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Soil Water Content Modeling using Artificial Neural Network in Arid Soils of Algeria

Abdelhafid Youcef[1,2], Rechachi Miled Zohra[1], Chebbah Mohamed[3], Menasria Hanane[1]

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ABSTRACT

Background: In order to model ecological and hydrological processes and schedule irrigation as efficiently as possible, soil water contents at field capacity (FC) and permanent wilting point (PWP) across a landscape are crucial. However, it takes a lot of time and money to measure them directly. An alternative is offered by pedotransfer functions (PTFs), which forecast them based on readily available or simpler soil variables.

Methods: The purpose of this study was to compare the performance of FC and PWP models, developed with artificial neural networks (ANN) to multiple linear regression (MLR). A total of 120 soil samples from various Biskra province locations were used. The developed models are evaluated using the statistical criteria of mean error (ME), coefficient of determination (R^2) and root mean square error (RSME).

Result: The results show that the ANN performs better than the traditional MLR. The obtened results were very positive and indicated that the ANN approach held promise for forecasting soil water contents in our area.

Key words: Arid soils, Artificial neural network, Multiple lineair regression, Random forest, Soil water contents, Support vector machine.

INTRODUCTION

Modeling ecological and hydrological processes and scheduling irrigations optimally require consideration of the soil's water capacity or bioavailable water (Dobarco *et al*., 2018). However, it is frequently noted that water supplies are determined empirically and without consideration of this data, especially in arid and semi-arid regions. This, leads to environmental damage pollution such as rising surface water tables, nutrient leaching and a loss of water reserves. In order to effectively use the limited water resources that are available, soil water contents at field capacity (FC) and permanent wilting point (PWP) are essential hydraulic characteristics (Santra *et al*., 2018). However, due to the time-consuming nature of direct measurements and the impossibility of applying them to large areas, these properties are typically only known for a small number of soils (Haghverdi *et al*., 2012; McNeill *et al*., 2018). In order to get around these challenges, pedotransfer functions (PTFs) are an alternate method for estimating them from readily available or more readily measurably available soil data, such as bulkdensity, organic matter content and soil texture (Cosby *et al*., 1984; Saxton *et al*., 1986). Although there are no truly universal PTFs, the study area's proximity and the parent materials' similarity are crucial factors in determining the potential of PTFs (Morvan *et al*., 2004). Therefore, it is important to carefully evaluate the validity of any given PTF before extrapolating it outside of its geographic training area. Nonetheless, the majority of studies on pedotransfer functions (PTFs) have been produced in humid climates (Julià-Ferrer *et al*., 2004). Despite the existence of several studies that are interested in the pedotransfer's function, such as those by Patil and Rajput (2014) and Mousavi (2015), in order to estimate and predict the amount of water retained in the soil The prediction of soil water retention properties has received relatively little attention, despite the fact that water availability is one of the primary factors limiting agricultural production in arides and semi-arides regions (Wösten *et al*., 2001; Khlosi *et al*., 2016; El Majou *et al*., 2016; Ghorbani *et al*., 2017; Santra *et al*., 2018). There has been relatively little published research on soil water properties for Algerian soils (Dridi and Dilimi, 2011 ; Dridi and Zemmouri, 2012). PTFs that describe soil water properties over large areas in Algeria's Bas Sahara are in high demand for creating sustainable farming systems, but their availability is limited. Artificial neural networks (ANNs) and other machine learning algorithms have recently shown greater accuracy than other approaches in predicting the water content at FC and PWP (Morvan *et al*., 2004; Merdum *et al*., 2006). The main benefit of employing ANN techniques over traditional approaches is that they are completely nonparametric, meaning they do not

[1]Scientific and Technical Research Center on Arid Regions (CRSTRA), BP 1682 RP, 07000, Biskra, Algeria.
[2]University Mohamed Khider of Biskra, Algeria.
[3]University Abdelhafid Boussouf of Mila, Algeria.

Corresponding Author: Rechachi Miled Zohra, Scientific and Technical Research Center on Arid Regions (CRSTRA), BP 1682 RP, 07000, Biskra, Algeria. Email: rechachimiledzohra@gmail.com

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consider the relationships between the input and output data (Santra *et al*., 2018). The goal of the current study was to predict soil water content at FC and PWP using artificial neural networks (ANN) and compare their performance to multiple linear regression (MLR) for various soil types in the region using relatively limited data on water content at FC and PWP.

MATERIALS AND METHODS

Study area and data collection

As illustrated in Fig 1, Biskra province (eastern Algeria) is situated at the base of the saharan Atlas and covers about 21 509.80 km^2. It is renowned for its phoenicicol heritage, estimated at 5 million of date palms and 98.478 ha of irrigated land (ANAT, 2003). This agro-ecological zone belongs to the Saharan bioclimatic stage. According to Word Reference Base classification (IUSS Working Group WRB, 2014), the main soil types in the province of Biskra are Fluvisols (50%), Calcisols and Gypsisols (37.8%) and solonshaks (13.1%) (ANAT, 2003). In all, 120 soil samples were collected from various locations throughout this region. All collected soil samples were analysed in the laboratory. The particle-size distribution (clay, silt and sand contents) were determined by the Robinson's pipette method, while the soil cylinder cores (100 cm^3) method was used to determine BD. Organic matter content (OM%) was determined by the wet oxidation method of Walkley and Black method and soil water contents at FC (-33 kPa) and PWP (-1500 kPa) were determined by pressure plate apparatus method.

Statistical modeling

The R program was used to carry out the statistical modeling in this investigation. To estimate FC and PWP, five parameters clay, silt, sand, OM and BD were employed as predictors. Seventy percent of the data were in the training subset after the data were randomly divided into training and testing subsets prior to statistical analysis. PTFs were trained and tested using 84 and 36 samples, respectively. The test and training data were both normalized. Based on their relationship to soil water contents and an assessment of multicollinearity between variables using the variance inflation factor (VIF), the soil variables were selected to serve as arguments for the development of models (Dobarco *et al*., 2018).

The backward stepwise method was used to select the most important input variables for MLR modeling, followed by the linear, quadratic and potential interaction terms of soil variables (Merdum *et al*., 2006 ; Rab *et al*., 2011). An equation of the following form was used to develop the PTF.

$$Y = b_0 + b_1X_1 ... + b_5X_5 + b_6X_6$$

Where,

Y= The dependent variable.

b_0= The intercept.

$b_{01}..b_n$= Regression coefficients.

X_1 - X_5= Independent variables referring to basic soil propreties.

The feed-forward multilayer perception (MLP) model was used for ANN modeling in order to predict FC and PWP. Clay, silt, BD and OM are the four input soil variables that make up the input layer. The input, hidden and output layers make up this network (Fig 2). The performance of the calibration and validation data sets determines how many hidden neurons are used (Van Looy *et al*., 2017). To create the hidden layer, the network's input layer is weighted, summed and biased. A similar process is used to process the hidden neurons' output, which is then converted by another activation function to generate the output. Through an iterative process, the objective function is minimized to obtain the weights and biases in ANN. Any transfer function, including log-sigmoid, tan-sigmoid and linear, can be used by neurons to produce their output. Since the tan-sigmoid (*Tanh*) transfer function is the most widely used transfer function in soil science, it was utilized in our case to create the output layer (Mohanty *et al*., 2015). Several statistical indices, including the mean of prediction (ME), root-mean-square error (RMSE) and coefficient of determination (R^2), were used to assess the model's performance. The most popular metrics for assessing a model's performance are these statistical indices (Van Looy *et al*., 2017).

The coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_1^N (Y_i - \hat{Y}_i)^2}{\sum_1^N (Y_i - \bar{Y}_i)^2}$$

Root-mean-square error (RMSE):

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

Mean of prediction (ME):

$$EM = \frac{1}{N}\sum_{1}^{N}(Y_i - \hat{Y}_i)$$

Where,

Y_i= The mesured value.

$\hat{Y}_i$= The estimated value.

$\bar{Y}_i$= The average of the measured value.

N= The number of samples.

RESULTS AND DISCUSSION

According to the Table 1, both data sets showed statistically similar features, for example, BD and sand, silt and clay contents were 1.058-1.940 $g.cm^{-3}$, 02-68%, 02-94% and 03-85%, respectively for the training data set. FC and PWP ranged from 0.03 to 0.42 $g.g^{-1}$ and from 0.016 to 0.36$g.g^{-1}$, respectively. It is obvious that the wide range of physical characteristics in Biskra province is caused by the presence of various soil types.

Fig 3 shows that, despite having opposite polarity, both FC and PWP have a reasonably strong and smooth

relationship (r>0.70) with clay and sand contents. Thus, it might be the most accurate indicator of FC and PWP. The relationships between BD, silt and OM and FC and PWP are rather slender. Additionally, it seems that BD has a bad relationship with PWP and FC. As a result, these characteristics by themselves are unlikely to be reliable indicators of FC and PWP; however, when combined with clay and sand in a multiple prediction model, they might enhance model performance. The relationship between FC and PWP seems to be solid and seamless. Because of its collinearity with clay, the sand content was eliminated. In order to predict FC and PWP, the following independent

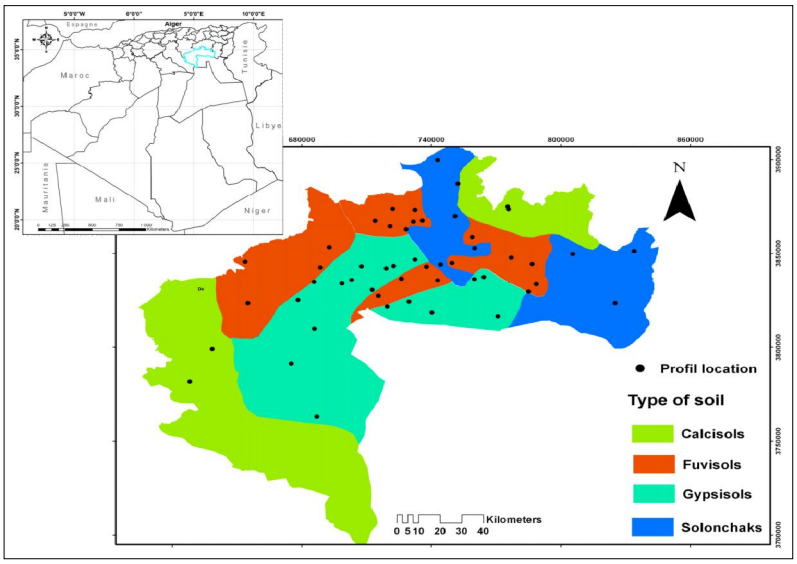


Fig 1: Location of the study area with soil profile locations.

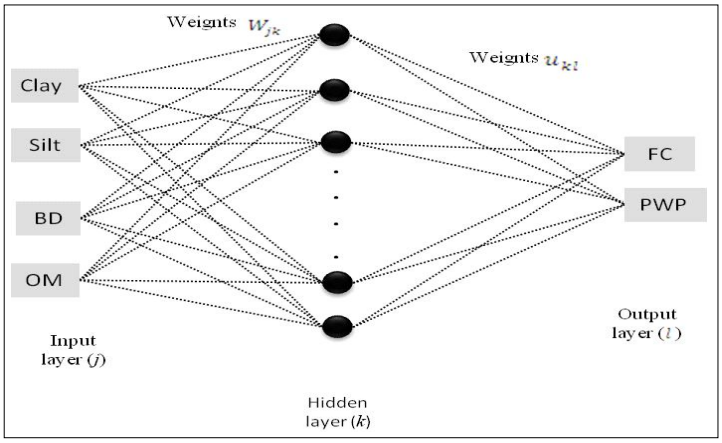


Fig 2: ANN model used in study.

Table 1: Statistic parameters of soil attributes for the training and test sets.

Variables	Training data set				Testing data set			
	Min.	Max.	Mean	S.D	Min.	Max.	Mean	S.D
Clay (%)	0.020	0.680	0.316	0.248	0.015	0.660	0.330	0.250
Silt (%)	0.030	0.850	0.382	0.204	0.090	0.663	0.415	0.166
Sand (%)	0.020	0.940	0.314	0.288	0.020	0.887	0.251	0.259
BD (g.cm^{-3})	1.058	1.940	1.441	0.171	1.028	1.732	1.436	0.164
OM (%)	0.000	0.031	0.011	0.272	0.000	0.024	0.090	0.205
FC (%, g.g^{-1})	0.030	0.416	0.239	0.215	0.061	0.408	0.246	0.198
PWP (%, g.g^{-1})	0.016	0.360	0.176	0.219	0.042	0.306	0.178	0.189

variables were selected for modeling: BD, silt, clay and OM content.

According to the results displayed in Table 2, the model 2 created using clay, silt and BD seems to perform better than the others during the training data sets. These predictor variables explained 76% and 62% of variation for FC and PWP respectively. Additionally, when combined with silt, BD seems to enhance the model's performance, however, OM only slightly enhances the regression. Overall, FC outperformed PWP in terms of evaluation indices (R^2, RMSE and ME). For FC, the R^2 and RMSE values were 0.76 and 0.095, while for PWP were 0.62 and 0.1161. Both models included the indipendent variables silt, bulk density, BD-silt, for FC and silt- BD and quadratic clay for PWP.

As indicated in Table 3, the model 2 for FC and PWP, respectively, had the lowest level of *RMSE* and the highest level of R^2. In general, a lower *RMSE* and higher R^2 value are statistical indicators of the model's strong performance. In our investigation, the R^2 and *RMSE* values for the training data set, are 0.761 and 0.095, for FC, while the values for PWP are 0.639 and 0,114, respectively. For the testing data set, the R^2 and RMSE values are 0.798 and 0.080 for FC, while for the PWP these values are 0.652 and 0.105, respectively.

For forecasting soil water contents at FC and PWP, the particle size distribution (PSD), OM and BD were frequently employed as predictors (Chakraborty *et al*., 2011; Wösten *et al*., 2001). In the present study, compared to BD and OM, particle size distribution demonstrated a stronger correlation with soil water content. Consequently, using clay, silt and BD provide a good prediction. Our results were consistent with those of Ostavari *et al*. (2015) Ghorbani *et al*. (2017) and Li *et al*. (2019). In MLR modeling, clay, silt and BD are the variables that explain 76 and 62% of variation in FC and PWP respectivly. The observed correlations between clay, FC and PWP are consistent with those reported for other soil types Cosby *et al*. (1984) and Rab *et al*. (2011). In our case, OM is unlikely to have an impact on the

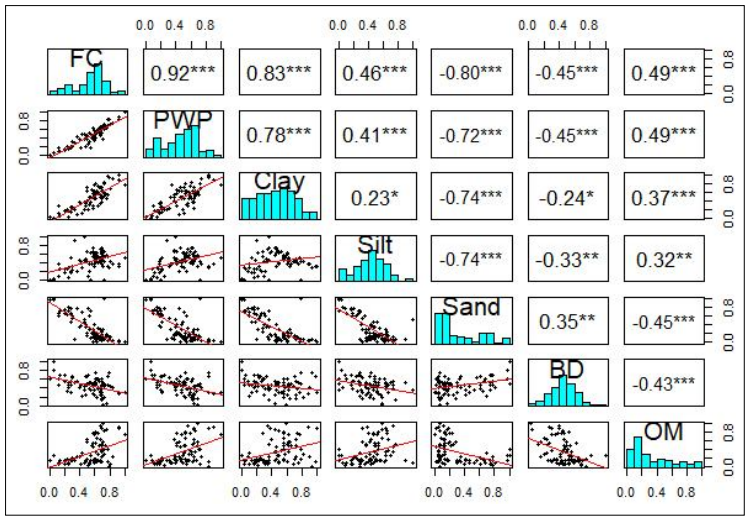


Fig 3: Correlation coefficients between soils attributs.

Table 2: Coeficients of variables used in MLR.

Variables	FC (%, g.g^{-1})				PWP (%, g.g^{-1})			
	C, Si.	C, Si., BD	C, Si. OM	C, Si, BD, OM	C, Si.	C, Si, BD	C, Si. OM	C, Si, BD, OM
Intercept	0.112***	0.258***	0.128***	0.369***	0.122***	0.114**	0.109**	0.321***
Clay (%)	0.663***	0.634***	0.638***	0.620***				
Silt (%)	0.303***	0.244***	0.204**		0.396***	0.658***	0.333***	0.304***
BD		-0.239***		-0.427***				-0.336***
OM							0.153**	
Silt×BD				0.469***		-0.683***		
SiltOM			0.227**					
Clay2					0.650***	0.644***	0.599***	0.620***
R2	0.710	0.758	0.740	0.757	0.536	0.622	0.587	0.642
RMSE	0.103	0.095	0.098	0.095	0.126	0.116	0.120	0.114

Note: (C): Clay; (Si): Silt; (BD): Bulk density; (OM): Organic matter.

FC and PWP predictions. This could be as a result of the clay or sand content variation being significantly greater than the OM content variation. As a result, any connection between FC and OM would have been concealed. Our findings are comparable to those obtened by Minasny and McBratney (2002); Khlosi *et al*. (2016) and Santra *et al*. (2018). Rab *et al*. (2011) noted that Australian soils have very little organic matter (OM) and did not include it in their PTFs.

From Table 4, it can be clearly apparent that the ANN produced low RMSE and high R^2 values during the training phase when compared to the conventional method MLR. The *RMSE* values varied from 0.082 to 0.090 $g.g^{-1}$ and from 0.082 to 0.090 $g.g^{-1}$ for FC and PWP, respectively. These values were lower than those of the MLR models, which ranged from 0.038 to 0.044 $g.g^{-1}$. The R^2 values of the ANN models ranged from 0.713 to 0.879 and 0.713 to 0.843, respectively, whereas the MLR models showed the lower values with 0.715-0.788. Nonetheless, the t-statistic ($P<0.05$) indicates that there was no significant difference in the two methods' performance for either FC or PWP. Similarity, Skalová *et al*. (2011) found that ANN performed slighly better than MLR with limeted data.

In contrast to MLR models, ANN models were able to generate accurate predictions during the testing phase (Table 4). The *RMSE* of ANN models varied from 0.002 to 0.048 and were smaller than those of the MLR models, witch ranged from 0.031 to 0.057 and from 0.035 to 0.040, respectively. The R^2 values of the ANN model ranged from 0.739 to 0.879 indicating a more accurate prediction than MLR models, for wich the values ranged from 0.647 to 0.821 and 0.692 to 0.849, respectively.

Overall, Fig 4 displays the performance of every prediction model created during the testing phase in the research area. The best-fit model for predicting FC and PWP was determined to be an ANN model with clay, silt and BD input variables. For all models, evaluation indices performed better at FC than PWP. Haghverdi *et al*. (2012) demonstrated that the better performance of either of data mining methods could be related to the PTF type and database characteristics rather than to inherent supremacy of either of the data mining methods. According to the developed PTFs, it was observed that ANN models with silt, clay and BD as predictors and four neurons in hidden layer had better performance in predicting soil water content at FC and PWP.

$FC = 0.146-1.131\times H_1-0.207\times H_2-1.14\times H_3+0.292\times H_4$

$PWP = 0.719+0.355\times H_1-0.584\times H_2+1.131\times H_3-0.889\times H_4$

Where H_1 = Tanh (0.5× (-0.254-1.747×Clay-0.554×Silt-0.174×BD), H_2 = Tanh (0.5×(0.032-1.048×Clay-2.980×Silt-

Table 3: Statistic performances of the ANN model.

Model	FC				PWP			
	Training		Testing		Training		Testing	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Clay, Silt	0.753	0.100	0.779	0.090	0.605	0.124	0.550	0.118
Clay, Silt, BD	0.761	0.095	0.798	*0.080*	0.639	0.114	0.652	0.105
Clay, Silt, OM	0.748	0.097	0.758	0.087	0.580	0.121	0.540	0.114
Clay, Silt, BD, OM	0.765	0.094	0.792	0.082	0.623	0.116	0.654	0.101

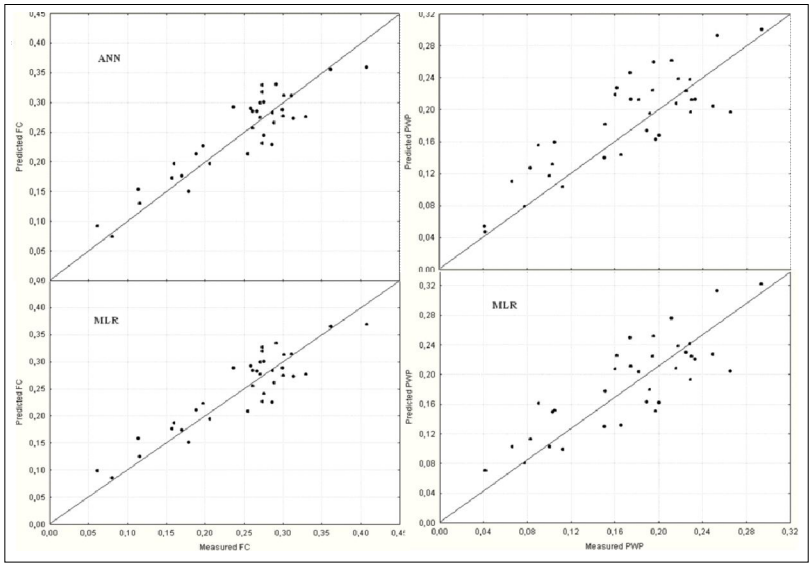


Fig 4: Scatter plots of measured and predicted FC and PWP using ANN and MLR models in testing.

Table 4: Goodness-of-fit for MLR and ANN models in predicting soil water contents at FC and PWP.

Output variables	Input variables	MLR			ANN		
		R^2	RMSE	ME	R^2	RMSE	ME
FC	Clay, Silt	0.750	0.090	-0.009	0.779	0.090	-0.008
	Clay, Silt, BD	0.796	0.082	*-0.007*	*0.800*	*0.080*	-0.007
	Clay, Silt, OM	0.750	0.090	-0.000	0.762	0.087	-0.001
	Clay, Silt, BD, OM	0.774	0.085	-0.006	0.792	0.082	-0.000
PWP	Clay, Silt	0.562	0.115	-0.037	0.550	0.118	-0.039
	Clay, Silt, BD	0.656	0.111	*-0.039*	*0.652*	*0.105*	-0.036
	Clay, Silt, OM	0.547	0.118	-0.032	0.553	0.114	-0.028
	Clay, Silt, BD, OM	0.630	0.113	-0.039	0.654	0.101	-0.030

0.075×BD), H_3=Tanh (0.5×(-0.656+1.349×Clay+0.136×Silt-1.016×BD), H_4 = Tanh (0.5× (1.815+1.555×Clay+0.049×Silt-0.180×BD)

Where Tanh stands for hyperbolic tangent of any given number.

CONCLUSION

This study examines the performance of using ANN and MLR for estimating soil water contents at FC and PWP in arid soils of Algeria. Relative data samples were used to create different models in order to accomplish this goal. The results indicate that texture is stronger correlation with FC and PWP. Organic matter improve a lower prediction. Clay, silt and BD explain 76 and 62% of the variation in FC and PWP respectively. Based on statistical criteria, the obtened results indicate that the overall performance of ANN model was better than of MLR, but this difference was statististically not significant. Also, it was observed that ANN with three input variables clay, silt, BD and four neurons in hadden layer had better performance in predicting of FC and PWP. Therfore, the results were highly encouraging and suggested that ANN methods were promissing in modeling of soil water contents.

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Disclaimers

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Informed consent

All animal procedures for experiments were approved by the Committee of Experimental Animal care.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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