Predicting Point Estimation of Soil Water Retention Curve and Steady Infiltration Rate Using Artificial Neural Network

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ABSTRACT

The soil water retention curve and the infiltration rate are important parameters in many soil, hydrological, ecological and agricultural studies. They play the main role as the input parameters in models for water flow and solute transport in the vadose zone. In this study, Multilayer Artificial Neural Network: using the backpropagation algorithm were selected to estimate the point estimation of the soil water retention curve (i.e. $\Theta_{-10\ kPa}$, $\Theta_{-20\ kPa}$, $\Theta_{-33\ kPa}$, $\Theta_{-1000\ kPa}$ *and* $\Theta_{-1500\ kPa}$) and the steady infiltration rate (I_c) covering different types of Libyan soils. The activation function was selected LOGSIG in the middle and exist layers. The input data were consisted of the percentages of sand, silt and clay and bulk density (ρ_b) for point estimation and the percentage of sand, silt and clay, bulk density, saturated hydraulic conductivity (k_s) and the $\Theta_{-10\ kPa}$ for steady infiltration rate (I_c). The performance of the ANN models was evaluated against a set of data that never seen by the model during the training phase. The evaluation of ANN model was performed against pedotransfer functions developed by Minasny et al. (1999) to determine the point estimation ($\Theta_{-10\ kPa}$, $\Theta_{-33\ kPa}$, *and* $\Theta_{-1500\ kPa}$). Multivariable linear regression model (MLR) based on the percentage of silt, k_s and $\Theta_{-10\ kPa}$ was also developed to determine infiltration rate for evaluation purpose, as well. The results obtained in this study showed good agreement between the actual and the ANN simulated data for point estimation and the steady infiltration rate. The overall performance of the ANN models for some selected point estimation (i.e, $\Theta_{-10\ kPa}$, $\Theta_{-33\ kPa}$, *and* $\Theta_{-1500kPa}$) was better than that of Minasny et al. (1999) PTFs. The values of mean absolute error (MAE) and root mean square error (RMSE) were slightly smaller in ANN steady infiltration rate model compared to MLR model which was developed to estimate the I_c. Although the results of these comparisons encourage the capability of using ANN in practice, it would be valuable to have large local soil database from many different sites, in order to make a stronger assessment of the ANN models.

Keywords: Artificial neural networks, multivariable linear regressions, soil water retention curve, steady infiltration rate, Libyan soils

INTRODUCTION

Like many soil hydraulic properties, soil water retention curve and the infiltration rate are important parameters in many soil, hydrological, ecological and agricultural studies. They play the main role as critical input parameters in models for variably-saturated flow and contaminant transport, and often serve as integrated indices for soil quality (Lin, 2003).

Soil water retention curve, which is the points at a series of matric potentials or parameters of analytical soil water retention equations, is needed for the study of plant available water, infiltration, drainage, hydraulic conductivity, irrigation, water stress on plants and solute movement (Brady, 1974). Moisture percentages in field capacity and permanent wilting point are the most common soil moisture constants used in soil-plant-water relationships and influenced by soil texture, bulk density (ρ_b). Field capacity (FC) is sometimes defined as the upper limit of available of soil water content which corresponding to matric potential ranging from -10 kPa for sands to -50 kPa or more for very fine- textured soils. However, a matric potential of -33 kPa is used to define field capacity for most soils (Larry, 1988). The lower limit of the available soil moisture is permanent wilting point which occurs at -1500 kPa. On the other hand, among the various components of the hydrological cycle, it can be stated that the infiltration rate is one of the most important component. Along with precipitation, it determines the amount of water that becomes available to plants, the runoff and water supply from reservoirs groundwater. There are many methods of direct measurement that can be used to determine the soil water retention curve and the infiltration rate in the field or in the laboratory (Klute, 1986). The limitations of such measurements are subjected to specific ranges of applicability with respect to the soil type and generally quite cumbersome and requires a substantial investment in both time and money. So many attempts were made at estimating soil characteristics from readily available data, such as textural soil properties (i.e, particle-size distribution, and porosity), which are the most common measured soil data across the world. Such relationships is Pedotransfer functions (PTFs) approach which can be extremely powerful since it can either be used at the local scale using point textural properties or at the watershed scale, where textural information has been aggregated (Delleur, 1999). The majority of PTFs are completely empirical, although physico-emprical models and fractal theory models have also been developed (Sobieraj *et al*, 2001). Recent studies in PTFs development focus on the development of better functions to estimate soil hydraulic properties (soil water retention curve, hydraulic parameters, etc) for different geographical areas or soil types and determination of the most important basic soil properties as input (i.e., particle size data and bulk density, etc.). Pachepsky and Rawls (1999) and Merdum *et al.*, (2006) employed ANN and regression pedotransfer functions for prediction of soil water retention and saturated hydraulic conductivity functions and indicated that the differences between the two methods were not statistically significantThe crucial step in deriving PTFs is by forming empirical relationships between basic soil properties and parameters to be predicted.

This can be achieved by various mathematical methods, such as multivariable linear regression (Wösten *et al*, 1995). A recent approach for fitting PTFs is to use artificial neural networks (ANN) (Pachepsky *et al*, 1996 and Schaap *et al*, 1998 a). Neural network applications have diffused rapidly due to their functional characteristics, which provide many advantages over Multivariable linear regression approaches (Koekkoek and Booltink, 1999). The key advantage of using the neural network approach is that no relationships need to be assumed beforehand. Instead the network is trained to find the relationship.

The purpose of this paper is to estimate the main points of soil water retention curve which included the moisture content at -10, -20, -33, -1000 and -1500 kPa and the steady final infiltration rate from basic soil physics properties using artificial neural network (ANN). In addition, the performance of the new method is evaluated and compared with the other developed PTFs.

MATERIAL AND METHODS

Theoretical concept and structure of feed-forward backpropagation

The feed-forward backpropagation neural network model was suggested and developed to be used as a tool to determine the soil water retention curve as represented by point estimation and the steady infiltration rate. The error backpropagation learning algorithm (Rumelhart *et al.*, 1986) which is a form of supervised learning was used as training algorithm to train ANN. The Error back propagation learning algorithm consists of two passes of computation through the different layers of the network a forward pass and a backward pass (Jacek, 1995). In the forward pass, the input vector is applied to the input nodes of network and its effect propagates to the units in the first layer and each unit produces a set of outputs. The outputs of these units are propagated to units in subsequent layers and this process continues. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weight of the networks are all fixed. The process of the forward pass can be summarized in mathematical form as follows

$$s_i = \sum_{i=1}^{k} w_{ij} y_i + \theta_i \quad 1$$

$$\hat{y}_i = f(s_i) \quad 2$$

Where w_{ji} = (w_{1i}, w_{2i}, .. w_{ki}) is the weight vector of unit i and k is the number of neurons in the layer that includes unit i. , y_i is the output from unit j, θ_i is the bias of unit i, s_i is the incoming signal of unit I, $\hat{y}$ is the estimated output vector, f is the transfer function. During the back pass the synaptic weights are all adjusted in accordance with an error-correction rule. The actual response of the network is subtracted from the desired response to produce an error signal which given by,

$$E(n) = \frac{1}{2}(Y'(n) - Y(n))^2 \qquad 3$$

Where $\hat{y}_i$ is the estimated state of the output unit in response to the n^{th} input exemplar and Y(n) is desired state of the output unit. This error signal is then propagated backward through the network against the direction of synaptic conditions. The synaptic weights are adjusted to make the actual response of the network move closer to the desired response.

The adjusted weight is defined by

$$\Delta w'_{ij}(n+1) = -\eta \frac{\partial E}{\partial w_{ji}} - \xi \Delta w'_{ji}(n) \qquad 4$$

Where η represents the learning rate, ξ is a constant (momentum term) that determines the effect of past weight changes on current weight change. However, when the error is acceptably small for all of the training pattern pairs, training can be discontinued. .

Parameter selection criteria and modeling

Multilayer networks using the backpropagation algorithm were selected to construct the network. Levenberg-Marquardt (LM) training algorithm was used. The hidden layers for both models started with a small number of neurons and increased progressively until the optimum structure was reached. The selection of the optimum network structure was performed by trial and error. Sigmoid transfer function is commonly used in multilayer networks that are trained using the backpropagation algorithm. The Log-sigmoid transfer function was used in the hidden and output layers. The structure of a feed-forward ANN is shown in Figure 1. This ANN is a popular neural network which known as the back propagation algorithm introduced by Karaca and Ozkaya (2006).

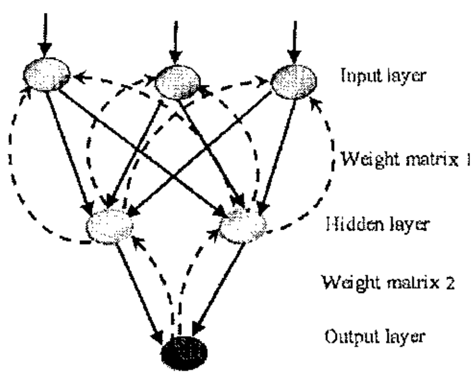

Figure 1: A typical three-layer feed-forward ANN

To build up and evaluate the ANN model independent datasets were acquired from many previous local studies on different areas of Libya (Great Man-Made River, 1997 and 1998; Alaswad, 1997 and Alzlait, 2000). The summary of the parameters and the statistics data sets soils are given in Table 1.

The data set was divided into three sections: the first section was used for training, the second was used for testing and the third was used to verify the ANN. The model output from the verifying phase was compared to the observed data and examined to evaluate the model performance with a data that was never seen by the model during the training stage.

In this study, it was suggested that the soil water retention characteristic is a function of soil particle distribution and bulk density. Many studies reported that the soil water retention characteristic and infiltration rate are strongly related to the particle-size distribution and bulk density (Gupta and Larson 1979 and Ghosh 1980). It was assumed that the retention curve could be represented by five point estimation at pre-defined potential, i.e., -10, -20, -33, -1000 and -1500 kPa, respectively. However, soil particle distribution which represented by the percent of sand, silt and clay and the bulk density (gm/ cm^3) of soil was selected to represent the input layer in the neural network sets. The outputs from the soil water retention ANN model were single- point estimation, i.e., the moisture contents at -10 , -20, -33, -1000 and -1500 kPa.

Table 1: Statistics of physical soil properties used in this study

models	Soil properties	Number of samples	Minimum	Maximum	Mean	Standard Deviation
$\theta_{-10\ kPa}$	Sand (%)	143	8.36	100	69.13	25.71
	Silt (%)	143	0	64.80	19.54	17.29
	Clay (%)	143	0	54.84	11.11	11.06
	ρ_b (gm cm^{-3})	143	1.24	1.73	1.48	0.13
	$\theta_{-10\ kPa}$ $(cm^3\ cm^{-3})$	143	2.09	44.86	18.53	12.58
$\theta_{-20\ kPa}$	Sand (%)	80	8.36	100	63.40	30.77
	Silt (%)	80	0	64.80	23.84	20.99
	Clay (%)	80	0	54.84	12.38	12.76
	ρ_b (gm cm^{-3})	80	1.24	1.61	1.39	0.09
	$\theta_{-20\ kPa}$ $(cm^3\ cm^{-3})$	80	0.99	36.31	17.32	11.81
$\theta_{-33\ kPa}$	Sand (%)	119	8.36	100	57.16	27.40
	Silt (%)	119	0	64.80	26.14	18.20
	Clay (%)	119	0	54.84	16.45	12.79
	ρ_b (gm cm^{-3})D_p	119	1.22	1.79	1.445	0.13
	$\theta_{-33\ kPa}$ $(cm^3\ cm^{-3})$	119	0.88	34.10	17.06	10.02
$\theta_{-1000\ kPa}$	Sand (%)	80	8.36	100	63.40	30.77
	Silt (%)	80	0	64.80	23.84	20.99
	Clay (%)	80	0	54.84	12.38	12.76
	ρ_b (gm cm^{-3})	80	1.24	1.61	1.39	0.09
	$\theta_{-1000\ kPa}$ $(cm^3\ cm^{-3})$	80	0.64	26.04	11.22	8.73
$\theta_{-1500\ kPar}$	Sand (%)	102	20.55	98.81	64.15	20.42
	Silt (%)	102	0.36	54.30	20.48	11.78
	Clay (%)	102	0.18	53.20	15.36	11.00
	ρ_b (gm cm^{-3})	102	1.22	1.79	1.57	0.11
	$\theta_{-1500\ kPar}$ $(cm^3\ cm^{-3})$	102	0.63	18.59	6.17	3.93
I_c	Sand (%)	159	4.70	95.90	65.20	29.55
	Silt (%)	159	0.30	60.00	15.72	16.65
	Clay (%)	159	0.38	88.50	19.06	18.36
	ρ_b (gm cm^{-3})	159	1.17	1.75	1.52	0.12
	K_s (cm h^{-1})	159	0.06	19.20	4.44	4.49
	$\theta_{-10\ kPa}$ $(cm^3\ cm^{-3})$	159	6.55	43.45	24.51	7.98
	I_c (cm h^{-1})	159	0.50	19.20	4.85	4.96

The input parameters (table 1) which used to develop the steady infiltration rate (I_c) model were selected based on theoretical studies. Such studies revealed that the infiltration rate is a function of saturated hydraulic conductivity, soil particle distribution and the matric potential behind the wetting front (Springer and Cundy, 1987, Bohne *et al.* 1993, Mishra and Parker, 1990 and Mahdian *et al* 2009). The input data used to perform the neural network for infiltration model included, the percentage of sand, silt and clay, bulk density (ρ_b), soil moisture content at -10 kPa ($\Theta_{-10\ kPa}$) and saturated hydraulic conductivity (k_s). The output for the steady infiltration rate ANN model was steady infiltration rate (cm/h) only. All data were processed and loaded into the neural modeling application Matlab® Version 7.0 of Neural Network Toolbox -Graphical User Interface (Demuth and Beale 1998) to develop the ANN.

2.3 Evaluation of performance

The adequacy of the ANN evaporation models was evaluated by several statistical measures, such as mean absolute error (MAE), root mean square error (RMSE), correlation coefficient(r), and index of agreement (d_2) and the linear regression equation with intercept equals zero. These statistical criteria can be calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \qquad 5$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \qquad 6$$

$$d_2 = 1 - \frac{\sum_{i=1}^{n}|\hat{Y}_i - Y_i|^2}{\sum_{i=1}^{n}(|\hat{Y}_i - \bar{Y}_i| + |Y_i - \bar{Y}_i|)^2} \qquad 8$$

Where, n is the total number of events considered. Y_i ad $\hat{Y}_i$ are the observed and predicted of the ith output, respectively And $\overline{Y}$ is the mean of the observed output.

The closer the MAE and RMSE is to zero closer to the better accuracy, while the closer the r and d_2 is to one closer to the better accuracy.

The linear regression equation with intercept equals zero was also used to determine the goodness of the predicted model. The general form of this equation is expressed as

$$y = \alpha x \qquad 9$$

Where *y* represent the simulated data, α the slope of the regression line and *x* represents the actual data.
The closer the slope is to 1 the better is the general predictive power of the model. A correlation analysis was performed between the actual and simulated data. The value of coefficient of determination (r^2) given in the correlation analysis would indicate the accuracy of the predictions. In addition, the results of comparison between the actual and simulated data were plotted against a 1:1 line. In case of perfect prediction all paired data would fall on the line across the graph signifying a slope of one (simulated= actual).

To verify the reliability of the ANN model, data other than those used in the training and testing phases are needed. Therefore some of the collected data were truncated for verification purpose. Moreover, a series of pedotransfer functions (PTFs) for predicting soil water retention after Minasny *et al.* (1999) were selected for determining the accuracy of the developed ANN model. These pedotransfer functions are expressed as:

$$\theta_{-10\,kPa} = 0.6561 - 2.8\times10^{-3}\ Sand - 0.141\rho_b + 1.9\times10^{-5}\ Sand.Clay \qquad 10$$

$$\theta_{-33\,kPa} = 0.5482 - 3.3\times10^{-3}\ Sand - 0.1\ \rho_b + 4.1\times10^{-5}\ Sand.Clay + 2.4\times10^{-5}\ Sand.Silt \qquad 11$$

$$\theta_{-1500\,kPa} = 0.26 + 9.2\times10^{-4}\ Clay - 2.7\times10^{-3}\ Sand + 8.58\times10^{-3}\ \rho_b + 1.64\times10^{-5}\ Clay.Sand \qquad 12$$

Where, $\theta_{-10\,kPa}$ is the volumetric water content at - 10 kPa, $\theta_{-33\,kPa}$ is the volumetric water content at - 33 kPa, $\theta_{-1500\,kPa}$ volumetric water content at -1500 kPa, *Clay* is the mass (%) of particles <0.002 mm, *Silt* is the mass (%) of particles (0.002 –0.20 mm), *Sand* is the mass (%)of particles 0.20–2 mm, and ρ_b is the bulk density (gm/cm^3).
Unfortunately, there is no available published PTFs has been constructed based on the suggested inputs (i.e., soil particle distribution, bulk density, soil moisture content at -10kPa and saturated hydraulic conductivity) could be used to verify the ANN model for steady infiltration rate. Therefore, it was suggested to build PTFs by the same available collected data which used to develop the steady infiltration rate ANN model. Such verification will show the accuracy of the ANN model compared to PTFs. The most common method used in estimation PTFs is to employ multivariable linear regressions (MLR). The suggested form of the regression equation is:

$$I_c = b_0 + b_1\ Sand + b_2\ Silt + b_3\ Clay + b_4\ \rho_b + b_5 K_s + b_6\ \theta_{-10\,kPa} \qquad 13$$

Where ; I_c is the steady infiltration rate (cm/ h), b_0 is the constant of regression, b_1, b_2, b_3, b_4, b_5 and b_6 are regression coefficients, ρ_b is the bulk density (gm/cm^3). and k_s is the saturated hydraulic conductivity (cm/ h). The soil particles distribution (i.e., Sand, Silt and Clay) are in percentage. The statistical package Minitab® version 14 was used to analyses the data.

RESULTS AND DISCUSSIONS

The optimum models structure of the point estimation of the soil water retention characteristic (i.e., $\Theta_{-10\ kPa}$, $\Theta_{-20\ kPa}$, $\Theta_{-33\ kPa}$, $\Theta_{-1000\ kPa}$ and $\Theta_{-1500\ kPa}$) and the steady infiltration rate (I_c) were accomplished through trial and error operations to determine the number of hidden layers. The input layer composed of 4 and 6 neurons for soil water retention characteristic and infiltration rate models, respectively. The output layer has only one neuron for each soil water retention characteristic and infiltration rate. The hidden layer was started with small number of neurons and increased progressively until the optimum structure was reached. Table 2 shows the neural network parameters used to specify the soil water retention characteristic and infiltration rate. The data sets were divided into three parts, (56 to 65%) of the data was used in the training phase, (13 to 19 %) of the data was used in the testing phase, while (19 to 25%) was used for verification purpose. The training phase reflects the repeat feature of an ANN model, while, the testing phase reflects the generalization feature. The verification involves evaluating the neural network performance on a set of test problems that were not used for training. If the results of comparisons between the actual and predicted data indicated high coincidence, it could then be reliably recommended in practice. Figure 2 plots the results of the simulated results via ANN models and the actual $\Theta_{-10\ kPa}$, $\Theta_{-20\ kPa}$, $\Theta_{-33\ kPa}$, $\Theta_{-1000\ kPa}$ and $\Theta_{-1500\ kPa}$ and I_c during training phase. As can be seen from the figure, there is high accordance between actual and simulated data of both soil moisture content at different matric potentials and infiltration rate whereas the actual data were closely matched by the simulated results by ANN.

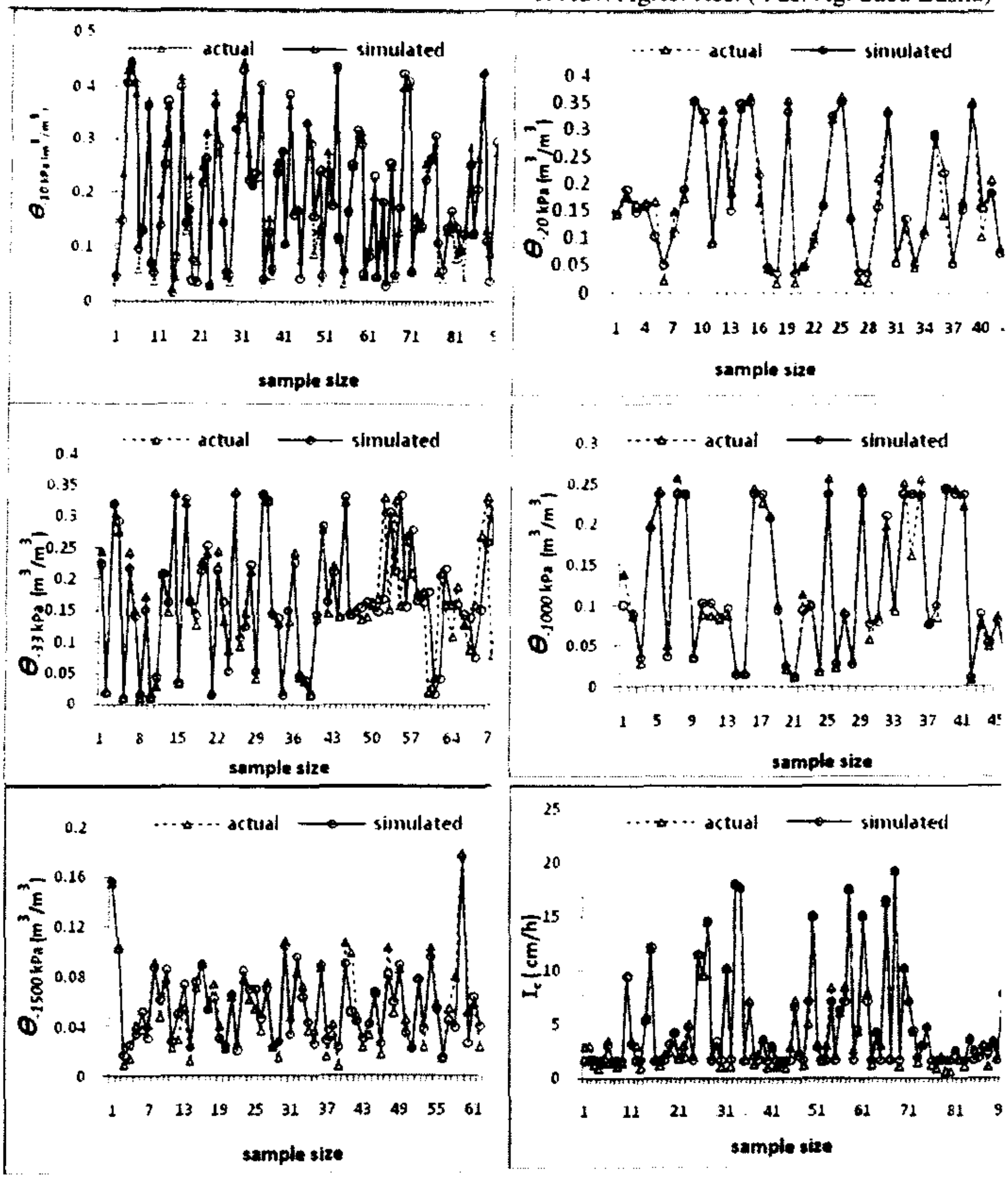

Figure 2: Actual and simulated soil moisture content (m^3/m^3) and steady infiltration rate (cm/ h) during training phase.

Table 2: Neural network parameters

Model	Number of neurons			Number of data sample		
	inputs	hidden	outputs	training	testing	verification
$\Theta_{-10\ kPa}$	4	5	1	93	20	30
$\Theta_{-20\ kPa}$	4	4	1	45	15	20
$\Theta_{-33\ kPa}$	4	4	1	75	20	22
$\Theta_{-1000\ kPa}$	4	5	1	45	15	20
$\Theta_{-1500\ kPa}$	4	4	1	62	20	20
I_c	6	10	1	96	30	33

In case of the point estimation of the soil water retention, the results of statistical analysis indicated that the MAE, and RMSE are generally close to their optimum values, Table 3.

The maximum values of MAE and RMSE are 0.037 and 0.067 m^3/m^3, respectively. It can also be noted that the minimum value of r and d_2 are 0.74 and 0.93, respectively. Even though these values represent the worst findings, they are very close to their optimum limit. The slope of the best-fit line (α) with interception equal to zero fluctuated from 0.96 to 0.99 with determination coefficients (r^2) which ranged from 0.85 to 0.97, indicating slight underestimation of the soil water retention characteristic. The same trend was observed with infiltration rate estimation. The calculated performance indicators, i.e., MAE, RMSE, r, d_2, α and r^2 are 0.45 cm/h, 0.64 cm/h, 0.99, 0.90, 0.989, and 0.99 respectively. Such results indicated that the ANN models during training phase have high predictive power and ability to track the path of the actual observations.

Table 3: The performance indicators for point estimation after training phase

Models	MAE (m^3/m^3)	RMSE (m^3/m^3)	R	d_2	α	r^2
$\Theta_{-10\ kPa}$	0.022	0.031	0.97	0.98	0.98	0.93
$\Theta_{-20\ kPa}$	0.017	0.020	0.97	0.98	0.99	0.95
$\Theta_{-33\ kPa}$	0.037	0.064	0.74	0.97	0.99	0.95
$\Theta_{-1000\ kPa}$	0.009	0.015	0.98	0.99	0.99	0.97
$\Theta_{-1500\ kPa}$	0.007	0.017	0.93	0.99	0.96	0.85

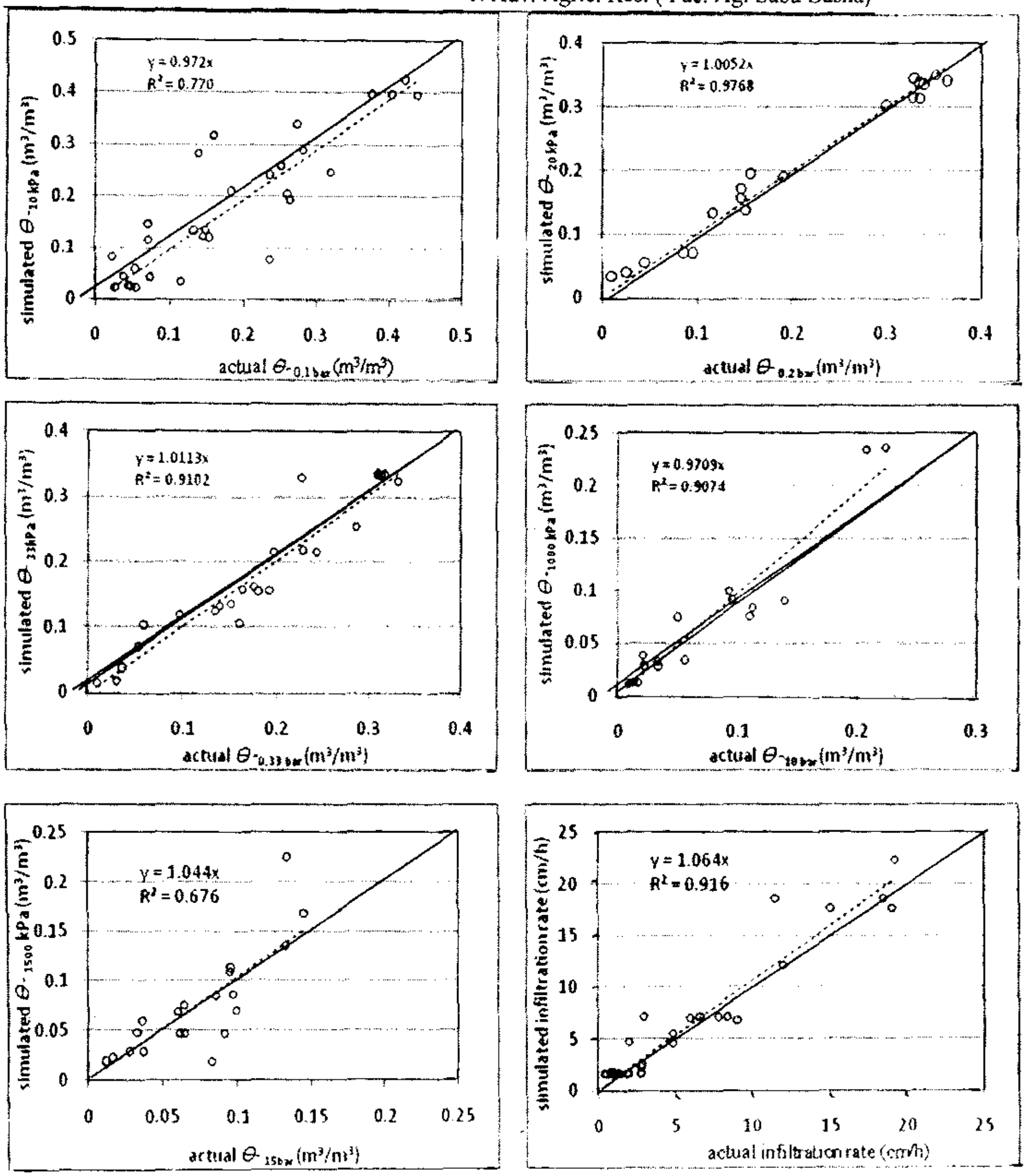

Figure 3. The scatter plot of the actual versus simulated Θand I_c during training phase

The performance of the model was further evaluated using the independent data which did not included during training phase. Hence the results of comparisons between the actual and simulated data indicated high coincidence; it could then be enable the model's users to estimate the point estimation of soil water retention characteristic and steady infiltration rate. The simulated data of the soil water retention data and infiltration rate as obtained from the ANN model versus the actual data is presented in scattergram as shown in Figure 3. Graphical depiction shows that the point are uniformly scattered around the line 1:1 line with slope of 0.97, 1.00, 1.01, 0.97, 1.04 and 1.064 $\Theta_{-10\ kPa}$, $\Theta_{-20\ kPa}$, $\Theta_{-33\ kPa}$, $\Theta_{-1000\ kPa}$, $\Theta_{-1500\ kPa}$ and I_c, respectively.

The coefficient of determination r^2 of the linear regression was found to be 0.77, 0.97, 0.91, 0.90, 0.67 and 0.91 for $\Theta_{-10\ kPa}$, $\Theta_{-20\ kPa}$, $\Theta_{-33\ kPa}$, $\Theta_{-1000\ kPa}$, $\Theta_{-1500\ kPa}$ and I_c, respectively. Since the value of r^2 could be interpreted as the proportion of variation in actual values that explained by the fitted model, this value indicates that the ANN models predictions in the soil water retention and infiltration rate were reasonably good.

Table 4 shows the performance indicators, i.e., MAE, RMSE, r and d_2 for soil water retention. As can be seen these values fluctuated from (0.015 to 0.042 m^3/m^3), (0.014 to 0.061 m^3/m^3), (0.76 to 0.99) and (0.93 to 0.99) for MAE, RMSE, r and d_2, respectively.

The performance indicators for the I_c are 1.19 cm/h, 1.68 cm/h, 0.94 and 0.98 for MAE RMSE, r and d_2, respectively.

Table 4: The performance indicators for point estimation after verifying phase

Models	MAE (m^3/m^3)	RMSE (m^3/m^3)	R	d_2	α	r^2
$\Theta_{-10\ kPa}$	0.042	0.061	0.76	0.93	0.97	0.77
$\Theta_{-20\ kPa}$	0.015	0.017	0.99	0.99	1.00	0.97
$\Theta_{-33\ kPa}$	0.023	0.0311	0.94	0.99	1.01	0.91
$\Theta_{-1000\ kPa}$	0.0154	0.020	0.95	0.99	0.97	0.90
$\Theta_{-1500\ kPa}$	0.0121	0.014	0.99	0.99	1.04	0.67

However, the results of the comparison between the actual and simulated data for both point estimation of the soil water retention and the I_c indicate a reasonable agreement and suggested that the ANN models performed well considering the discrepancies may be resulting from model and experimental error.

Comparisons between different ANN and Minasny et al. (1999) PTFs developed to estimate moisture content at -10, - 33 and -1500 kPa are shown in figures 4. It is clear from the figure, there is high accordance between actual and ANN predicted data compared with Minasny et al. (1999) PTFs. The reliability of the ANN model and Minasny et al. (1999) PTFs predictions can be estimated also from the Table 5. The values of the performance indicators support the findings as mentioned previously, whereas their values are closed to their optimum in case of the ANN models compared to Minasny et al. (1999) PTFs. For instance, the error percentage was found to be -3%, 1% and 4% in ANN model compared to +21%, 93% and 93% in Minasny et al. (1999) PTFs for Θ-10 kPa, Θ-33 kPa and Θ-1500 kPa , respectivelyThe discrepancies may be attributed to the fact that Minasny *et al.* (1999) PTFs model was developed based on basic soil properties data across Australia. This is consistent with both theory and studies in other parts in the world. For instance, van den Berg *et al.* (1997) and Amini *et al.* (2005) also reported similar results where the neural network-based models provided more reliable predictions than the PTFs model. Schaap *et al.* (1998b) estimated van Genuchten parameters for 1209 soil samples from the US using ANN. They distinguished their PTFs based on available in formation level: texture class; clay, silt and sand; texture + bulk density; texture +bulk density + measured θ at -33 and -1500 kPa. They found that ANN performed better than four published PTFs and accuracy of prediction generally increased if more input data are used, but there was always a considerable difference between predicted and measured values. Koekkoek and Booltink (1999) applied similar approach to estimate soil water retention at different potentials from Dutch and Scottish data bases. They found that ANN performed somewhat better than PTFs of Gupta and Larson (1979). A multivariable linear regression approach (MLR) using *Minitab* 14 statistical package was used to find out the best-fit coefficients for Equation 13.

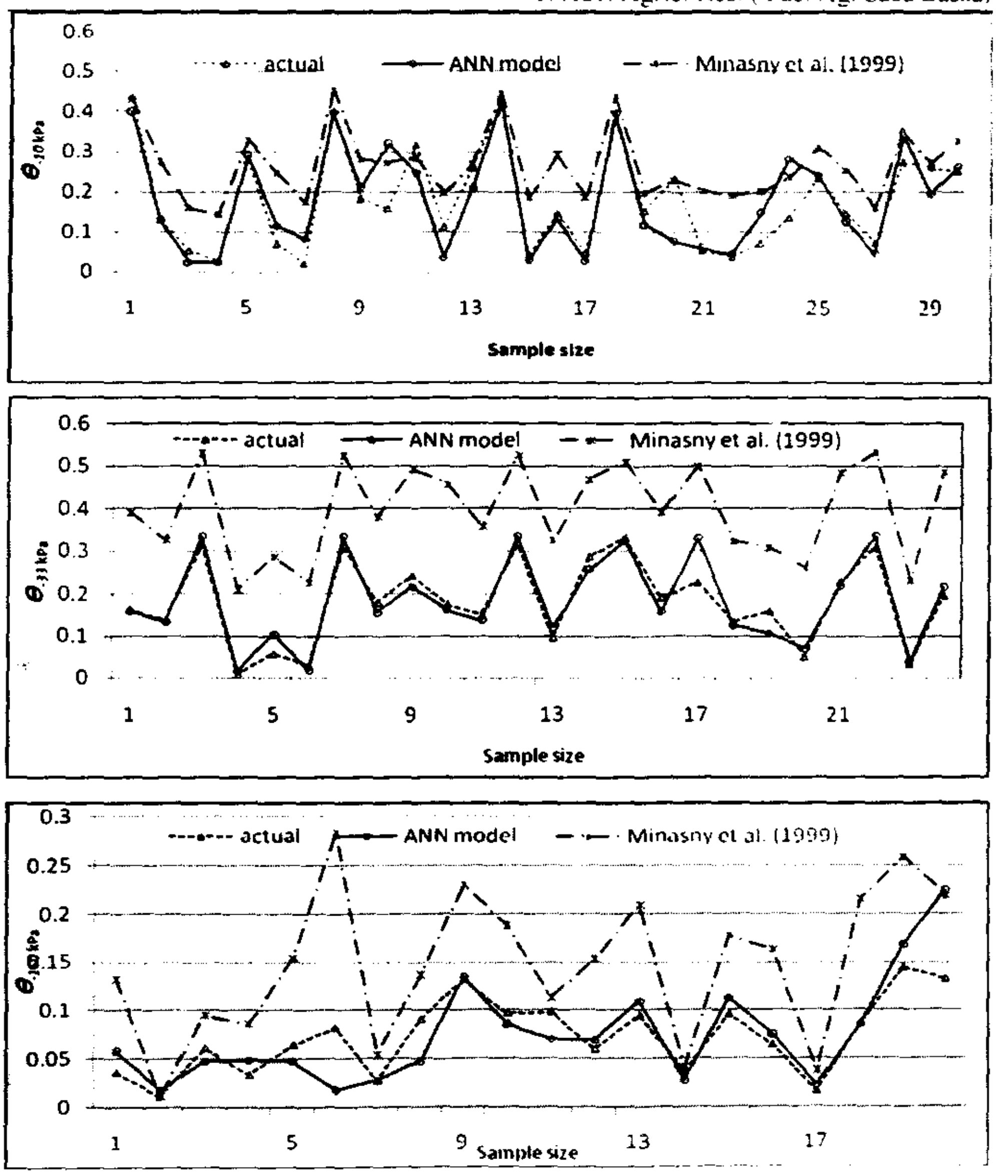

Figure 4: Comparison between ANN model and Minasny *et al.* (1999) PTFs for predicting $\Theta_{-10\,kPa}$,$\Theta_{-33\,kPa}$, $\Theta_{-1500\,kPa}$

The results of the regression analysis showed that the saturated hydraulic conductivity, moisture content at -10 kPa and silt (%), were significantly correlated with the I_c whereas

(r= 0.84, t-value at probability level $P<0.05$).

Table 5. Comparison of ANN model and Minasny et al. (1999) performance in predicting θ at -10, -33, -1500 kPa the verification set

Models		MAE (m^3/m^3)	RMSE (m^3/m^3)	r	d_2	α	r^2
$\theta_{-10\ kPa}$	ANN model	0.042	0.061	0.76	0.93	0.97	0.77
	Minasny et al. (1999)	0.088	0.101	0.95	0.83	1.21	-0.08
$\theta_{-33\ kPa}$	ANN model	0.023	0.031	0.94	0.99	1.01	0.91
	Minasny et al. (1999)	0.215	0.218	0.95	0.84	1.93	0.03
$\theta_{-1500\ kPa}$	ANN model	0.012	0.014	0.99	0.99	1.04	0.67
	Minasny et al. (1999)	0.057	0.077	0.81	0.93	1.93	0.65

Similarly, Mbagwu (1995) reported that the k_s was significantly related to I_c on 18 sites with different land use histories on a watershed in the Nsukka plains of southeastern Nigeria.The similar results were also obtained by Canarache *et al.* (1968). They found that the steady state infiltration rate depended on the initial moisture content, total porosity, non capillary porosity and hydraulic conductivity.

The estimated coefficients of the I_c equation and statistical tests are presented in Table 6.

The derived multivariable -linear regression infiltration rate I_c model is as follows:

$$I_c = 4.648 + 0.821\ k_s - 0.168\ \theta_{-10\ kPa} + 0.043\ Silt \qquad 14$$

Table 6: Coefficients and diagnostic tests for multivariable-linear regression model for steady infiltration rate

Predictor variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	4.648	0.973	4.775	0.000
K_s	0.821	0.065	12.559	0.000
$\theta_{-10\,kPa}$	-0.168	0.041	-4.082	0.000
Silt	0.043	0.020	2.121	0.036

The multivariable linear regression model (MLR) was used to evaluate the steady infiltration rate ANN model. The comparison between the actual data of the I_c and those predicted from the ANN and MLR models is shown in Figure 5. As can be seen from the figure, there is high accordance between actual and predicted data of I_c whereas the actual data was closely matched by the predicted data.

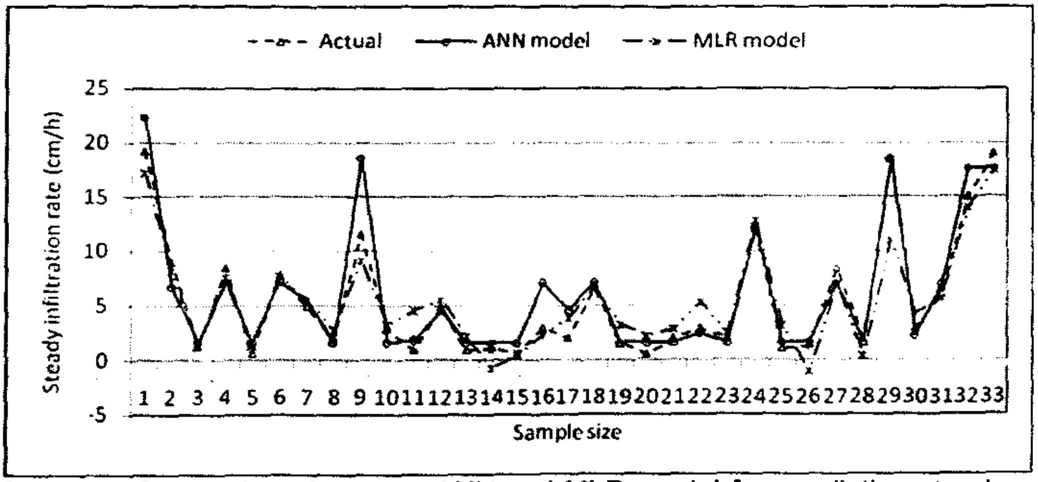

Figure 5: Comparison between ANN and MLR model for predicting steady infiltration rate

The reliability of the ANN and the MLR models predictions can be estimated also from the Figure 6 where the predicted data was plotted versus the actual. The figure shows also the equity line and best fitted line for the observed and the predicted of the I_c. The points are closely lie on and around the 1:1 line with slope value found to be 1.064 and 0.879, with determination coefficient of 0.91 and 0.86 for ANN and MLR models, respectively. The slope values reveal that the percent error between the actual and predicted data is + 6.4 % and – 12% for ANN and MLR models, respectively.

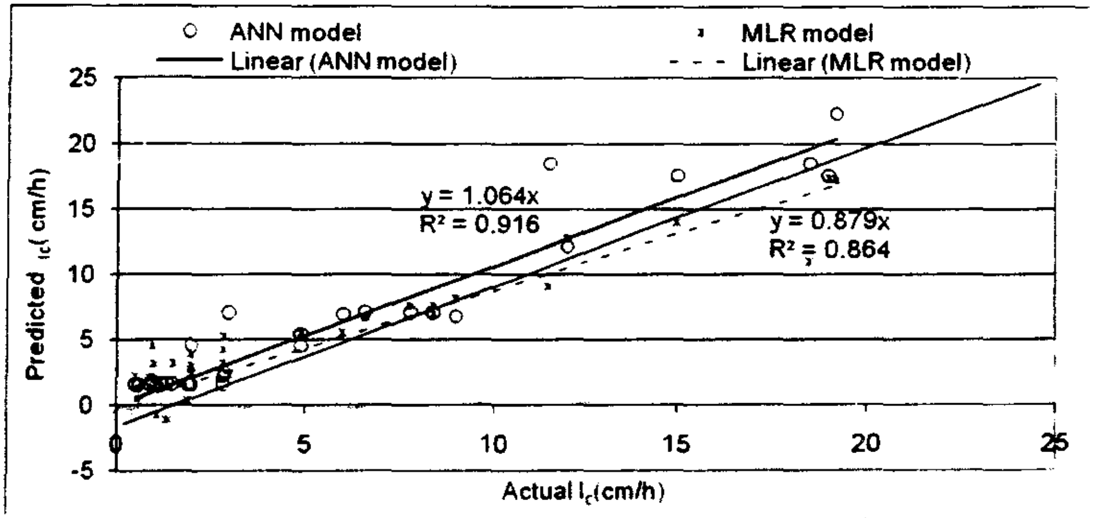

Figure 6. The scatter plot of the actual versus the simulated I_c

Table 7 shows the performance indicators for ANN and MLR models and suggested that both models performed well considering the discrepancies may be resulting from the model and the experimental error. The values of MAE, RMSE are slightly smaller in ANN model compared to MLR. The similar results have been reported by the Tamari *et al.* (1996), as well. They found that using artificial neural network leads to less RMSE values than the multivariable linear regression. Koekkoek and Booltink (1999) also reported that ANN performed slightly better, but the differences were not significant. Even though these results indicate a reasonable agreement between the ANN and MLR models for predicting the I_c, ANN model is a more realistic and reliable since it does not predict negative I_c values, as is the case with the MLR using the untransformed data.

Table 7. Comparison of ANN and MLR models performance in predicting steady infiltration rate

Models	MAE (cm/h)	RMSE (cm/h)	R	d_2
ANN	1.19	1.82	0.95	0.98
MLR	1.41	1.95	0.95	0.97

CONCLUSION

The results obtained showed very good agreement between the measured point estimation (i.e., $\Theta_{-10\ kPa}$, $\Theta_{-20\ kPa}$, $\Theta_{-33\ kPa}$, $\Theta_{-1000\ kPa}$ and $\Theta_{-1500\ kPa}$) and the steady infiltration rate (I_c) by ANN moaels during training phase. The performance resulted in R^2 values of 0.74–0.98 in the point estimation using ANN model and 0.99 for infiltration rate ANN model. ANN models also provided quite acceptable estimates of point estimation and infiltration rate in spite of the use independent data which did not included during training phase. The overall performance of the ANN models for some point estimation (i.e., $\Theta_{-10\ kPa}$, $\Theta_{-33\ kPa}$, and $\Theta_{-1500\ kPa}$) was better than that of Minasny *et al.* (1999) PTFs. The error percentage was found to be -3%, 1% and 4% in ANN model compared to +21%, 93% and 93% in Minasny *et al.* (1999) PTFs for $\Theta_{-10\ kPa}$, $\Theta_{-33\ kPa}$, and $\Theta_{-1500\ kPa}$, respectively. The discrepancies may be attributed to the fact that Minasny *et al.* (1999) PTFs model was developed based on the basic soil properties data across Australia. The values of MAE and RMSE were slightly smaller in ANN infiltration model compared to Multivariable linear regression model which developed to estimate the infiltration rate. The higher accordance between ANN and MLR models in case of infiltration rate predictions may be explained by the fact that the ANN and MLR models were they both developed from the same data set of Libyan soils. However, it would be valuable to have large local soil database from many different sites, in order to make a stronger assessment of the ANN models.

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الملخص العربى

التبؤ بالتقدير النقطي لمنحنى احتفاظ التربة بالماء ومعدل الرشح الثابت باستخدام الشبكات العصبية الاصطناعية

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إن منحنى احتفاظ التربة بالرطوبة ومعدل الرشح من البارمترات المهمة في العديد من دراسات التربة والبيئة والزراعة. كما أنهما يلعبان الدور الرئيسي كأهم المدخلات في نماذج تدفق المياه والمذيبات في منطقة الفادوز. في هذه الدراسة، تم استعمال الشبكات العصبية الاصطناعية متعددة الطبقات باستخدام خوارزمية الانتشار العكسي للتقدير النقطي لمنحنى احتفاظ التربة بالماء عند قيم ضغط – 10، –20، – 33، – 10000، –15000 كيلو باسكال وكذلك لتقدير معدل الرشح الثابت لبعض الترب الليبية. تم استعمال دالة تنشيط لوغارتمية وذلك خلال الطبقة الوسطى والنهائية. البيانات التي تم استعمالها كمدخلات تحتوي على نسبة الرمل، السلت، الطين، الكثافة الظاهرية وذلك في حالة التقدير النقطي، أما في حالة معدل الرشح الثابت فان هذه المدخلات اشتملت على نسبة الرمل، السلت، الطين، الكثافة الظاهرية، معامل التوصيل الهيدروليكي التشبعي وكذلك على المحتوى الرطوبي الحجمي للتربة عند قيمة ضغط – 10

كيلوباسكال. تم تقييم أداء نماذج الشبكات العصبية الاصطناعية بمقارنتها بمجموعه من البيانات التي لم يتم استخدامها خلال مرحلة تدريب الشبكات العصبية الاصطناعية. كما تم اجراء تقييم لأداء نماذج الشبكات العصبية الاصطناعية بمقارنتها بمعادلات خواص التربة المطورة من قبل .Minasny et al (1999) لتحديد نقطة التقدير على منحنى احتفاظ التربة بالماء عند قيم ضغط – 10، -20، -33، -10000، -15000 كيلو باسكال. كما تم تطوير نموذج منحنى انحدار متعدد المتغيرات بناء على نسبة السلت ومعامل التوصيل الهيدروليكي التشبعي و المحتوى الرطوبي الحجمي عند – 10 كيلو باسكال وذلك لغرض عملية التقييم. ولقد دلت النتائج المتحصل عليها أن هناك دقة جيدة للشبكات العصبية الاصطناعية لكل من التقدير النقطي ومعدل الرشح الثابت. إن الاداء العام للشبكات العصبية الاصطناعية لبعض نقط التقدير المختارة على منحنى احتفاظ التربة بالماء عند قيم ضغط – 10، ، -33، 1000، -15000 كيلو باسكال كانت أفضل من تلك المتنبأ بها من قبل .Minasny et al (1999). كما أن قيم متوسط الخطأ المطلق والجذر التربيعي لمتوسط مربع الخطأ كانت أقل انخفاضا عند استعمال الشبكات العصبية الاصطناعية في تقدير معدل الرشح الثابت مقارنة بنموذج منحنى انحدار متعدد المتغيرات الذي تم تطويره لتقدير معدل الرشح الثابت. وعلى الرغم من أن نتائج هذه المقارنات تشجع القدرة على استعمال الشبكات العصبية الاصطناعية في الممارسات العملية ، إلا أنه من المفيد استعمال قاعدة بيانات محلية كبيرة ومن مواقع مختلفة وذلك لإجراء تقييم أكثر كفاءة للشبكات العصبية الاصطناعية.