (sand, silt, clay, soil electric conductivity, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density) and unsaturated hydraulic conductivity of soil. The root mean squared error (0.000333251 cm/sec), mean relative error (4.184%) and mean absolute error (0.000284699 cm/sec) for testing data set were showed a small error between the actual and the predicted values of unsaturated hydraulic conductivity of agricultural soils, suggesting that the employed ANN model was very accurate in estimating the values of the unsaturated hydraulic conductivity of agricultural soils.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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