

Original Research Article

Calibration of soil water content data from EnviroSCAN system using artificial neural network

ABSTRACT

Irrigation is one of the essential problems of agriculture in developing countries. Usually in these developing countries unqualified farmers are likely use more water than required by manual techniques hence wasting them. Hence, soil moisture sensors are typically needed in such situations to indicate to the former when it is needed to irrigate the field and when not needed. One of these sensors is EnviroSCAN system. It has a potential to monitor and estimate soil water content continuously at various soil depths and the calibration accuracy of it is important job to obtain accurate results. In this study, volumetric soil water content and scaled frequency from EnviroSCAN system were recorded throughout a 60-cm- soil profile. An artificial neural network (ANN) was used for calibration of soil water content compared with regression analysis using field data at different soil depths in sandy clay loam soil. Several ANN architectures were employed in order to determine the optimum architecture. Coefficients of determination (R^2) of regression calibration equation of scaled frequency against soil water content were 0.9225, 0.9623 and 0.9593 for 0-20 cm, 20-30 cm and 30-60 cm soil depth. The R^2 between gravimetric soil water content and the estimated by ANN for 0-20 cm soil depth was 0.9928, for 20-30 cm soil depth; 0.9809 and for 30-60 cm soil depth, it was 0.9878. Using the data set from the entire 60-cm soil profile for calibration by ANN, the R^2 value was 0.9715.

Keywords: Soil water content, artificial neural network, calibration, EnviroSCAN system.

1. INTRODUCTION

Irrigation is one of the essential problems of agriculture in developing countries. Usually in these developing countries **unqualified** farmers are likely use more **water** than required by manual techniques hence **wasting them**. Soil moisture sensors are typically needed in such situations to indicate to the former when it is needed to irrigate the field and when not needed [1]. Besides, on-line sensors for real-time measurement of soil water content can be particularly useful tools for farmers because these sensors can lead to reduced labor, time and cost of soil sampling/analysis [2]. **As a result, reaching soil water content after irrigation to its optimum case is a key variable for successful irrigation practices.** The benefit of precise estimation of soil water content is a good way for determination of irrigation efficiency [3]. Soil moisture monitoring is also fundamental to timely and effective irrigation and enables irrigators to save water through precision irrigation technology [4].

Soil water content can be measured by means of collecting soil samples then oven drying. Currently, newly developed sensors, including the EnviroSCAN capacitance system are available to monitor soil water content on-line. The EnviroSCAN system continuously measure the frequency of a capacitance circuit coupled with the soil-water-air medium as influenced by this medium, and then estimates its soil water content using calibration equations. So, field calibration is major operation. Several calibration procedures have been conducted under field conditions [5-8]. There has been some interest in applying newer computational techniques, such as artificial neural networks (ANNs), to the field of calibration gravimetric soil water content monitoring by using the soil moisture sensors, since accurate estimation of soil water content through calibration equation influences planning, design, operation and management of irrigation practices.

ANNs are a branch of artificial intelligence developed in the fifties in order to imitate human brain's biological structures, is a very frequently used method in recent years for modeling and prediction purposes instead of regression [9]. They do not depend on assumptions about functional form, probability distribution or smoothness, and have been proven to be universal approximators [10-11]. ANN models are well suited to situations where the relationship between the input variable and the output is not explicit. Instead, ANN, map the implicit relationship between inputs and outputs through training by field observations [12].

ANN requires input(s) and a known target for training the system. The training phase modulates the internal layers of the system based on the training inputs. Different studies have applied ANN method to obtain calibration equation for soil water content obtained by the using of soil moisture sensors. As example, Jiang and Cotton [13] implemented and tested ANN for soil moisture estimation. The performance of the ANN model was evaluated by direct comparison between the soil moisture estimated by the ANN model and the field measurements by examining the correlation between them. Strong correlation is demonstrated between the two variables. The work suggested that the ANN model was a promising alternative to soil moisture estimation. Persson et al. [14, 15] used ANN methodology to calibrate Time Domain Reflectometry (TDR) measurements

of soil water content of light texture soils. However, TDR exploits the difference in dielectric constant values between the solid phase, air phase and liquid phase. They showed that ANN model provided better prediction of the dielectric constant and soil water content relationship than other commonly used models. They concluded that ANN predictions were as good as a soil specific calibration with comparable coefficient of determination and RMSE. Jing et al. [16] represented a RBF neural network calibration method of soil water content based on TDR soil moisture sensor and wireless sensor networks. Experiment results showed that the calibration method was effective, simple and practical, and provided an effective method for real-time monitoring of soil water content. Davood et al. [17] established ANN model to fit TDR calibration data for the soils of different textures. However, TDR has become a method for soil volumetric water content measurement. They decided that ANN method behaves was good for the calibration. Koksall et al. [9] detailed a calibration procedure for the neutron moisture method using ANN. They modelled in successful way gravimetric soil water content versus neutron moisture meter count ratio. Kuang [2] reported that ANN combined with partial least squares regression has provided better calibration accuracy than the partial least squares regression or principal component regression analysis alone for data of soil water content obtained by on-line sensors.

By browsing literature review, it is concluded that calibration equations vary greatly in their ability to define the magnitude and variability of the soil water content. So, it is necessary to develop another approach to estimate the soil water content rather than regression analysis. Thus, the aim of this study was to focus on the investigation and development of a methodology using ANN technique for executing calibration of soil water content data versus scaled frequency of EnviroSCAN system. Since ANN has better modeling flexibility and capability rather than regression analysis as reported by other research studies.

2. MATERIALS AND METHODS

2.1. EnviroSCAN system

EnviroSCAN capacitance sensor (Fig. 1) is a complete and stands alone continuous soil moisture monitoring system. It is acclaimed by growers and researchers as the world's leading irrigation monitoring and scheduling device. The system consists of a network of probes supporting an array of soil moisture sensors. The sensors continuously monitor changes in soil moisture, highlighting the crop's dynamic water use with respect to environmental conditions and irrigation management strategies [18]. In addition, it can be installed at various depths to continuously monitor water content in the soil profile. The sensors, which are installed within a vertical PVC access tube, are mounted one above another along the probe length and can be adjusted in 10-cm intervals. Probes are networked via buried cables to a central data logging facility enabling continuous monitoring of soil water content. Data is stored in the data logger and downloaded onto a computer for display using special software. The multiple sensors measure the frequency of a capacitance circuit of the surrounding soil-air-water mixture, and the EnviroSCAN system converts signals into a percentage of volumetric water content. The following equation was used to convert three different frequencies (soil, air and water) to scaled frequency [19]:

$$SF = \frac{AF - SF}{AF - WF} \dots \dots \dots (1)$$

The default manufacturer's equation that converts scaled frequency to volumetric water content is:

$$\theta_v = \left(\frac{SF - 0.02852}{0.1957} \right)^{\frac{1}{0.404}} \dots \dots \dots (2)$$

Where SF is scaled frequency, AF is air frequency, SF is soil frequency, WF is water frequency and θ_v is soil water content by volume.

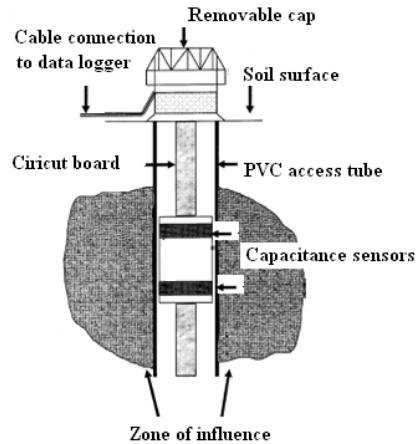


Fig. 1. EnviroSCAN capacitance sensor as installed in a PVC access tube in the field [6].

2.2.Experiments location and equipment installations

The study was conducted at a farm belonging to the college of food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia. In order to make particle size analyses, disturbed soil samples of the related soil layers were taken, air dried, crushed and sieved to 2 mm diameter. The particle size distribution of the soil at this location was 63% sand, 13% silt and 23% clay, so, the soil is classified as a sandy clay loam. For determination of bulk density, undisturbed core samples, have 53 mm diameter and 50 mm length, were taken by using holes, and methods given by Blake and Hartge [20] were followed. The bulk density values were varied from 1.40 to 1.46 g/cm³.

Experimental plot has an area of 250 m². Tomatoes are grown and irrigated by drip irrigation system. The water was delivered through nine drip lines of 16 mm in diameter at distances of 80 cm. On each line, 29 drippers are fixed; the distance between drippers on the line is 40 cm. The experimental plot was equipped with one EnviroSCAN system (Sentek Sensor Technologies, Stepney, South Australia, Australia). The probes (Sentek Company Ltd., South Australia) were installed at 10, 20, 30, 40, and 60 cm depth below the top of the surface. The soil moisture probe was installed in a PVC pipe access tube, which was stoppered at the soil end. A screw cap was placed at the end of the access tube protruding above the soil level. A radio telemetry communication system (Grow Smart Soil Moisture System, Lindsay Manufacturing Co., Lindsay, NE) was used to transmit the soil moisture data from the probes into a computer. Readings were monitored continually, recorded to a depth of 60 cm at 10 cm intervals, on a daily basis every 30 minute during growing season. IrriMax Version 8.0 software (Sentek Company Limited, South Australia) was used for data analyses and graphic presentation of the data. The sensor installation process and operational procedures were done according to the manufacturer's recommendations and instructions [21]. Moreover, soil water content was measured by the gravimetric method at the same depth from the soil surface, which was used for calibration, proposes. In this method, soil samples were taken from fields three times each week and soil water content was measured by drying the sampled soil in an oven at a typically at 105 °C to a constant weight and measuring the soil mass before and after drying.

2.3.Artificial neural networks modelling

Commercially available QNET 2000 was employed in this study [22]. 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 training and test sets, design the network architecture and feed values for the training parameters. The ANN used in this study was a standard back-propagation neural network with three layers: an input layer, a hidden layer and an output layer. However, it was reported in the literature that one hidden layer is normally adequate to provide an accurate prediction and can be the first choice for any practical feed-forward network design [23-24]. Therefore, a single hidden layer network was used in this study. The neurons in the three 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 sigmoid function value based on its inputs. More specially, for the j th hidden neuron [25].

$$\left\{ \begin{array}{l} net_j^h = \sum_{i=1}^n w_{ji}^h x_{i-1} + b_j \quad , \\ y_j = f(net_j^h) \end{array} \right. \quad \dots\dots\dots(3)$$

While for the output neuron

$$\left\{ \begin{array}{l} net^o = \sum_{j=1}^m w_j^o y_j + c \quad , \\ \tilde{x}_t = f(net^o) \end{array} \right. \quad \dots\dots\dots(4)$$

Where b_j and c are thresholds (bias), this network has n 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 (5) or hyperbolic tangent (tanh) as shown in equation (6).

$$f(x) = \frac{1}{1 + e^{-x}} \quad \dots\dots\dots(5)$$

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad \dots\dots\dots(6)$$

Before training, a certain pre-processing steps on the network inputs and targets to make more efficient neural network training was performed using the following formula:

$$T = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \quad \dots\dots\dots(7)$$

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 training data set, respectively. The training data was used to compute the network parameters. The testing data was used to ensure robustness of the network parameters.

The input parameter of the network was scaled frequency, and output parameter was volumetric soil water content (θ_v , %) in the case for each soil layer. When modelling the EnviroSCAN moisture meter scaled frequency for data from the entire soil profile, the input parameters of the network were scaled frequency and soil depth, and output parameter was volumetric soil water content (θ_v , %). Different networks with single hidden layer topology were tried. The most popular approach to finding the optimal number of neurons in hidden layer is by trial and error [26]. In this study, trial and error approach was used to determine the optimum neurons in hidden layer of the network (examined from 2 to 14 neurons). Also, transfer function was varied; however, they were sigmoid and hyperbolic tangent (tanh) in the hidden layer. The iteration was fixed to 100000. The learning rate and momentum coefficient was fixed and were to be 0.15 and 0.8, respectively.

Two different ANN approximations were applied as follows: the first ANN approach which was applied to individual training data sets for 0–30 cm and sigmoid transfer function (ANN1), 0–30 cm and tanh transfer function (ANN2), 30–40 cm and sigmoid transfer function (ANN3), 30–40 cm and tanh transfer function (ANN4), 40–50 cm and sigmoid transfer function (ANN5), 40–50 cm and tanh transfer function (ANN6), and the second ANN approach for which the training data set consist of all the data from the 0- to 50-cm (ANN6) soil profile (Table 1). Thus, there were six different ANN for the first approximation, one for each soil layer and only one ANN for the entire soil profile to 50 cm depth. The iteration steps and hidden layer of both ANN approximations were the same. The best ANN model was elected based on highest correlation coefficient and lowest training error. In the case of one input and in the case of two inputs, the best ANN architectures had 4 neurons in the hidden layer as depicted in Fig. (2), respectively. Training error and correlation coefficient of different neural network structures is illustrated in Table (2).

2.4.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 means square error (RMSE) and mean relative error (MRE) as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} |\theta_{v\ i\ obs} - \theta_{v\ i\ pre}| \dots\dots\dots(8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} (\theta_{v\ i\ obs} - \theta_{v\ i\ pre})^2}{N}} \dots\dots\dots(9)$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left(\frac{\theta_{v\ i\ pre} - \theta_{v\ i\ obs}}{\theta_{v\ i\ obs}} \right) \dots\dots\dots(10)$$

Where $\theta_{v\ i\ obs}$ and $\theta_{v\ i\ pre}$ are experimental and predicted soil water content by different models, 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 [27]. The closer the R^2 value is to 1, the better the model fits to the actual data [28].

Table 1. Structure of ANN for volumetric soil water content.

Soil depth (cm)	ANN model	Inputs SF	Soil depth (cm)	Hidden layer	No. of neurons in hidden layer	Iteration	Transfer function	Output (%)
0-20	ANN1	√	---	1	2,4,6,8,10,12,14	10000	Sigmoid	θ_v
	ANN2	√	---	1	2,4,6,8,10,12,14	10000	Tanh	θ_v
20-30	ANN3	√	---	1	2,4,6,8,10,12,14	10000	Sigmoid	θ_v
	ANN4	√	---	1	2,4,6,8,10,12,14	10000	Tanh	θ_v
30-60	ANN5	√	---	1	2,4,6,8,10,12,14	10000	Sigmoid	θ_v
	ANN6	√	---	1	2,4,6,8,10,12,14	10000	Tanh	θ_v
	ANN7	√	20,30,60	1	2,4,6,8,10,12,14	10000	Sigmoid	θ_v
	ANN8	√	20,30,60	1	2,4,6,8,10,12,14	10000	Tanh	θ_v

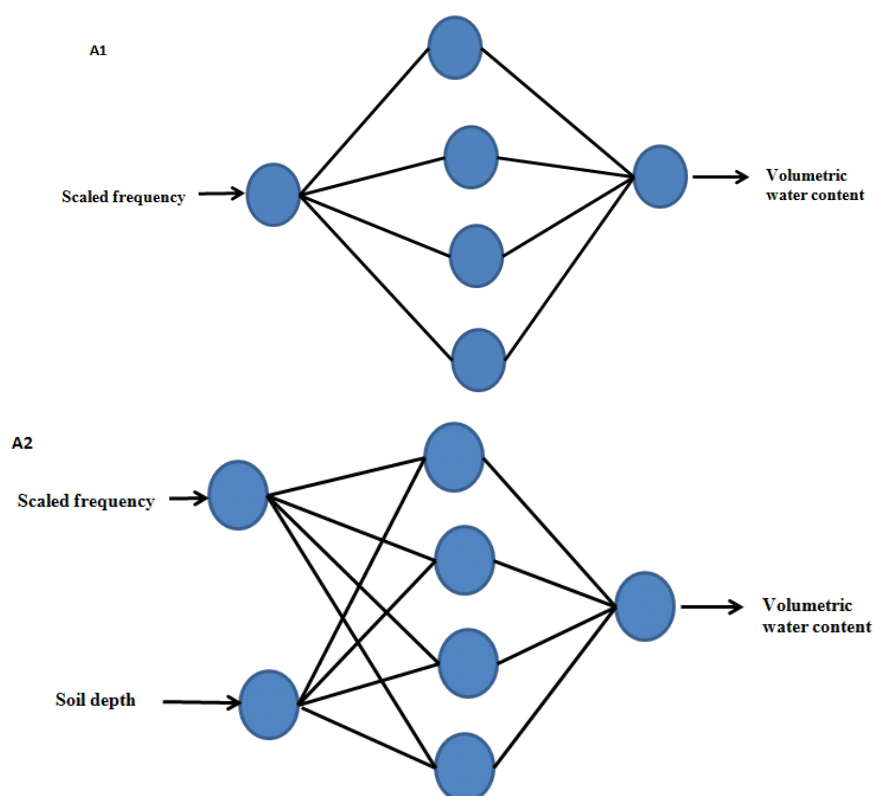


Fig. 2. Structure of the best ANN used in this study in the case of one inputs (A1) and in the case of two inputs (A2)

Table 2. Training error and correlation coefficient of different neural network structures.

Soil depth (cm)	ANN model	Structure	Training error	Correlation coefficient
0-20	ANN1	1-2-1	0.02187	0.994432
		1-4-1	0.01944	0.995585
		1-6-1	0.020731	0.994987
		1-8-1	0.020840	0.994929
		1-10-1	0.021111	0.9940399
		1-12-1	0.021145	0.994782
		1-14-1	0.020662	0.995018
	ANN2	1-2-1	0.020075	0.995299
		1-4-1	0.017589	0.996381
		1-6-1	0.01904	0.995495
		1-8-1	0.020732	0.994984
		1-10-1	0.019968	0.995345
		1-12-1	0.020666	0.995014
		1-14-1	0.020762	0.994968
20-30	ANN3	1-2-1	0.029208	0.990020
		1-4-1	0.029470	0.989842
		1-6-1	0.030500	0.989149
		1-8-1	0.030679	0.989026
		1-10-1	0.031538	0.988429
		1-12-1	0.031609	0.988379
		1-14-1	0.032346	0.987855
	ANN4	1-2-1	0.029146	0.990063
		1-4-1	0.028654	0.990397
		1-6-1	0.029365	0.989913
		1-8-1	0.029261	0.989984
		1-10-1	0.029355	0.989920
		1-12-1	0.029276	0.989974
		1-14-1	0.02932	0.989943
30-60	ANN5	1-2-1	0.034386	0.984042

0-60	ANN6	1-4-1	0.021240	0.993902
		1-6-1	0.032413	0.985807
		1-8-1	0.032271	0.985930
		1-10-1	0.032367	0.985848
		1-12-1	0.032415	0.985808
		1-14-1	0.033298	0.985043
		1-2-1	0.032372	0.985851
		1-4-1	0.022722	0.993024
		1-6-1	0.032084	0.986086
		1-8-1	0.031709	0.986410
		1-10-1	0.031956	0.986196
		1-12-1	0.032036	0.98613
		1-14-1	0.031741	0.98638
	ANN7	2-2-1	0.033084	0.978388
		2-4-1	0.031129	0.980892
		2-6-1	0.031162	0.980849
		2-8-1	0.031154	0.980859
		2-10-1	0.031122	0.980898
		2-12-1	0.031252	0.980738
		2-14-1	0.031235	0.980758
		2-2-1	0.031245	0.980749
	ANN8	2-4-1	0.027037	0.985624
		2-6-1	0.031013	0.981035
		2-8-1	0.03123	0.980760
		2-10-1	0.0280641	0.984505
		2-12-1	0.031104	0.980921
		2-14-1	0.030987	0.981066

3. RESULTS AND DISCUSSION

3.1. Analysis of volumetric soil water content data

Regression analysis between scaled frequency and volumetric soil water content is depicted in Fig. (3) for all soil profile depths. All relationship between scaled frequency and volumetric soil water content is exponent function ($\theta_v = a \times \exp(b \times SF)$). Regression R^2 for soil profile depth of 0-20 cm was 0.9225, for 20-30 cm, R^2 was 0.9623, for 30-60 cm, R^2 was 0.9593 and for all data from the entire 60-cm soil profile depth, R^2 was 0.9381. The effect of soil profile depth on the parameters a and b is depicted in Fig. (4) and Fig. (5), respectively. It is obvious from Fig. (4), that, the parameter a is higher for soil depth of 20-30 cm compared with other depths and this is may be due to higher volumetric soil water content at this depth. Meanwhile, it is obvious from Fig. (5), that, the parameter b is lower for soil depth of 20-30 cm compared with other depths and this is may be due to higher parameter a .

3.2. Characteristic of ANN models

After a number of training trials, the best neural network was determined to be feed forward network with three layers: an input layer of 1 and 2 neurons, first hidden layer with 4 neurons, and the output layer with 1 neuron. The input neurons are soil depth and scaled frequency. The output neuron gives the soil volumetric water content. The progress of the training was checked by plotting the measured (actual) volumetric water content and estimated volumetric water content by ANN and regression models as shown in Fig. (6) for 0- 20 cm, 20-30 cm, 30-60cm and 0-60 cm soil layers. The number of samples for 0- 20 cm, 20-30 cm, 30- 60 cm was 22, 18 and 19, respectively. Mean absolute error, root means square error, mean relative error and coefficient of determination (R^2) between soil volumetric moisture content estimated by ANN model, regression model and actual values are presented in Table (3). Meanwhile, mean absolute error, root means square error, mean relative error and coefficient of determination (R^2) between soil volumetric moisture content estimated by regression model and actual values are presented in Table (4).

RMSE between soil volumetric moisture content estimated by ANN model and actual values were 0.4270%, 0.6948%, 0.5596% and 0.8622% for 0- 20 cm, 20-30 cm, 30-60 cm and 0-60 cm soil layers, respectively. The root mean squared error is a measure of the accuracy of the calibration [29-30] and should be lower than 0.01 m^3/m^3 . Larger RMSE values indicate unfamiliarity with the sensor and soil sampling tools and methods or some errors in sampling or data analysis. The obtained results demonstrated a very good agreement between measured θ_v by the traditional gravimetric procedure and θ_v predicted using the ANN models. Also, the fits of the calibration equations using ANN were evaluated by using coefficient of determination which is ranged from 0.9715 to 0.9928 for soil layers and this result is better than obtained by regression analysis as coefficient of determination is ranged from 0.9525 to 0.9724 for soil layers as illustrated in Table (4).

Table 3. Mean absolute error, root means square error (RMSE), mean relative error and coefficient of determination (R^2) between soil volumetric moisture content estimated by ANN model and actual values.

Soil depth (cm)	MAE (%)	RMSE (%)	MRE (%)	R^2
0-20	0.3727	0.4270	0.0433	0.9928
20-30	0.5342	0.6948	0.0313	0.9809
30-60	0.4275	0.5596	0.0435	0.9878
0-60	0.6140	0.8622	0.1995	0.9715

Table 4. Mean absolute error, root means square error (RMSE), mean relative error and coefficient of determination (R^2) between soil volumetric moisture content estimated by regression model and actual values.

Soil depth (cm)	MAE (%)	RMSE (%)	MRE (%)	R^2
0-20	1.2178	1.4192	-0.1525	0.9261
20-30	0.7426	0.9484	-0.0337	0.9649
30-60	0.6202	0.8539	-0.0416	0.9724
0-60	0.8804	1.1226	-0.0806	0.9525

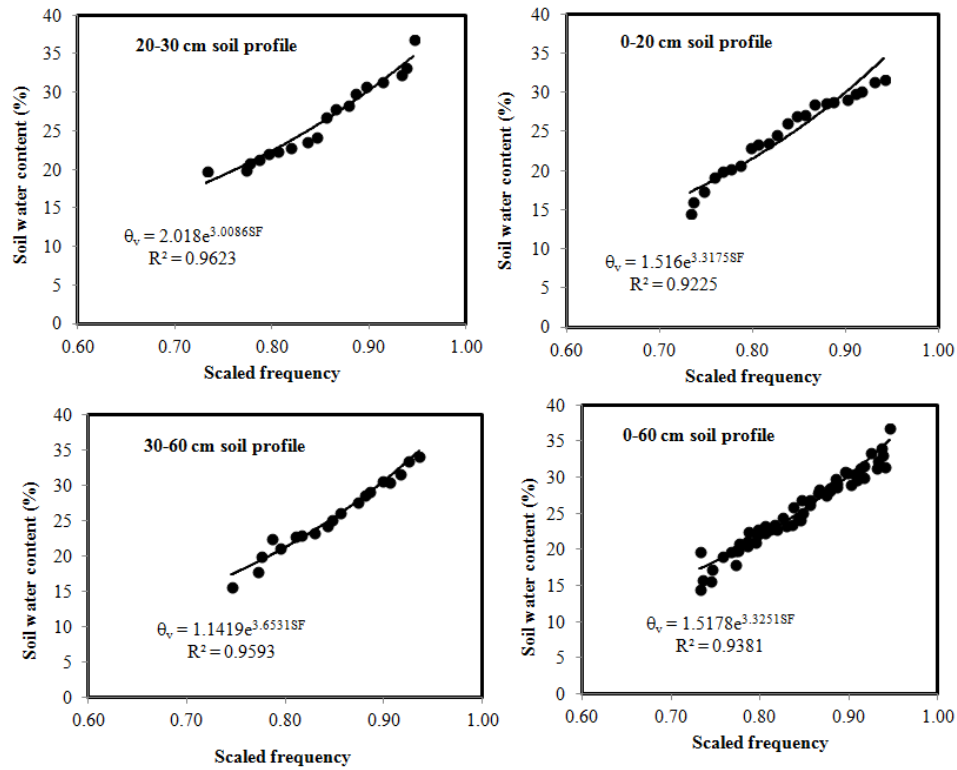


Fig. 3. Regression analysis between scaled frequency (SF) and volumetric soil water content

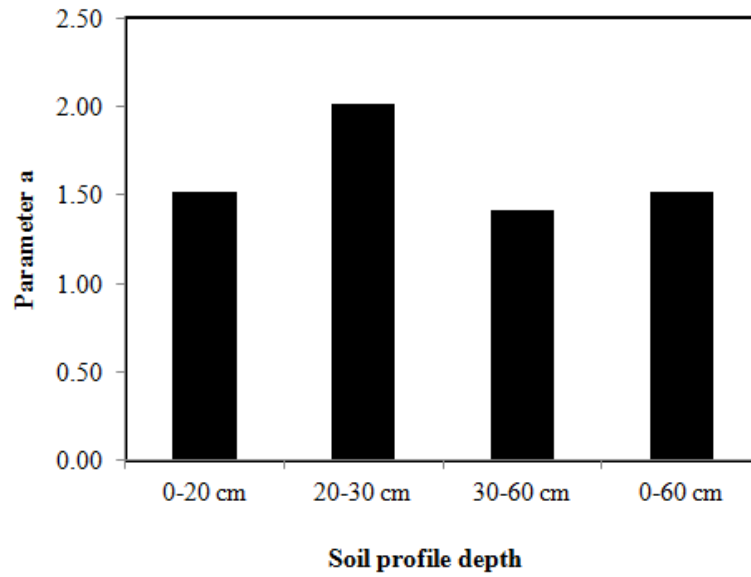


Fig. 4. The effect of soil profile depth on the parameter a

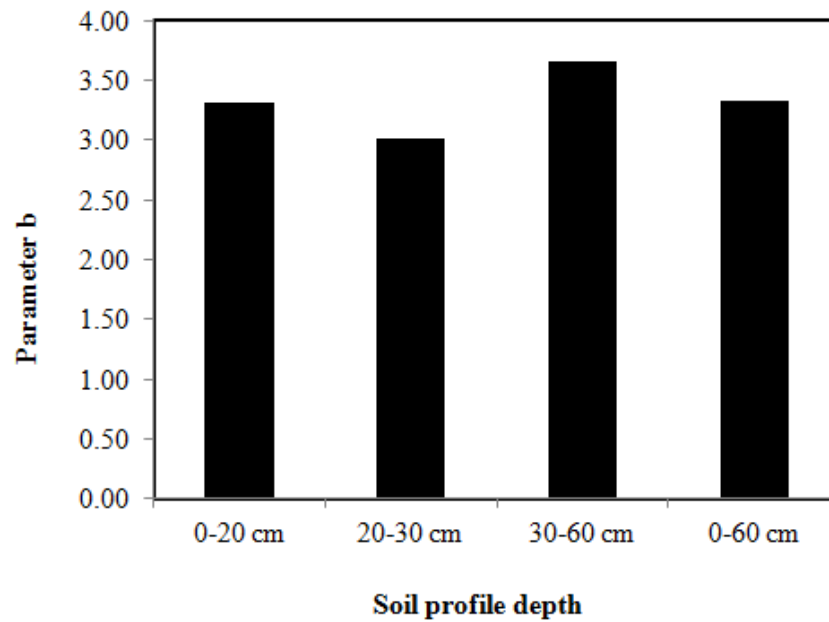


Fig. 5. The effect of soil profile depth on the parameter b

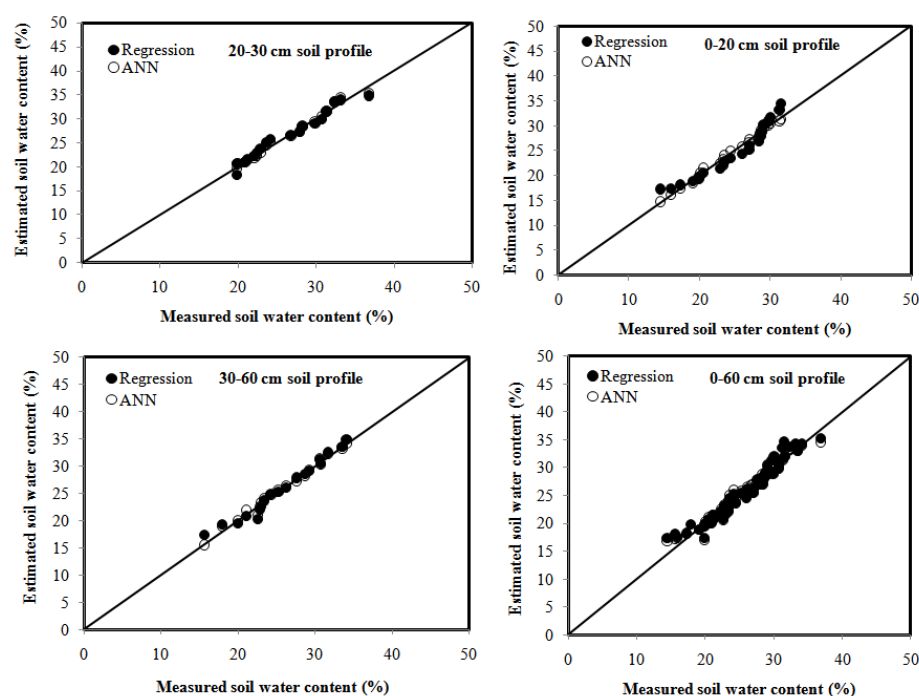


Fig. 6. Relationship between actual soil water content and estimated values by ANN and regression models.

4. CONCLUSION

This study concluded the feed forward neural network could be an effective alternative calibration method for soil water content using EnviroSCAN capacitance sensor. Better performance from the ANN could be seen compared with regression analysis calibration equations. The fits of the calibration equations using ANN were evaluated by using coefficient of determination which was ranged from 0.9715 to 0.9928 for soil layers and this result was better than obtained by regression analysis as coefficient of determination was ranged from 0.9525 to 0.9724 for soil layers. This study also concluded the supervised learning algorithms could be an effective alternative calibration method for estimation of soil water content using the EnviroSCAN capacitance sensor.

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