International Journal of New Technology and Research (IJNTR)
ISSN:2454-4116, Volume-3, Issue-12, December 2017 Pages 36-41

Evaluation of Feedforward Artificial Neural Networks (ANN) to Adjust Soil Moisture Estimates Derived From Time Domain Reflectometry (TDR) Measurements Using Soil Temperature and Gravimetric Data

Arturo Méndez-Patiño, Jose Antonio Gutierrez-Gnecchi, Enrique Reyes-Archundia, Adriana del Carmen Tellez Anguiano

Abstract—**Soil temperature is one of the soil characteristics that greatly influences the accuracy of Time Domain Reflectometry (TDR) measurements for estimating soil moisture content. The authors examine the performance of two feedforward Artificial Neural Networks (ANN) configurations, commonly used for data regression analysis, to adjust TDR soil moisture estimates using soil temperature and gravimetric data. The data used for this study was obtained during a period of six weeks (October-November 2017) in three adjacent test sites in the Purepecha Plateau (Michoacán, México) managed under different tillage practices: at rest, reduced tillage and intensive tillage respectively. 10 TDR measurements per week were obtained from each test site. 60 Soil samples from each measurement site were also collected simultaneously, to determine the soil moisture content by the gravimetric method, and the soil temperature at 20 cm depth. 24 different configurations of ANNs were tested. The best result was obtained using a feedforward ANN with 11 tanh-sigmoid neurons in the input (hidden) layer. In addition, the authors also analyze the effect of different tillage practices on the soil moisture data. The results corroborate that tillage practices influence the soil moisture measurements and thus the best ANN results are obtained when the data used for training the ANNs is derived from sites managed under the same tillage practice.**

Index Terms— **Soil moisture, time domain reflectometry, Artificial Neural Networks, temperature effect on soil moisture measurements.**

I. Introduction

Quantitative description of the soil moisture content, is fundamental for agronomic, geological, ecological, biological and hydrological applications [1] to understand water balance, plan irrigation schemes, and to predict the dynamics of transport of chemicals (fertilizers and/or pollutants) on the surface and within the soil. Multiple analytical and numerical models are continuously proposed to try to predict the dynamics of water infiltration, and identify hydraulic parameters that influence the accurate measurement of soil moisture. For instance, the advances in satellite-based [2]–[3] surface soil moisture monitoring systems offer opportunities to qualify wide areas simultaneously considering spatial and temporal dynamics. However, there are limitations in satellite-based soil moisture measurement systems [4]-[6] and thus it is still necessary to conduct local surveys to assess soil hydraulic properties from direct observations [7]. One of the preferred methods used for estimating in situ soil moisture content is the use of electromagnetic techniques. In particular, Time Domain Reflectometry (TDR) has gained worldwide acceptance because it allows rapid in situ estimation of soil water content [8]. In addition the continuous introduction of commercial TDR devices in the market has lowered TDR device cost and thus it has become a cost-effective tool suitable for obtaining in situ soil moisture measurements [9]. However, soil water content is a dynamic process [10]-[12], non-linear in nature and depends on a large number of variables, ranging from the type of soil, geo-localization and the use fertilizers and chemical content of the soil, to tillage practices and weather conditions. Although, in principle, TDR measurements are considerable immune to soil properties other that water content, it has been shown that TDR measurements have to be compensated to account for particular soil characteristics [13]. Consequently, reports of theoretical and practical methods for compensating electromagnetically-derived measurements for accurate measurement of soil moisture, can rarely be extrapolated to predict the properties of soils with respect to the soil evolution and usage, even for the same region and/or terrain. Soil temperature [14] and tillage [15] have been shown to influence electromagnetic soil moisture measurements. Here, the authors examine the performance of two Artificial Neural Network (ANN) configurations commonly used for data regression analysis to improve the measurement accuracy of TDR-derived measurements using soil temperature data. In addition, this study investigates the

Arturo Méndez-Patiño. División de Estudios de Posgrado e Investigación, Tecnológico Nacional de México/Instituto Tecnológico de Morelia, Morelia, Michoacán, México.

José Antonio Gutiérrez-Gnecchi. División de Estudios de Posgrado e Investigación, Tecnológico Nacional de México/Instituto Tecnológico de Morelia, Morelia, Michoacán, México.

Enrique Reyes-Archundia. División de Estudios de Posgrado e Investigación, Tecnológico Nacional de México/Instituto Tecnológico de Morelia, Morelia, Michoacán, México.

Adriana del Carmen Tellez-Anguiano, División de Estudios de Posgrado e Investigación, Tecnológico Nacional de México/Instituto Tecnológico de Morelia, Morelia, Michoacán, México

degree of accuracy of TDR measurements on three adjacent test sites managed under different tillage practices.

II. Materials and Methods

The study presented in this work considers three test sites (test site 1: S1; test site 2: S2, test site 3: S3) located in region known as the Purepecha Plateau of the Michoacán state, Mexico. The test sites are rain fed. Test Site 1 is at rest, whereas S2 and S3 are maize crops, but are managed under different tillage practices: conservation (S2), and intensive tillage (S3) respectively. The predominant soil type of the test region is andosol [16] with high clay content (Table 1). Most of the rainfall precipitation was reported by the local weather station from July to September 2017 with occasional precipitations in October-November 2017 (Fig. 1).

Thus, after the rain season has faded away, 10 soil moisture measurements were obtained weekly in each test site starting at noon, using a TDR probe (CS616: Campbell Scientific) for a period of six weeks, yielding a total of 60 TDR measurements per test site. In addition, due to the volumetric nature of the TDR measurements, a soil sample was collected at a depth of 20 cm for each TDR measurement site to determine the water content by the gravimetric method. Moreover, the soil sample temperature was measured immediately after the sample was collected using a linearized semiconductor transducer (LM35) and associated signal conditioning circuitry. Other parameters determined from the soil sample were also determined from the soil samples: soil taxonomy, apparent density and pH. Table 1 shows a summary of the soil type, pH and apparent density.

In order to compare the TDR measurements with gravimetric data as reference, the TDR measurements were adjusted based on the manufacturer guidelines [17] using the temperature information obtained in situ. Two different configurations of two-layer, feedforward Artificial Neural Networks (ANN) commonly used for regression analysis, were implemented using MATLAB in order to determine the degree of improvement that can be obtained to correct TDR measurements using gravimetric data as reference (target values) and by varying the parameters of the input layer. Fig. 2 shows the ANN architectures used. The input parameters (TDR measurements and corresponding temperature measurements) are assembled in a 2 x n matrix, P, where n is the number of measurements used for training. The target values for training correspond to the soil measurements obtained from the gravimetric method assembled in a vector of size 1 x n.

Table 1. Summary of soil characteristics per test site

Test site	Soil characteristic per test site				
	Apparent Density	Clay	Lime	Sand	pH
	$g\ cm^{-3}$	%	%	%	
S1	0.63	49.10	40.10	10.8	6.09
S2	0.61	48.80	40.33	10.9	6.13
S3	0.69	51.20	38.50	10.3	6.21

The first ANN uses a logarithmic-sigmoid activation function in the input layer (1):

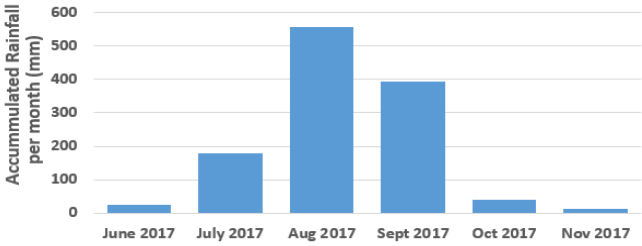

Fig. 1: Accumulated rain fall per month in the test sites preceding and during the survey period (October – November 2017)

$$d_1 = logsig(c_1) = \frac{1}{1+e^{(-c_1)}} \quad (1)$$

where c_1 is the weighted sum of the input pair TDR-temperature. The second ANN uses a hyperbolic tangential activation function (2):

$$d_1 = tanh(c_1) = \frac{2}{(1+e^{(-2c_1)})-1} \quad (2)$$

In both cases the output activation function is linear (3):

$$d_2 = linear(d_1) = W_2 d_1 + b_2 \quad (3)$$

where W_2 and b_2 correspond to the weight and biases of the second layer. The networks are trained with momentum (4):

$$\Delta W_{i,j} = mc\Delta W_{i,j} + (1-mc) lr\ D(i)P(j) \quad (4)$$

where ΔW(i,j) represents the weights adjustment, mc is the momentum constant (mc=0.95), D(i) are derivatives of errors (delta vectors), an lr=0.1 is the learning rate [18]. The input data is presented to the network and trained for 200 epochs maximum. Given the non-linear nature of the relationship TDR-temperature, choosing the number of neurons of the input layer and the number of data used for training and validation is a compromise. On the one hand, choosing the data for training and validation is essential to avoid overfitting.

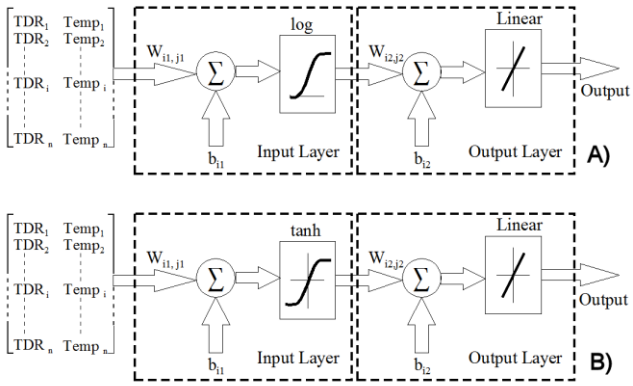

Fig. 2: Architecture of Artificial Neural Networks (ANNs) used for data regression analysis. The difference is the input layer: A) log-sigmoid and B) hyperbolic tangent-sigmoid activation functions.

Thus, data was chosen at a rate of 70% (training)-15% (testing)-15% (validation) for sub-sampling validation on two cases: all data from the three sites, and data corresponding to each test site. In addition, in the case of the analysis for each test site, two conditions were examined to investigate the effect of the number of samples available: 60 and 40 data pairs. Moreover, the number input neurons was varied from 1 to 12 neurons to investigate the effect on accuracy as well.

III. Results and Discussion

A. *TDR and gravimetric measurements*

Fig. 3 shows a comparison of the measurements obtained for each test site arranged in ascending order, considering that gravimetric (direct) measurements represent accurately the soil moisture content (SWC) in the measuring depth. TDR measurements from the test site at rest (S1) appear to be close to gravimetric data; this is probably due to the undisturbed condition of the terrain. However, in contrast with assumptions that TDR tends to overestimate [19] on clay-type soils due to dielectric loss, the TDR measurements appear to underestimate slightly SWC in test sites S2 and S3.

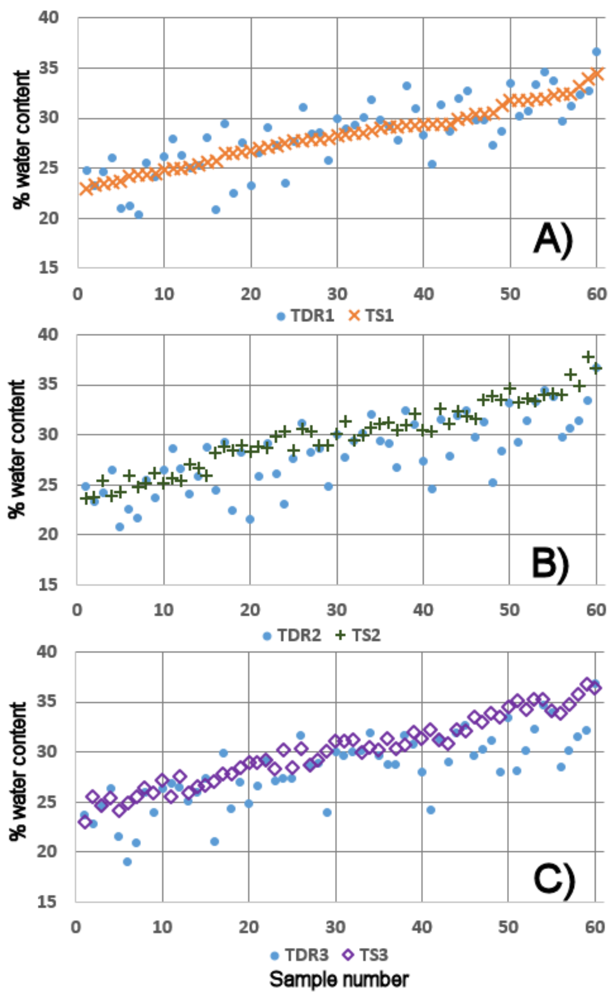

Fig 3: Comparison of measurements obtained on the three test sites (S1, S2, S3) using Time Domain Reflectometry (TDR1, TDR2, TDR3 respectively) temperature corrected values, and gravimetric measurements (TS1, TS2, TS3 respectively). Results are presented by test site: A) test site 1 (S1), B) test site 2 (S2) and C) test site 3 (S3).

Table 2. Comparison of mean (μ) and standard deviation (σ) values of Time Domain Reflectometry (TDR) and gravimetric measurements per test site and overall considering the entire data set.

TDR measurements (%) water content			Gravimetric measurements (%) water content		
	Mean μ	Std dev σ		Mean μ	Std dev σ
TDR1	28.24	3.66	TS1	28.18	2.93
TDR2	28.15	3.61	TS2	29.95	3.47
TDR3	28.23	3.59	TS3	30.10	3.45
TDR_all	28.21	3.60	TS_all	29.41	3.39

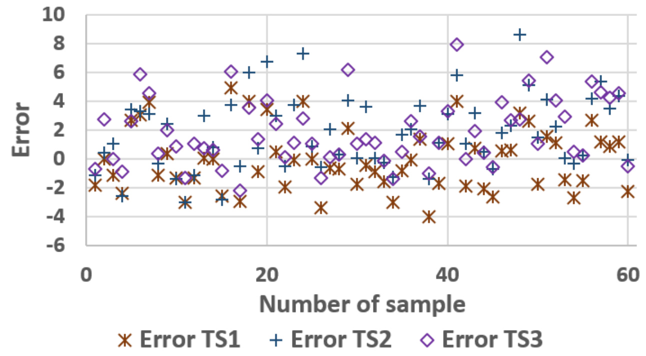

Fig 4: Comparison of measurements obtained on the three test sites (S1, S2, S3) using Time Domain Reflectometry (TDR1, TDR2, TDR3 respectively and gravimetric measurements (TS1, TS2, TS3 respectively). Results are presented by test site: A) test site 1 (S1), B) test site 2 (S2) and test site 3 (S3).

In addition, the data dispersion is larger for test sites S2 and S3 which is congruent with other works. Qualitatively, overall, the mean and standard deviation values of the measurements obtained from the three test sites appear to yield TDR values fairly close to gravimetric measurements (Table 2). However, upon closer inspection by plotting the individual error values, it can be observed that many of the values differ significantly (Fig 4). Fig. 4 shows the error graph of each TDR measurement with respect to its gravimetric counterpart; there are values with error as large as 25%. The Mean Squared Error (MSE) Calculation indicates an overall MSE of 7.742 (Fig. 5).

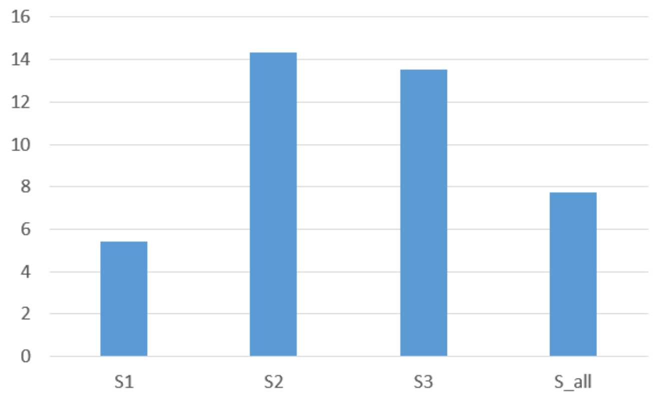

Fig. 5: Mean Squared Error of TDR measurements with respect to gravimetric measurements per site and overall

Thus, there are incentives to examine data regression analysis methods to improve the quality of information obtained from TDR measurements.

B. *Correcting TDR measurements using soil temperature measurements*

One of the advantages of using ANNs for data regression analysis is that fairly simple architectures may result in quite powerful tool to produce estimates from complex input patterns. In section I., it was pointed out that there are many factors that influence TDR measurements. Previous works have reported the usefulness of ANN to correct TDR information in sandy soils [20]-[21] and soils from tropical areas [22]. This work focuses on the usefulness of using soil temperature information as a key parameter to correct TDR measurements. Thus, given the complex nature of the TDR different configurations of ANN were tested to determine the degree of accuracy as a function of number of input layer neurons and number of samples available. The networks were trained first using the data pertaining each individual test site. The test trials later proceeded using all available data considering that the three test sites are adjacent have similar soil taxonomy.

1) *Case study 1: Training the ANNs for correction of TDR measurements per test site*

Fig. 6 shows a summary of MSE values obtained after training the two ANN configurations with 40 and 60 TDR-temperature data values. Using a low number of input neurons appears to lead to underfitting. Results are shown up to 12 neurons in the input layer; after 12 the MSE values does not diminish and appears to lead to overfitting. The tanh-sigmoid activation function in the input layer appears to yield better results than the log-sigmod activation function. The best result was obtained using the whole data set (60 input pair TDR-temperature values). Thus, three sets of weights and biases were obtained for each test site. Thus, correction of the TDR values will be reported for an ANN with 11 neurons in the input layer with its corresponding weights and biases (Fig. 7).

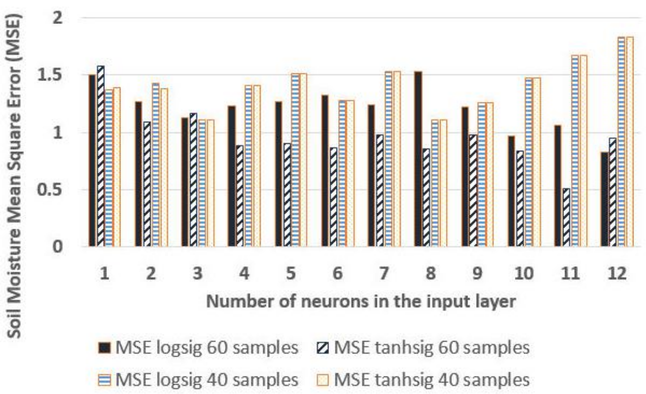

Fig. 6: Comparison of MSE errors obtained using 40 and 60 measurements for each test site. Results are shown for 24 ANN configurations varying the number of neurons in the input layer: 12 MSE results using logsigmoid activation functions and 12 MSE results using tanh-sigmoid activation functions in the input layer.

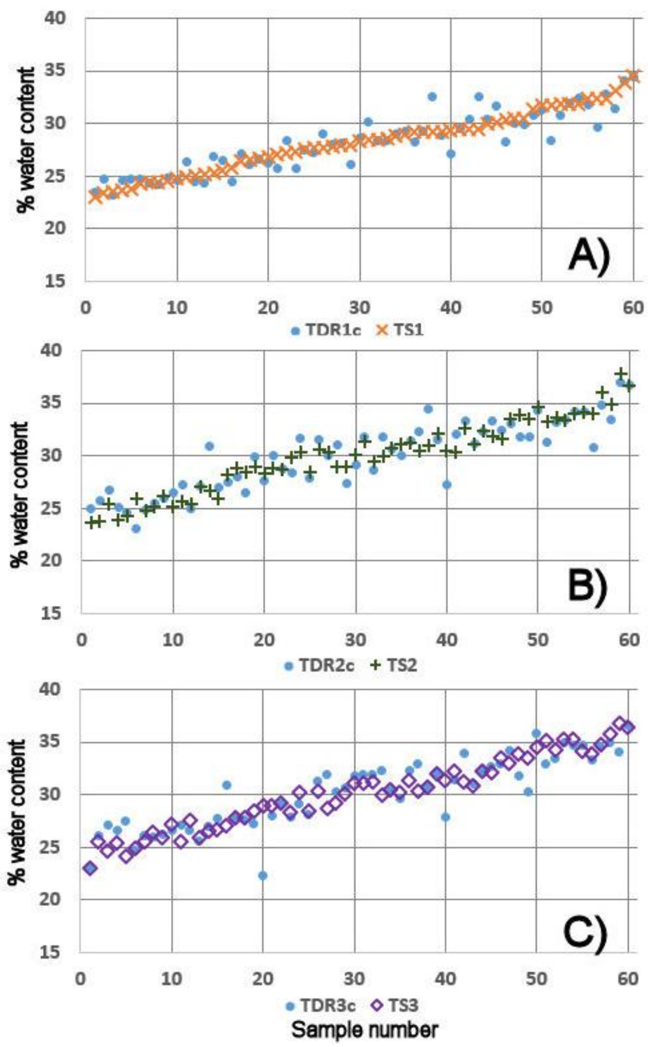

Fig. 7: Result of correcting TDR values using soil temperature information and an ANN with 11 tanh-sigmoid neurons in the input layer. Results shown for A) test site 1 (S1), B) test site 2 (S2), C), test site 3 (S3).

The results shown in Fig. 7 suggest that the networks, trained for each particular test site, yield information closer to gravimetric data. In addition the data dispersion is smaller, which suggests an improvement in data regression.

2) *Case study 2: Using the entire data set*

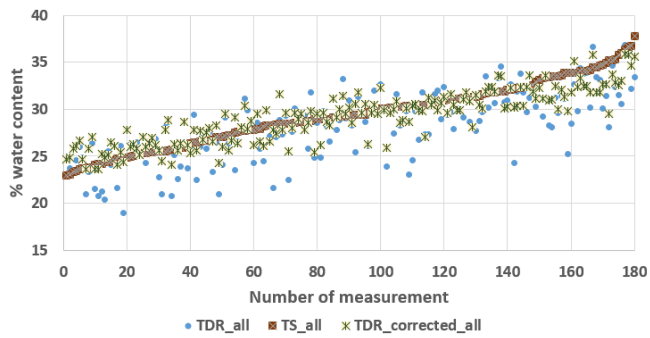

Fig. 8. Result of correcting TDR data considering the entire data set for training and testing. The corrected TDR values (TDR_corrected_all) appear to have a smaller dispersion with reference to the gravimetric data (TS_all).

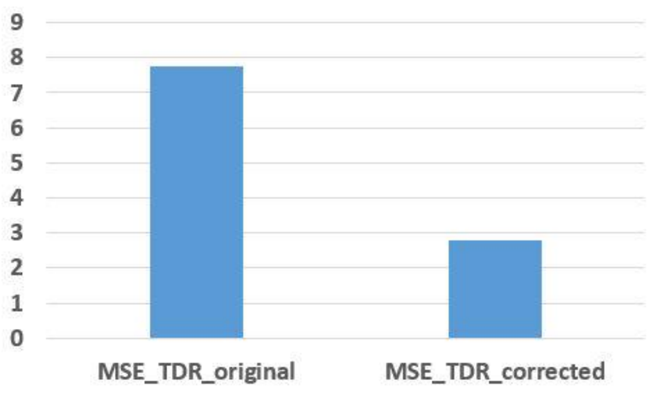

Fig. 9. Comparison of TDR MSE values before and after correction using the entire 180 data set for training and testing the ANN.

Since the three test sites are located adjacently and the soil composition is consistent throughout the three test sites, in this section, the entire data set is used for training the ANNs disregarding that data correspond to sites managed under different tillage practices. The corrected TDR values shown in Fig. 8 (TDR_corrected_all) appear to have a smaller dispersion and closer to the gravimetric data (TS_all) than the original, TDR values (TDR_all). Indeed, the MSE obtained is smaller for the corrected data (Fig. 9). However the best MSE figure obtained training the network without segregating the data according to the test site, is larger than that obtained separating the data per test site (Table 3). The best MSE value of TDR measurements was obtained for test site 1; again, this is probably due to the undisturbed nature of the field. The TDR values increasingly differ as the tillage intensifies; this finding is consistent with reports that tillage influences TDR measurements. Using soil temperature information appears to be a suitable candidate to adjust TDR data.

IV. Conclusion

Although the search continues for a universal formula [23] that can accommodate the effect of predominant soil variables, in the meantime, it is still necessary to use information from each particular site of interest. Manufacturers of TDR measurement equipment give guidelines for calibrating their commercial products based on their laboratory findings. In addition researchers often report the results of case studies.

Obtaining in situ data intended for laboratory analysis may be a painstaking endeavor, especially if surveys are conducted regularly. However, due to the non-linear nature of the soil dynamics, it is still necessary to resort to in situ sampling in order to adjust for spatio-temporal changes in the soil water content.

Table 3. Comparison of MSE values of TDR measurements with respect to gravimetric data before and after ANN regression analysis.

	Mean Squared Error (MSE)	
Test site	TDR Uncorrected	TDR Corrected
Test site 1 (S1)	5.42	1.21
Test site 2 (S2)	14.33	1.22
Test site 3 (S3)	13.50	1.68
All data	7.74	2.78

Thus, this work examines the degree of improvement that can be obtained from using ANNs to correct TDR data using soil temperature information.

Data was obtained for three test sites managed under different tillage practices: undisturbed, conservation and intensive tillage. Overall the results indicate that TDR measurements deliver information close to gravimetric data using the calibration data provided by the manufacturer. Upon closer inspection, there are discrepancies between the TDR measurements and gravimetric data. The TDR measurements were closer to gravimetric measurements in the test site 1; since the soil was allowed to attain even hydraulic properties, due to lack of tillage; the TDR measurements appear to be consistent with gravimetric data. However, when the instrument was tested in soils managed with conservation and intensive tillage, it appears that the effect of ploughing, fertilizers and organic content greatly influence the TDR measurements. The results also suggest that using soil temperature and gravimetric information for regression analysis can compensate for some of the effects of tillage on TDR measurements. It is also worth noting that the manner in which the measurements are performed also affect the TDR response. Although the instrument was installed in the measurement sites using a guide to insert the electrode array, clay type soils are hard and inevitably a small deviation in the distance between the electrodes may occur that may also influence the TDR measurement. In any case, it was shown that ANN regression analysis can improve the quality of information obtained from TDR measurements. In order to reduce the probability of training a network with results biased towards accommodating the given measurement set, different configurations were tested using and different amounts of training and testing data available. Again, even for test sites of similar taxonomy, the results indicate that it is important to consider obtaining data pertaining to a particular test site. Current and future work is directed towards implementing the methodology presented in this work to develop cost-effective electromagnetic soil moisture measurement equipment that can easily be adjusted to particular test sites.

Acknowledgment

The authors acknowledge the financial support from Tecnológico Nacional de México under grant No. 4328.11-P to carry out this work.

References

[1] S. U. Susha Lekshmi, D. N. Singh, M. Shojaei Baghini, "A critical review of soil moisture measurement," Measurement, vol. 54, 2014, pp. 92–105

[2] B. Fang, Venkat Lakshmi, "Soil moisture at watershed scale: Remote sensing techniques," J. Hydrol., vol. 516, 2014, pp. 258-272.

[3] L. Zhuo, D. Han, "The Relevance of Soil Moisture by Remote Sensing and Hydrological Modelling", Procedia Engineering 154, 2016, pp.1368 – 1375 [12th International Conference on Hydroinformatics, HIC 2016].

[4] E. Cho, H. Moon, M. Choi, "First assessment of the Advanced Microwave Scanning Radiometer 2 (AMSR2) soil moisture contents in Northeast Asia. J. Meteorol. Soc. Jpn. 2015, vol. 93, 117–129.

[5] T. J. Jackson, M. H. Cosh, R. Bindlish, P. J. Starks, D. D. Bosch, M. Seyfried, D. C. Goodrich, M. S. Moran, J. Y. Du, "Validation of

advanced microwave scanning radiometer soil moisture products. IEEE Trans. Geosci. Remote Sens. vol. 48, 2010, pp. 4256–4272.
[6] M. Owe, R. de Jeu, T. Holmes, "Multisensor historical climatology of satellite-derived global land surface moisture. J. Geophys. Res. Earth Surf., vol. 113, 2008, pp. 1855-1866.
[7] N. romano, "Soil moisture at local scale: Measurements and simulations", J. Hydrol. 516 (2014) pp. 6–20.
[8] P. Dobriyal, A. Qureshi, R. Badola, S. A. Hussain, "A review of the methods available for estimating soil moisture and its implications for water resource management," J. Hydrol. vol. 458–459, 2012, pp. 110–117.
[9] J. L. Varble, J. L. Chavez, "Performance evaluation and calibration of soil water content and potential sensors for agricultural soils in eastern Colorado,", Agric. Water Manag., vol. 101, 2011, pp. 93– 106.
[10] S. Kang, X. Hao, T. Du, L. Tong, X. Su, H. Lu, X. Li, Z. Huo, S. Li, R. Ding, "Improving Improving agricultural water productivity to ensure food security inChina under changing environment: From research to practice", Agric. Water Manag., vol. 179, 2017, pp. 5-17.
[11] Li, C.X., Zhou, X.G., Sun, J.S., Wang, H.Z., Gao, Y., 2014. Dynamics of root wateruptake and water use efficiency under alternate partial root-zone irrigation.Desalin. Water Treat. 52, 2805–2810.
[12] H. Vereecken, J. A. Huisman, Y. Pachepsky, C. Montzka, J. van der Kruk, H. Bogena, L. Weihermüller, M. Herbst, G. Martinez, J. Vanderborght, "On the spatio-temporal dynamics of soil moisture at the field scale," J. Hydrol., vol. 516, 2014, pp. 76-96.
[13] R. Stangl, G. D. Buchan, W. Loiskandl, "Field use and calibration of a TDR-based probe for monitoring water content in a high-clay landslide soil in Austria" Geoderma, vol. 150, 2009, pp. 23–31
[14] F. Kizito, C. s. Campbell, G. S. Campbell, D. R. Cobos, B. L. Teare, B. Carter, J. W. Hopmans, "Frequency, electrical conductivity and temperature analysis of a low-cost capacitance soil moisture sensor," J. Hydrol., 2008, vol 352, pp. 367– 378
[15] V. B. Ella, R. Padre, "Conservation agriculture and tillage effects on soil organic matter and residual moisture content in selected upland crop production systems in the Philippines", in Proc. Proceedings International Conference of Agricultural Engineering, Zurich, July 2014.
[16] M. C. Gutiérrez-Castorena, "La clasificación de los suelos de la meseta tarasca," Terra latinoamericana, vol. 19. pp. 227-239.
[17] CS616 and CS625 Water Content Reflectometers Instruction Manual. Cambbell Scientific 815 West 1800 North Logan, Utah U.S.A. Available on-line http://www.campbellsci.com/
[18] H. Denuth, M. Beale. Neural network toolbox for use with Matlab. The Math Works Inc. Natick, Massachusetts. 1992.
[19] M. Bittelli, F. Salvatorelli, P. Rossi Pisa, "Correction of TDR-based soil water content measurements in conductive soils", Geoderma, vol. 143, 2008, 133-142.
[20] S. Arsoy, M. Ozgur, E. Keskin, C. Yilmaz, "Enhancing TDR based water content measurements by ANN in sandy soils," Geoderma, vol. 195–196, pp. 133–144.
[21] M. Persson, B. Sivakumar, R. Berndtsson, O. H. Jacobsen, P. Schjønning, "Predicting the dielectric constant–water content relationship using artificial neural networks," Soil Sci. Soc. Am. J. vol. 66, no.5, pp. 1424–1429.
[22] S. S Zanetti, R. A. Cecílio, V. H. Silva, E. G. Alves, "General calibration of TDR to assess the moisture of tropical soils using artificial neural networks," J. of Hydrol. vol. 530, 2015, pp. 657–666
[23] C. Rüdiger, A. W. Western, J. P. Walker, A. B. Smith, J. D. Kalma, G. R. Willgoose, "Towards a general equation for frequency domain reflectometers", J. Hydrol., vol. 383, 2010, pp. 319–329.

Dr. Arturo Méndez Patiño, (PhD, U. Politécnica de Valencia, Spain). His work focuses on development hardware and methods for Applied Digital Signal Processing.

Dr. José Antonio Gutiérrez Gnecchi, (PhD, MSc, UMIST, United Kingdom). Prof. Gutiérrez-Gnecchi works on the development of applied instrumentation methods for Image analysis, digital signal processing and control.

Enrique Reyes Archundia. (PhD, IT Morelia, México; MSc, CENIDET, México). His work includes the development of artificial intelligence methods for signal analysis and control.

Dra. Adriana de Carmen Téllez Anguiano, (PhD, MSc, CENIDET, México). Her work is directed towards development of applied digital signal processing systems.