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Calibration of Soil Water Content Data from EnviroSCAN System Using Artificial Neural Network

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Authors' contributions

This work was carried out in collaboration between all authors. Author HMAG managed the experiments, reviewed the measurements and the final manuscript. Author MSAEM run the field experiments, managed the literature review and wrote the first draft of the manuscript. Author AMA participated in the field experiments, made data analysis, managed the literature review and wrote the first draft of the manuscript. Author MM managed the literature review and participated in writing the first draft of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Irrigation is one of the essential issues in agriculture in developing countries. Usually, in the developing countries, traditional farmers are likely to use more water than the required for crop production, thus wasting water. Hence, soil water sensors are typically needed in such situations to alert the farmer when the field needs irrigation and when it does not. One of these sensors is the EnviroScan system. It has the potential to monitor and estimate the soil water content continuously at various soil depths. Calibration is important to obtain accurate results. In this study, the volumetric soil water content and scaled frequencies from the EnviroScan system were recorded in a 60- cm soil profile. An artificial neural network (ANN) was used to calibrate the soil water content compared with a 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. The

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coefficients of determination (R^2) of a regression calibration equation of scaled frequency against the gravimetric soil water content were 0.9225, 0.9623, and 0.9593 for 0–20 cm, 20–30 cm, and 30–60 cm soil depths. The R^2 between gravimetric soil water content and the estimated by ANN model was 0.9928 for a 0–20 cm soil depth, 0.9809 for a 20–30 cm soil depth, and 0.9878 for a 30–60 cm soil depth. Using the data set for the entire 60-cm soil profile for calibration by ANN model, 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 issues in agriculture in developing countries. Usually in the developing countries traditional farmers are likely use more water, seed, laborers, cultural practices etc than the required for crop production, thus lot of unused water goes to streams as waste and costs more [1-3]. Soil water sensors are typically needed in such situations to alert the farmer when a field and when needs to be irrigated and when it does not [4]. Online 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 [5]. As a result, reaching soil water content after irrigation to its optimum case is a key variable for successful irrigation practices. The benefit of the precise estimation of soil water content is that it is a good way to determine irrigation efficiency [6]. Soil water monitoring is also fundamental to timely and effective irrigation and enables irrigators to save water through precision irrigation technology [7].

Soil water content can be determined by a way of collecting soil samples from the field. These samples are dried in an electric oven at specific temperature and time. Then, by recording the soil weights before and after drying, soil water content is determined. Currently, newly developed sensors, including the EnviroSCAN capacitance system are available to monitor soil water content online. The EnviroSCAN system continuously measures 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. Thus, field calibration is an essential task. Several calibration procedures have been conducted under field conditions [8-11]. There has been some interest in applying newer computational techniques such as artificial neural networks (ANNs) to the field of calibration soil water sensors. However, accurate estimation of soil water content influences planning, design, operation and management of irrigation practices.

ANNs are a branch of artificial intelligence developed in the 1950s to imitate the human brain's biological structures. They have been a frequently used method in recent years for modelling and prediction instead of regression [12]. ANNs do not depend on assumptions about functional form, probability distribution or smoothness, and have been proven to be universal approximators [13-14]. ANN models are well suited to situations where the relationship between the input variable and the output is not explicit. Instead, ANNs map the implicit relationship between inputs and outputs through training by field observations [15].

An ANN model requires input(s) and a known target for training process. The training process modulates the internal ANN layers based on the inputs. Different studies have applied ANN models to extract calibration equation for soil water sensors. As example, Jiang and Cotton [16] implemented and tested ANN model for soil water content estimation. The performance of the ANN model was evaluated by direct comparison between soil water content estimated by both the ANN model and by the field measurements through examining the correlation between them. A strong correlation was demonstrated between the measurements. The result indicated that the ANN model was a promising alternative calibration method for soil water content. Persson et al. [17,18] 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. The results showed that ANN model provided better prediction of the dielectric constant and soil water content relationship than other commonly used models. Moreover, ANN predictions were as good as a soil specific calibration with comparable coefficient of determination and root mean square error. Jing et al. [19] studied an

ANN model for calibration of TDR soil water sensor and wireless sensor networks. Experiment results showed that the ANN calibration was effective, simple and practical, and provided an effective method for real-time monitoring of soil water content. Davood et al. [20] established ANN model to fit TDR calibration data for the soils of different textures. The results showed that performance of the used ANN model for calibration was good. Koksal et al. [12] detailed a calibration procedure for the neutron soil water content meter using ANN model. The results indicated that ANN was able to predict gravimetric soil water content versus count ratio of the meter. Kuang [5] reported that for data of soil water content obtained by online sensors, an ANN combined with regression analysis provided better calibration accuracy than regression or principal component regression analysis alone.

By browsing literature review, it is found that calibration equations are varying 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 as a replacement for regression analysis. The aim of this study was to focus on the investigation and development of a methodology using the ANN technique to calibrate the soil water content data versus the scaled frequency of the EnviroSCAN system.

2. MATERIALS AND METHODS

2.1 EnviroSCAN System

The EnviroSCAN capacitance sensor (Fig. 1) is a complete and stands alone continuous soil water monitoring system. It is acclaimed by growers and researchers as the world's leading irrigation monitoring and scheduling device. The EnviroSCAN consists of a network of probes supporting an array of soil water sensors. The sensors continuously monitor changes in soil water, highlighting the crop's dynamic water use with respect to environmental conditions and irrigation management strategies [21]. 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 above another along the probe length and can be adjusted at 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 then they download to a computer for analysis 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 soil water content. The following equation was used to convert three different frequencies (soil, air and water) to scaled frequency [22]:

$$SF = \frac{AF - FF}{AF - WF} \tag{1}$$

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

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

Where SF is scaled frequency, AF is air frequency, FF is soil frequency, WF is water frequency and θ_v is volumetric soil water content.

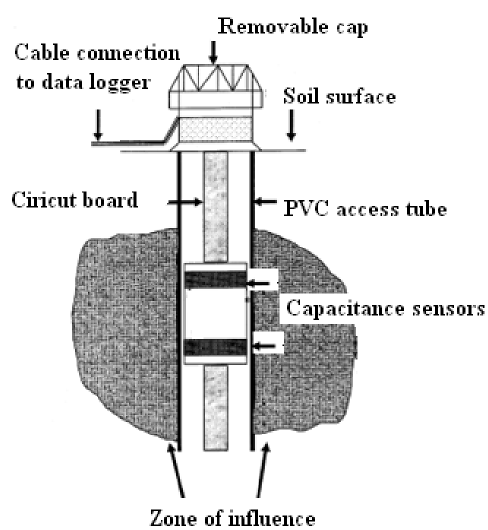

Fig. 1. EnviroSCAN capacitance sensor as installed in a PVC access tube in the field [9]

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 conduct particle size analyses, 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 the experiment site was 63% sand, 13% silt and 23% clay, so, the soil is classified as a sandy clay loam. To determine the soil bulk density, core samples with a 53- mm diameter and 50- mm length were obtained by using holes and methods given by Blake and Hartge [23] were followed. The soil bulk density values were varied from 1.40 to 1.46 g/cm^3.

The experimental plot had an area of 250 m^2. Tomatoes were 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 were fixed; the distance between drippers on the line was 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 depths of 10, 20, 30, 40, and 60 cm below the top of the surface. The soil water content 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 water content data from the probes to a computer. Readings were monitored continually, recorded to a depth of 60 cm at 10 cm intervals, on a daily basis every 30 min 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 [24]. Moreover, soil water content was measured by the gravimetric method at the same depths from the soil surface. The measurements of the gravimetric soil water contents were used for calibration proposes. In this method, soil samples were taken from fields three times each week. Soil water content was obtained by drying the soil samples in an electric oven adjusted at 105°C to a constant weight.

2.3 Artificial Neural Networks Modelling

The commercially available QNET 2000 was employed in this study [25]. This software is a Windows-based package that supports a 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 architecture 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 [26,27]. Therefore, a single hidden layer in the developed ANN 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 jth hidden neuron [28].

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

While for the output neuron,

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

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).

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

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

Before training, certain pre-processing step on the network inputs and targets to make more efficient neural network training was performed using the following formula [25]:

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

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.

Different ANN models with single hidden layer topology were tested. However, the inputs to the ANN models were scaled frequency alone or combined with soil depth (Fig. 2) and the output was volumetric soil water content (θ_v, %). The most popular approach to investigate the optimal number of neurons in a hidden layer is by trial and error [29]. In this study, trial and error approach was used to determine the optimum neurons in the hidden layer of the ANN model (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 10000. The learning rate and momentum coefficient were fixed and were at 0.15 and 0.8, respectively.

Different ANN models were applied for training data set. For the depth of 0–20 cm and using sigmoid transfer function in the hidden layer, the ANN model was labelled as ANN1. For the depth of 0–20 cm and using tanh transfer function in the hidden layer, the ANN model was labelled as ANN2. For the depth of 20-30 cm and using sigmoid transfer function in the hidden layer, the ANN model was labelled as ANN3. For the depth of 20-30 cm and using tanh transfer function in the hidden layer, the ANN model was labelled as ANN4. For the depth of 30–60 cm and using sigmoid transfer function in the hidden layer, the ANN model was labelled as ANN5. For the depth of 30-60 cm and using tanh transfer function in the hidden layer, the ANN model was labelled as ANN6. Moreover for the depth of 0-60 cm and using sigmoid transfer function in the hidden layer, the ANN model was labelled as ANN7. For the depth of 0-60 cm and using tanh transfer function in the hidden layer, the ANN model was labelled as ANN7 (Table 1). The best ANN model was selected based on the highest correlation coefficient and the lowest training error. In the case of one input and in the case of two inputs, the best ANN architectures had four neurons in the hidden layer, as depicted in Fig. (2). Training error and correlation coefficient of different ANN structures is illustrated in Table (2).

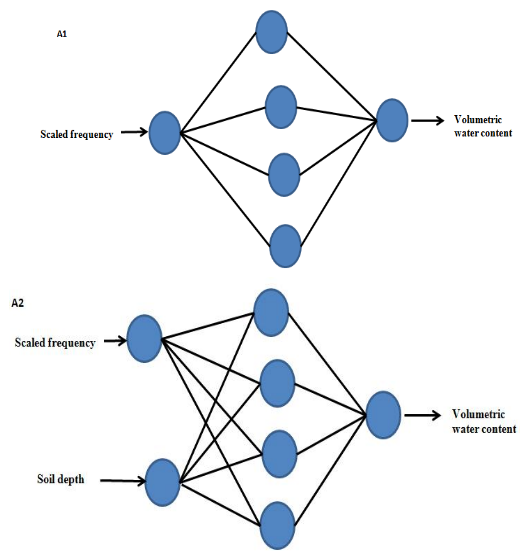

Fig. 2. Structure of the best ANN used in this study in the case of one inputs (A1) and in the case of two inputs (A2)

2.4 Evaluation of ANN Models 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. Popular measures are the mean absolute error (MAE), root mean square error (RMSE) and mean relative error (MRE) as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| \theta_{v\,iobs} - \theta_{v\,ipre} \right| \qquad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left(\theta_{vi\,obs} - \theta_{vi\,pre} \right)^2}{N}} \qquad (9)$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left(\frac{\theta_{vipre} - \theta_{viobs}}{\theta_{viobs}} \right) \qquad (10)$$

Where $\theta_{v\,iobs}$ and $\theta_{v\,ipre}$ are experimental and predicted soil water content by different ANN models, N is the number of observations. In addition, the coefficient of determination (R^2) was selected to measure the linear fit between the experimental and the predicted values [30]. The closer the $R^{2\circ}$ value is to 1, the better the ANN model fits to the actual data [31].

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

Soil depth (cm)	ANN model	Inputs		Hidden layer	No. of neurons in the hidden layer	Iteration	Transfer function	Output (%)
		SF	Soil depth (cm)					
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
0-60	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

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
		1-4-1	0.021240	0.993902
		1-6-1	0.032413	0.985807

Soil depth (cm)	ANN model	Structure	Training error	Correlation coefficient
		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
	ANN6	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
0-60	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
	ANN8	2-2-1	0.031245	0.980749
		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 relationships between scaled frequency and volumetric soil water content are 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 soil profile depth of 20-30 cm, R^2 was 0.9623, for soil profile depth of 30-60 cm, R^2 was 0.9593 and for all data from the entire 60- cm soil profile depth, R^2 was to be 0.9381. The effect of soil profile depth on the parameters a and b of the exponent function in Fig. (3) 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 the 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 a result of a higher parameter a.

3.2 Characteristics of ANN Models

After a number of training trials, the best feed forward ANN model was consisted of three layers: an input layer of one and two neurons, a hidden layer with four neurons, and the output layer with one neuron. The input neurons are soil depth and scaled frequency. The output neuron gives the volumetric soil water content. The progress of the training was checked by plotting the measured (actual) volumetric soil water content and estimated volumetric soil water content by ANN models and regression models as shown in Fig. (6) for depths of 0- 20 cm, 20-30 cm, 30-60 cm and 0-60 cm. The mean absolute error, root mean square error, mean relative error, and coefficient of determination (R^2) between volumetric soil water content estimated by ANN models and actual values are presented in Table (3). Meanwhile, these parameters between volumetric soil water content estimated by regression models and actual values are presented in Table (4).

The RMSE between volumetric soil water content estimated by ANN models and actual values were 0.4270%,0.6948%,0.5596% and 0.8622% for depths of 0- 20 cm, 20-30 cm, 30-60 cm and 0-60 cm, respectively. However, RMSE is a measure of the accuracy of the calibration [32,33] 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. In addition, the fits of the calibration equations using ANN models were evaluated by using coefficient of determination which is ranged from 0.9715 to 0.9928 for soil depths as shown in Table (3). This result is better than one obtained by regression analysis as coefficient of determination is ranged from 0.9525 to 0.9724 for soil depths as illustrated in Table (4).

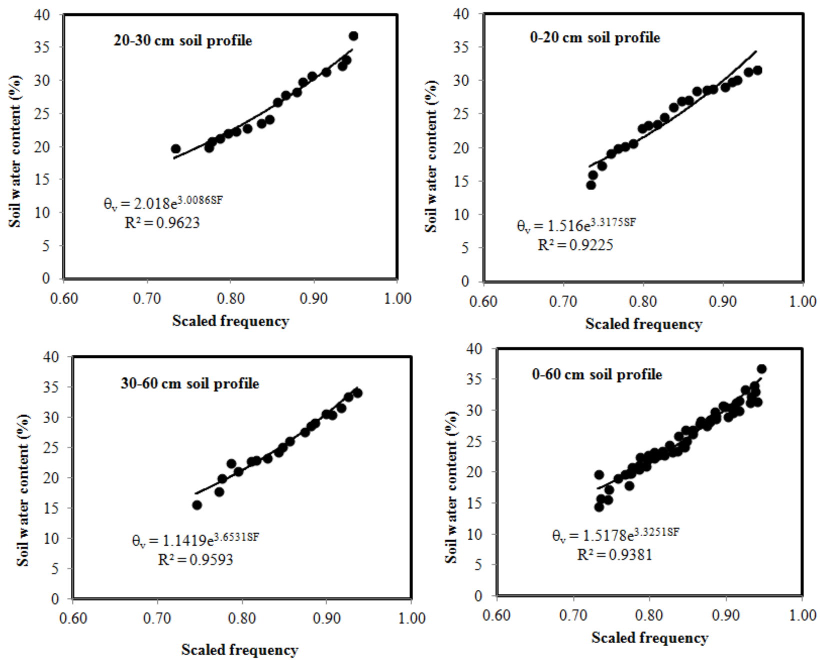

Fig. 3. Regression analysis between scaled frequency and volumetric soil water content

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

Soil depth (cm)	ANN model	MAE (%)	RMSE (%)	MRE (%)	R^2
0-20	ANN2	0.3727	0.4270	0.0433	0.9928
20-30	ANN4	0.5342	0.6948	0.0313	0.9809
30-60	ANN6	0.4275	0.5596	0.0435	0.9878
0-60	ANN8	0.6140	0.8622	0.1995	0.9715

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

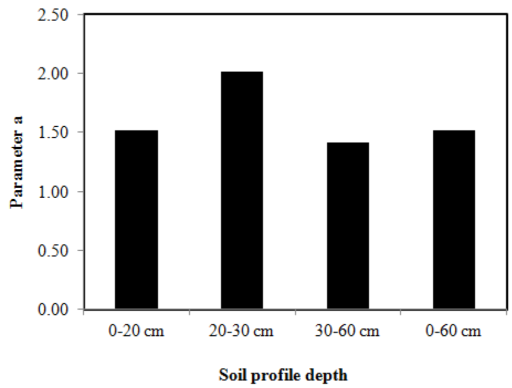

Fig. 4. The effect of soil profile depth on the parameter a depth on the parameters of the exponent function in Fig. 3

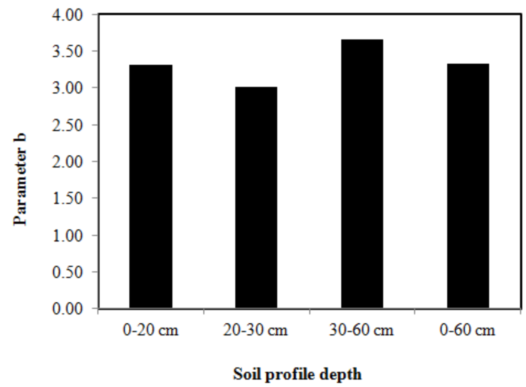

Fig. 5. The effect of soil profile depth on the parameter b depth on the parameters of the exponent function in Fig. 3

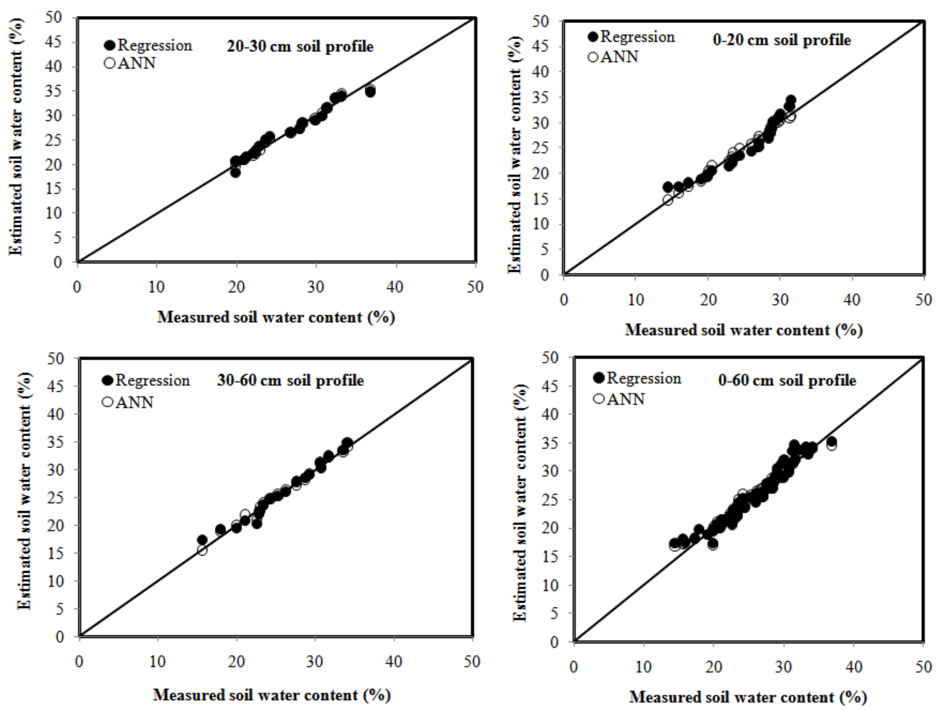

Fig. 6. Relationship between actual soil water content and estimated values by ANN and regression models

4. CONCLUSION

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

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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