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Neural networks for the prediction of soil water retention in the upper Cheliff watershed, Algeria

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Abstract

A comprehensive understanding of the water retention properties of soils is imperative for effectively managing these resources and addressing the prevailing paucity of soil data. In recent years, significant attention has been directed towards predicting soil retention properties within the soil physics community. Due to the challenges associated with direct measurement, many researchers have sought to predict this capacity using soil properties that are more readily quantifiable. In this context, the present work aims to find an approach that can contribute to the estimation of water retention and consequently improve the management of water resources, which are in deficit in the inputs. The methodology employed in this study is a modelling-based approach, utilising the method of Artificial Neural Networks (ANN) of the Multilayer Perceptron (MLP) type, which is applied to a selection of soils from the Upper Cheliff catchment area, located in the northwestern region of Algeria. The retention of these soils is predicted using a neural model, and the optimal network architecture is identified through the combination of predictive parameters. The analysis demonstrates the significant learning and prediction capacity of neural networks in relation to retention following textural stratification. However, the ANN model that showed the most remarkable efficacy was established for the clay loam soils at the potential level of -1600 kPa. This model incorporated clay, organic matter, and fine silts, which were identified as the most informative.

1. Introduction

Water availability for plant life is inextricably linked to understanding water reserves within cultivated soils. While such soils may possess the essential characteristics for achieving optimal agricultural yields, their potential can only be fully realised if adequate water reserves support plant growth throughout their development cycle (Ben Hassine et al., 2003). Effective management of soil and water resources is vital, given the critical role that water plays in plant development (Kouakou et al., 2021).

To enhance agricultural productivity and ensure consistency, improving the conditions under which crops utilize soil water is imperative. In semi-arid regions, where water resources are severely constrained, the meticulous management of agricultural water use becomes essential. Although soil physical properties are typically well-documented in surveys, the water properties are often inadequately characterized due to their inherent challenges (Dridi et al., 2012). The measurement of soil water properties is a complex and time-consuming process that is also costly. This has prompted numerous studies in recent decades that have sought to estimate these properties based on the physical and chemical characteristics of the soil. (Minasny and McBratney, 2002; Wöstenet al., 2001; Nemes et al., 2006; Pachepsky and Rawls, 2003; Rawls et al., 2003; Vereecken et al., 1989; Bruand et al., 2004). Recent research has demonstrated that artificial neural networks (ANNs), which are modelled after the functioning of biological neurons, are highly effective for simulation and prediction tasks (Piechowicz, 2004; Coursini, 2005). The integration of artificial intelligence into various research fields has gained significant traction in recent years (Bruton et al., 2000; Kim and Kim, 2008, Kim and Kim, 2009; 2012; Kisi, 2006; Kisi, 2009; Arunkumar and Jothiprakash,2013; Guven and Kisi, 2011; Sudheer et al., 2002; Jothiprakash et al., 2011; Raza et al., 2014). ANNs are sophisticated mathematical and computational models composed of interconnected artificial neurons inspired by the human nervous system.

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ANNs are crucial to statistical applications and artificial intelligence methodologies (Ameur Zaimeche, 2014). They are particularly adept at addressing complex recognition problems (Bouriel et al., 2005) and are typically optimized through statistical learning methods (Coulibaly et al., 2000). As non-parametric and non-linear statistical models, they provide a robust alternative to traditional mathematical modeling, effectively tackling identification and prediction challenges.The structure of a neural network consists of artificial neurons linked by weights, which influence the overall behavior of the network, with the learning algorithm defined by the rules governing the adjustment of these connections (Lachhab et al., 2005).

A substantial body of research has employed artificial neural networks (ANNs) to effectively combine field variables to estimate near-surface parameters that exhibit high temporal variability. This includes, but is not limited to, soil moisture (Lavado et al., 2006), soil color (Noshadi et al., 2013), and soil salinity (Ziane et al., 2021). As a result, ANNs are strongly recommended for modeling non-linear data (Ziane et al., 2022).

In arid and semi-arid regions, despite the critical role of water availability in limiting agricultural production, limited research has focused on predicting the water retention properties of soils (Al Majou et al., 2016). This is particularly evident in the Haut Cheliff basin, which possesses significant water potential; however, the absence of a coherent development and management policy has impeded the region's ability to capitalize on this potential (Douaoui et al., 2006). As a result, there has been minimal investigation into the water retention properties in this area. This study aims to assess the performance of neural network models utilizing a database of soil profiles from the Upper Cheliff basin.

Mathematical modelling is a field of study that falls into the category of non-parametric and non-linear statistical models. It possesses the capacity to address identification and prediction issues. A neural network is constituted by a series of artificial neurons that are interconnected by weights, the values of which influence the behaviour of the entire structure. The rules that govern the adjustment of these connections are known as the learning algorithm of the network (Lachhab et al., 2005). Several authors have combined the use of field variables with artificial neural networks (ANN) to estimate near-surface parameters with high temporal variability, such as soil moisture (Lavado et al., 2006).), soil color (Noshadiet al . 2013), and soil salinity (Ziane et al., 2021). It is therefore a highly recommended statistical technique for the nonlinear modeling of data (Ziane et al., 2022).

Although water availability is one of the main factors limiting agricultural production in arid and semi-arid regions, little work has been done on predicting the water retention properties of soils (Al Majou et al., 2016). This is the case for the Haut Cheliff basin, which offers significant water potential. Still, unfortunately, the lack of a rational development and management policy means that the plain does not benefit from this (Douaoui et al., 2006) where limited studies have been conducted on water retention properties. This study aims to discuss the performance of neural network models based on a database of soil profiles located in the Upper Cheliff basin.

2. Materials and methods

2.1. Location and description of the study area

The study area covers part of the Haut Cheliff plain in northwestern Algeria, 120 km southwest of Algiers, between 36°12' and 36°30' N and 2°02' and 2°44' E (Fig. 1). The climate is semi-arid Mediterranean with a distinct continental character.

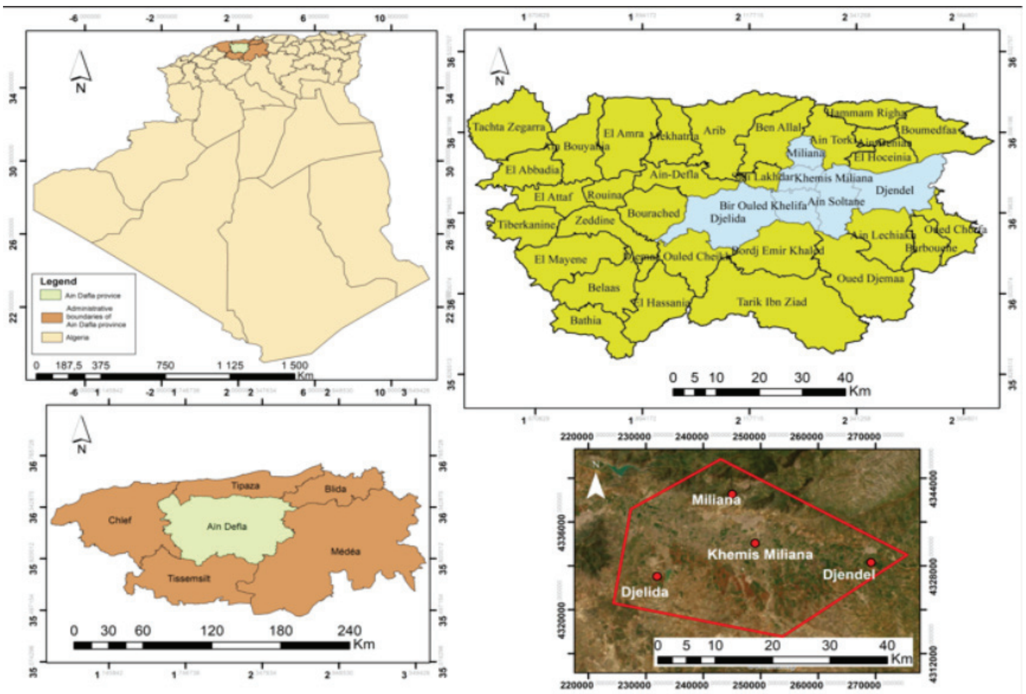

Fig. 1. Location of the study area

2.2. Soils studied

In the Upper Cheliff region, the nature of the soil varies with the relief, allowing us to distinguish between alluvial silt soils and recent terraces (Boulaine, 1957). In terms of granulometry, the soils of the region have a high proportion of fine elements (clay silt+>50%), which contributes to increasing their water retention, apart from the property of the beat due to the presence of high rates of silt, despite their physical constraints, these soils are sought after by farmers, the potential of these soils can only be fully expressed with sufficient water reserves to meet the water needs of crops throughout their vegetative cycle; The results of the granulometric analysis (Table 1) show a high content of fine silt (31.41% on average), while clays are present in significant proportions (37.76%). Conversely, fine sands are relatively low, not exceeding 11.71%, while coarse sands average 6.46%.

The soils are calcareous and alkaline, with an average pH not exceeding 7.71, while the electrical conductivity is moderately low. The average organic matter content is 2.39%, with a maximum of 4.3%, which shows the poverty of certain horizons in organic matter. As for the cation exchange capacity, it shows a relatively high richness, reaching 39.12 cmol (+) kg^{-1} soil for some horizons.

2.3. Artificial Neural Networks

ANNs are an alternative for mathematical modelling and belong to the non-parametric and non-linear statistical models suitable for predictive identification problems (Outanoute et al., 2014).

The Multilayer Perceptron (MLP) is the most important class of neural networks due to the simplicity of its learning algorithm and its ability to approximate and generalize, an MLP consists of at least three layers: input, output, and hidden (Chokmani et al., 2008).

The construction of a neural network begins with the design of its architecture, which involves determining the number of inputs and the number of neurons contained in each layer, as well as the choice of activation functions for each neuron (Fig. 2). According to Lallahem (2003), the sigmoid function is the most commonly used because it is directly inspired by the behaviour of the neurons in front of the received signals and introduces the non-linearity of the system.

Table 1
Soil physical, chemical and biological parameters

Parameters	Maximum	Minimum	Average	Standard deviation
Clay %	57.18	19.79	37.76	8.39
fine Silt %	53	6	31.41	8.21
Coarse silt %	5.89	0.09	19.12	11.13
Fine sands %	40.64	0.03	11.71	6.06
Coarse sands %	15.42	0.31	6.46	3.59
CaCO3 % %	30	1	16.65	7.07
pH	8.10	7	7.7	0.21
EC (dSm^{-1}).	6.50	1.40	1.85	1.31
O.M. %	4.3	1.01	2.39	0.83
C%	1,45	1.09	1.54	0.03
CEC cmol(+) kg^{-1} soil	39.12	6.59	25.63	8.99
Bulk density D_b (g/Cm^3)	1.5	1.3	1.39	0.07

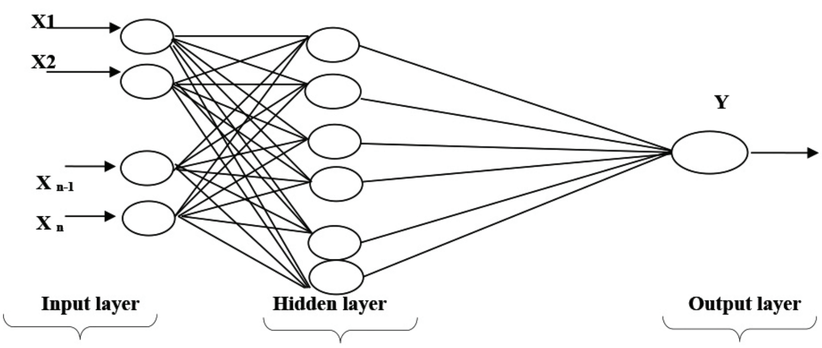

Fig. 2. Architecture of an MLP Neural Network

2.4. Methods

To predict water retention in the soils of the Upper Cheliff Basin and to integrate the influence of pedological data on water retention at different water potentials, artificial neural networks (ANN) were applied to data taken from the database of the agro-pedological study of the Upper Cheliff Basin, carried out by the Pedology Department of the National Agency for Water Resources (A N R H, 2003), containing a set of 493 horizons (A horizons, B horizons, and E horizons) from soil profiles described according to an adaptation of the FAO 'Guidelines for the description of soil profiles, including laboratory measurement data (granulometry, organic matter, pH, electrical conductivity, cation exchange capacity, bulk density, total limestone), these soils are representative of the study region.

The main phase of ANN modelling is constructing the optimal architecture of the ANN model. Indeed, to optimise the performance of the ANN model, we have adopted an approach that includes the selection of input variables, followed by an iterative phase to optimise the learning of the network and the determination of the architecture of the adapted network, as well as the use of a reliable validation methodology (Maier and Dandy, 2001).

The number of neurons in the hidden layer is determined automatically by the computer tool (Statistica, 12), which records the optimal number of hidden neurons for each iteration. The structure of the neural models is a compromise between learning and validation. This requires trial-and-error approach to define the best architecture for the established networks (Kharroubi et al., 2016). Each time, we introduce a new parameter at the input of the network and monitor the evolution of the model performance. We ran several simulations with different combinations to ensure exploration of the field of possibilities, different ANN models were tested using various variable selections, the soil parameters used as independent explanatory variables are clay content, fine silt content, organic matter content and bulk density, while the dependent variable to be predicted is water retention measured at different water potentials:

–10 kPa (pF = 2), – 33 kPa (pF = 2,5), – 100 kPa (pF = 3),
– 1600 kPa (pF = 4,2).

The artificial neural network used in this study is a multilayer perceptron (MLP) network, consisting of an input layer, a hidden layer, and an output layer. It was chosen for its simplicity and speed of construction. The activation function chosen for the nodes of the two hidden and output layers is sigmoidal logistics. To improve the performance of the ANN, it is preferable to normalize the input and output data of the model in the interval [0, 1] (Tymvois et al., 2005). The function used for normalisation is expressed as:

$$\overline{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where:
X is the actual value to be normalized;
X_{min} is its minimum value;
X_{max} is its maximum value
$\overline{X}$ is the normalized value

Several environments are available for the development of neural networks, but in this study, Statistica12 was used.

The different weights (parameters) of the neural models were adjusted in this computer environment using supervised learning with the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm.

The exploited data from the database are randomly divided into three groups. The first group, consisting of 70% of the total data, is used for the system training. The second group, containing 20% of the total data, will be used to validate the network, and the remaining 10%, which did not participate in the training of the model, will be used as an independent test to approve the generalisation of the model (Benatiallah et al., 2020). There is no rule for determining this split quantitatively. It is often the result of a compromise that considers the available data and the allotted time for training.

2.4.1. Performance evaluation of the developed models

To evaluate the performance of the developed Artificial Neural Network (ANN) models and to ensure that they generalize effectively, several statistical metrics are commonly utilized. Among these, the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) are particularly important. These metrics provide insights into the model's predictive accuracy by measuring the differences between predicted and actual values.

Root Mean Square Error (RMSE): This metric quantifies the average magnitude of the errors by taking the square root of the average of the squared differences between predicted and actual values. A lower RMSE indicates better model performance, as it shows that the model's predictions are closer to the true values.

$$\text{RMSE} = \sqrt{\frac{\sum_i^n (\hat{}y - y_i)^2}{n}} \tag{2}$$

Mean Absolute Error (MAE): This metric assesses the average absolute differences between predicted and actual values, providing a straightforward measure of prediction accuracy. Like RMSE, a lower MAE signifies a better-performing model.

$$\text{MAE} = \frac{\sum_{i=1}^n |\hat{}y - y_i|}{n} \tag{3}$$

Or:
n: is number of values in the database.
y_i: is the observed value
^y: is the value predicted by the model

2.4.2. Quality of model prediction

Once the neural network models predicting water retention are selected, we used a set of horizons not used during training to test the performance of the prediction by the ANNs, the coefficient of determination R^2.

$$R^2 = \frac{\sum_i (y_i - \overline{y}_i)(\tilde{y}_i - \overline{\tilde{y}}_i)}{\sum_i (y_i - \overline{y}_i)2 \sum_i (\tilde{y}_i - \overline{\tilde{y}}_i)2} \quad (4)$$

y_i: Measured values
$\tilde{y}_i$: The values simulated by model
$\overline{y}_i$: The mean of the measured values
$\overline{\tilde{y}}$: The mean of the values simulated by model

3. Results and discussion

After training and several trials with different RNA combinations, the neural models were able to this approach allowed the neural models to be built. It is from the architecture of the network that the influence of each parameter is introduced, intending to produce reliable models. The number of layers and the number of neurons per layer determine the architecture of the ANN.

3.1. Neural network models developed

The development of neural network models involved the creation of various ANN model combinations, which were then subjected to rigorous testing. This testing process involved the selection of different variables, including soil parameters at varying potentials. This approach aimed to identify the most suitable input variables for the prediction model. The output of this process is the water retention at different potentials. The inputs to the model comprise a range of combinations of clay, fine silt and organic matter parameters, and bulk density.

To refine the results, a texture stratification approach was developed with three texture classes, corresponding to the texture classes in the texture triangle (USDA, 1960).

Among the different configurations of the network tested at different water retention potentials, those that gave the best coefficient of determination R^2 for the learning and validation phase were selected. The performance criteria during the learning and validation phases of the models are presented in Table 2. The results evaluated according to the performance criteria seem to be satisfactory for all combinations with R^2 values higher than 0.70. The performance of the model changes with each addition of a soil parameter and at different water potentials. However, we note that the best results are obtained after textural stratification. The best performing model, kept for all horizons, has 3 inputs, respectively clay, fine silt, and organic matter at water potential (–1 600 kPa), and the hidden layer has 4 networks.

Indeed, the findings of this study demonstrate that soil water retention is significantly influenced by the fine fraction (clay and fine silt) at low potentials (Tessier et al., 2007), as well as the effect of organic matter at this level of potential.

For the explanatory variables of the model established for the silty clay loam horizons, the network has 4 entries, namely clay, organic matter, fine, silt, and bulk density at potential

(–100 kPa), while the number of neurons in the hidden layer is 6. Regarding the model of the whole horizons, the validation performances improve, and the R^2 increases from 65% to 78%, which explains the favourable effect of the bulk density on the water retention in the domain of high potentials. In this case, the macro porosity resulting from the structural assembly retains most of the water. The water retention properties in the high potential range can be better estimated by considering the bulk density (Bruand et al., 2004).

In addition, the model developed for the clay-loam horizons, the explanatory variables are clay, organic matter and fine silt at potential (–1600 kPa). The number of neurons in the hidden layer increases to 9, the performance improvement performance is obvious (89% for the validation), which again shows the important role of the fine fraction of the soil on the one hand and the organic matter on the other hand for water retention at low potential (–1600 kPa) (Bigorre, 2000; Rawls et al., 2003; Eden et al., 2017). These results are already confirmed by the work of Martiniello (2012) and Emerson (1995), it seems that organic matter effects on the structure to increase the macro- and mesoporosity of the soil; they showed, on compact clay-silt assemblages, the formation of clay bridges between the silt grains, which can explain the formation of a fine porosity, as well as the role of energy, indeed the water content increases when the water potential decreases. This is already confirmed by the work of Duchaufour (1995), who explains that the texture conditions the energy of retention, and this energy is all the more important the smaller the pores are.

The inputs to the model developed for the fine silt horizons are clay and organic matter and bulk density at potential (–1600 kPa), there are 8 neurons in the hidden layer, however this model shows lower performance than the previous models,

Table 2
Performance of RNAs developed in different combinations

Neural networks	Horizon type	Inputs of models	Potential Water	R^2	
				Learning	Validation
MLP 3-4-1	All of the horizons	C + SL + OM	–1600 kPa	0.70	0.65
MLP 4-6-1	Silty clay loam horizons	C + SL+ OM +Bd	–100 kPa	0.85	0.78
MLP 3-9-1	Clay loam horizons	C + SL + OM	–1 600 kPa	0.93	0.89
MLP 4-8-1	silt loam horizon	C + SL + OM + Bd	–1 600 KPa	0.87	0.80

Explanations: C – clay SL – silt loam, OM – organic matter, Bd – bulk density.

while the bulk density effect did not improve the prediction at low potential. The weight of bulk density is more important at high potentials (Bruand et al., 1996).

From the results obtained, and referring to the coefficient of determination R^2, all the models express more than 80% of the variation in water retention, these results are good performance criteria that vary according to the potential (Tessier et al., 2007), they indicate that the combinations clay, fine silt and organic matter have the best predictive quality of soil water retention, this is explained by the predominance of the fine fraction contributing to soil water retention. They ensure that the input variables (clay, fine silt, and organic matter) contain a significant amount of predictive values at low potential (1600 kPa). It appears that the best performances of the models obtained are obtained after textural stratification, and the best performing model is the one obtained for clay-loam soils at potential (1600 kPa), which leads us to deduce that textural stratification improves the quality of predictions by ANN.

3.2. Performance evaluation of the developed models

To evaluate the performance of the developed ANN models and to have a model that generalises best. Several statistical tests are commonly used. The root mean square error (RMSE) and the mean absolute error (MAE) (Rivals, 1995) are given by the following equations:

$$\text{RMSE} = \sqrt{\frac{\sum_i^n (\hat{}y - y_i)^2}{n}}$$

$$\text{MAE} = \frac{\sum_{i=1}^n |\hat{}y - y_i|}{n}$$

Where:
n – number of values in the database.
y_i – the observed value
^y – the value predicted by the model

The evaluation of the ANN modelling was carried out through the performance criteria of root mean square error (RMSE) and mean absolute error MAE (Table 3), the results obtained are satisfactory and acceptable. The evaluation of the ANN modelling was carried out through the performance criteria of root mean square error (RMSE) and mean absolute error (MAE) (Table 3). The results obtained are satisfactory and acceptable, significant informative power is demonstrated by the predictive variables clay, fine silt, and organic matter. This finding is further substantiated by the low RMSE, indicating a reduced margin of error when transitioning from all horizons to the textural stratification. This finding is further substantiated by the low root mean square error (RMSE), which indicates a reduced margin of error when transitioning from all horizons to the textural stratification. Notably, the clay loam and silty clay loam horizons exhibited a lower error rate compared to that observed in the silty clay loam horizons. However, the most efficient ANN model is the one with 3 inputs, clay, fine silt, and organic matter, developed for clay-loam soils at potential (-1600 kPa), with performance criteria of about 0.46 for the root mean square error (RMSE) and a mean absolute error (MAE) of 0.26. Indeed, the prediction models developed reproduce well the water retention of the tested horizons. There may be some discrepancies between the water retention measured and that predicted by these models, but overall the water retention measured and predicted using the networks are superimposed, showing a reliable forecast (Fig. 3).

Table 3
Performance of the developed models

Model developed	RMSE	MAE
All horizons	0.51	0.31
Fine clay loam	0.48	0.29
Clay loam	0.46	0.26
Silty- Fine	0.49	0.28

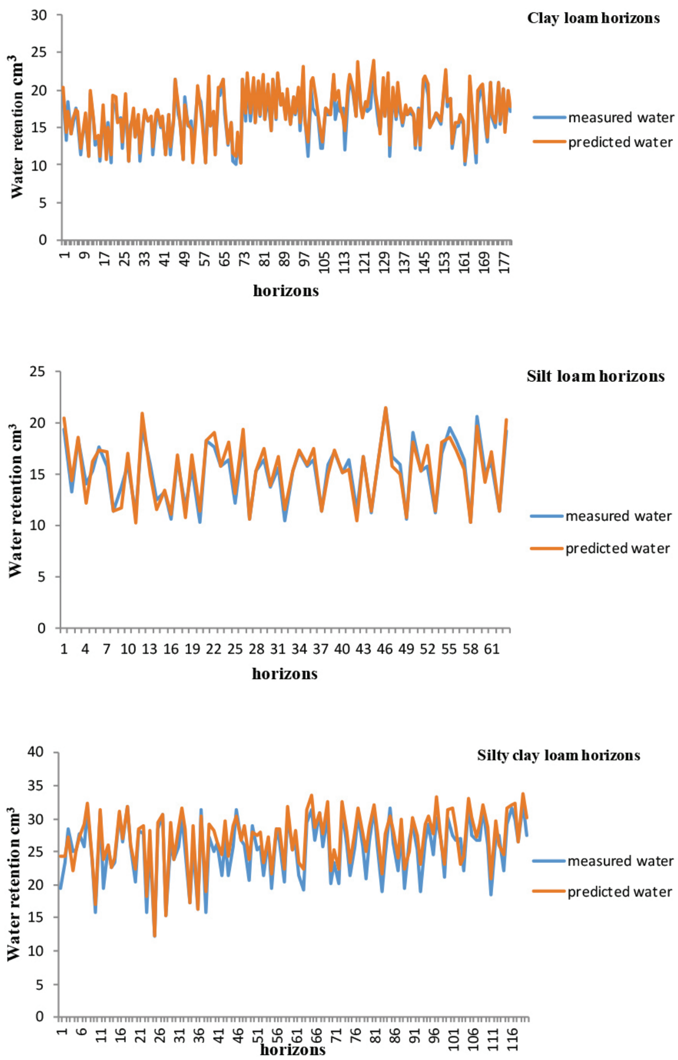

Fig. 3. Observed and predicted water retention of validation horizons after textural stratification

3.3. Quality of model prediction

After selecting the neural network models that predict water retention, we used a group of horizons not used during training to assess the performance of the predictions made by the ANNs, using the coefficient of determination R^2 as an indicator.

$$R^2 = \frac{\sum_i (y_i - \bar{y}_i)(\tilde{y}_i - \bar{\tilde{y}}_i)}{\sum_i (y_i - \bar{y}_i)2 \sum_i (\bar{y}_i - \bar{\tilde{y}}_i)2}$$

where:
y_i – Measured values
$\tilde{y}_i$ – The values simulated by model
$\bar{y}_i$ – The mean of the measured values
$\bar{\tilde{y}}$ – The mean of the values simulated by model

This describes the closeness of the predicted value to the observed value according to the ANN models during the test phase, is shown graphically in Fig. 4.

According to the three ANN models selected, after texture stratification. The representation of the predicted data with the measured data forms a scatter plot around the line (Y=X). The scatter plots are distributed in a 45° orientation with a linear trend line coinciding with the line Y=X. This linear arrangement of the scatter plot indicates the presence of a good correlation between the measured and predicted values, as the measured water content values are relatively close to those predicted by the 3 ANN models established after textural stratification. However, the model of the clay-loam horizons at potential –1 600 kPa shows a better correlation with an R^2 of 0.93, so the predictions of water retention by the selected established ANN models are satisfactory (Fig. 5).

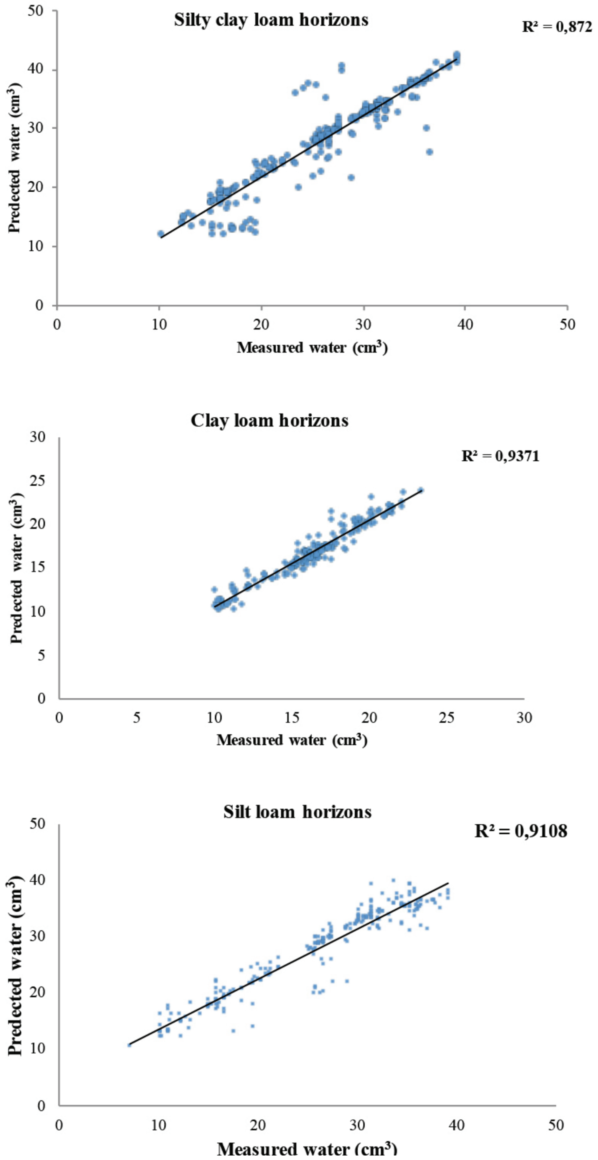

Fig. 4. Coefficient of determination of the ANN models in the test after textural stratification

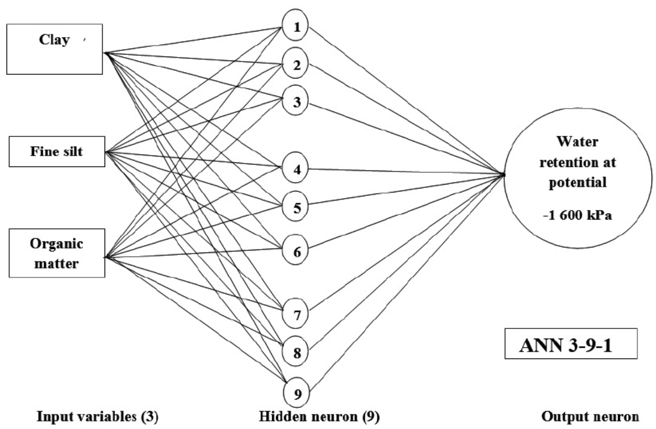

Fig. 5. Optimal architecture developed for clay-loam horizons

4. Conclusions

The approach to predicting water retention at different potentials, using the PMC (Multilayer Perceptron) type artificial neural network (ANN) method, applied to the soils of the Upper Cheliff catchment area based on granulometric characteristics, organic matter and apparent density, has demonstrated the effectiveness of this ANN methodology as a tool for predicting soil water retention. The acquired results are satisfactory, and the high-performance neural networks have indicated a promising learning and predictive capacity for water retention.

The recommended approach indicates two fundamental aspects. Firstly, the prediction results are contingent on the quality of the input data. Secondly, the level of potential is a crucial factor in prediction accuracy. However, textural stratification has been observed to affect the quality of the prediction using RNA. Consequently, RNA models capable of making satisfactory predictions for the soils studied were obtained, and it was determined that the combination of clay, fine silt, and organic matter in the prediction of soil water retention can explain a large proportion of water retention, particularly at the low potential (1600 kPa). The present study demonstrates the RNA approach's suitability for predicting retention, and a multilayer perceptron with a single hidden layer and a limited number of neurons is sufficient to predict the soils of the Upper Cheliff catchment with satisfactory performance. Furthermore, RNA models can be applied to other soil types and regions.

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Conflict of interest

The authors declare no conflict of interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This research did not involve human or animal subjects.

Author Contributions

Samia Zemouri – Conceptualization, Writing– original draft. **Abdelkader Douaoui** – Supervision, Methodology. **Samir Hadj Miloud** – **S**oftware. **Nassir Harrag** –Visualization.

All authors read and approved the final manuscript.

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