https://doi.org/10.46344/JBINO.2022.v11i01.21

ESTIMATION OF EXCHANGEABLE SODIUM PERCENTAGE WITH THE AID OF SODIUM ADSORPTION RATIO IN SEDIMENTARY SOILS

SORUSH NIKNAMIAN

MD PHD DR.PH, MILITARY MEDICINE DEP., LIBERTY UNIVERSITY, USA

E-mail: so.niknamian@gmail.com

ABSTRACT

Soil salinity and sodicity are two main factors limiting plant growth in irrigated agricultural land. Sodium adsorption ratio (SAR) and exchangeable sodium percentage (ESP) are two different criteria as an index of soil sodicity and salinity. Various approximate relationships between ESP and SAR have been reported for soils in different regions of the world. Since there is possibility that these relationships change substantially with clay content, mineralogy, salinity of equilibrium solution, and saturation percentage of soils, it seems essential doing specific studies for different regions. The purpose of this research was to i) find the relationship between ESP and SAR, and ii) estimate the ESP from SAR in alluvial soils of Sistan, the dry plain in east of Iran. Thus, 301 soil samples were collected from study area and analyzed. The best linear and logarithmic equations found between ESP and SAR using Datafit software were $ESP = 8.89 \times \ln(SAR_{1:1}) + 14.04$ and $ESP = 8.73 \times \ln(SAR_{1:5}) + 14.59$, that ESP variation was justified 78% and 76%, respectively. Then, the multi-layer perceptron neural network (MLP) and ANFIS system performance were investigated in order to estimate ESP. Results showed superior performance of MLP and ANFIS compared with the regression models. ESP estimation from $SAR_{1:1}$ using ANFIS was more accurate than other models (coefficient of determination and root mean square error values were 0.99 and 0.014, respectively). These results indicate the superiority of the intelligent models in order to explain the relationship between ESP and SAR over linear and non-linear regression equations.

Keywords: Soil salinity, Soil sodocity, Regression equations, SAR, ESP, MLP, ANFIS

Introduction

Knowing the relationships and correlations among different soil properties and expressing them quantitatively in the form of statistical models is one of the important aspects of soil investigation. These models, called pedo-transfer functions, comprising regression and artificial neural networks (Minasny et al., 2004). Important soil properties which are costly and time consuming in measurement, express as a function of easy obtaining attributes. First, PTFs was made of linear regression analysis, but gradually this analysis was replaced by nonlinear regression. Statistical analyses are based on accurate observed variables; while in the natural systems like soils, precision of observations is lower and the relationships arevague. Thus using the fitting methods of functions which are able to explain the ambiguous structure of system and provide real patterns is essential (Mohamadi and Taheri, 2005). In this regard, the artificial intelligence models which designed based on the nervous system of the human brain in the learning process is increasingly taken into consideration. Not requiring historical information about relationships amongst input and output and less sensitivity regarding error in data, are advantages of these models in comparison with regression transitional functions (Agyare, 2007). In other words, these models are able to predict variations of output variables with the lowest measured parameters and acceptable accuracy.

Soil salinity and sodicity are two main factors limiting plant growth in irrigated agricultural land. Salinization is the accumulation of soluble salts in the soil profile to the level that limits agricultural production. Soil salinity becomes important when salt concentration in soil solutions exceed crop tolerance level. Excessive amounts of salt accumulations occur in poorly drained soils subjected to intense evaporation (Wang et al., 2008). Of the current 230 million hectares of irrigated land globally, 45 million hectare (20%) are affected by salinity (FAO, 2008). Soil sodicity is another important characteristic affected by salinity which influences soil chemical and physical properties (Farahmand et al., 2011). When exchangeable sodium percentage (ESP) exceeds 15%, soil sodicity becomes effective. Degrading soil structure, decreasing soil hydraulic conductivity, soil aeration, and infiltration rate, and increasing soil pH up to 8.5 are the main reasons for decreased agricultural production in sodic soils (Richards, 1954).Soil salinity can be controlled by measures such as drainage, irrigation and accurate cropping pattern (Ceti and Kirda, 2003).

To evaluate the degree of soil sodicity (relative amount of Na in comparison with calcium and magnesium in transitional sites) sodium adsorption ratio (SAR) (with a threshold limit of 13 Cmol kg^{-1}) and exchangeable sodium percentage (ESP) (with a threshold limit of 15 percent) used, which is defined as follow (Sumner, 1993; Quirk, 2001):

$$SAR = Na^{+} \Big/ \sqrt{\left({(Ca^{2+} + Mg^{2+})}/{2} \right)} \quad (1)$$

Where:

SAR : Sodium adsorption ratio (Cmol kg^{-1})$^{0.5}$,

Na^{+}, Ca^{2+}, Mg^{2+} : Measured exchangeable Na^{+}, Ca^{2+} and Mg^{2+}, respectively (cmol kg^{-1})

$$ESP = \left({Na^+}/{CEC} \right) * 100$$

(2)
Where:
ESP : Exchangeable sodium percentage (%),
Na : Measured exchangeable Na (Cmol kg $^{-1}$),
CEC : Cation exchange capacity (Cmol kg $^{-1}$)

Recognition of numerical values of ESP and its variations in sodic or saline and sodic soils for estimating the amendment contents and land management is essential in agricultural lands. The measurement of ESP is time-consuming, costly and comes with errors. Its measurement errors are related to CEC and exchangeable sodium content. Numerous sources of error have been reported in measuring the CEC with Bower method (Bower et al, 1952) which comprises not removing excess indicator cations in rinsing stage and presence of zeolite mineral in soil which leads to CEC overestimation and consequently underestimating the ESP value In addition, lack of complete saturation in transitional sites with indicator cation, soil wasting and indicator exchangeable cation hydrolyzing during the rinsing stage, incomplete replacement of sodium with ammonium and dissolution of gypsum, result in poorly measuring CEC value and subsequently overestimating ESP (Rhoades,1982). Furthermore, CEC measurement is costly and time consuming. Measuring exchangeable sodium contents in soils with $EC_e \geq 110$ dSm $^{-1}$ is influenced by anionic repulsive effect error thatresults in underestimation of ESP (Jurinak et al, 1984). In order to overcome mentioned problems, presenting a method that could use another parameter to calculate ESP in an indirect manner, is more economical. Sodium adsorption ratio (SAR) is a parameter that various relationships have reported between ESP and itfor soils in different regions of the world. However, there is possibility that these relationships changes with that clay content, mineralogy and salinity of equilibrium solution, and soil saturation percentage (Evangelou and Marsi, 2003; Kopittke et al., 2006; Seilsepour et al., 2009, Chi et al., 2011). In other words, these studies have done for specific regions and soils. Thus, it is necessary to do them considering soil type and properties in different sites.The United States Salinity Laboratory (USSL) proposed one of the earlier models to predict soil ESP from soil SAR as ESP = - 0.0126 + 0.01475 × SAR for United States soils (Richards, 1954).

Studying soils of southeastern Australia, Rengasamy et al. (1984) proposed: ESP = 1.95 × $SAR_{1:5}$ + 1.8 (R^2 = 0.82) to estimate ESP from SAR in the soil extract with a 1:5 ratio of soil to water. Seilsepour et al. (2009) suggested ESP = 1.95 + 1.03 × SAR (R^2 = 0.92) in dry soils of Varamin region, Iran.Chi et al. (2011) investigated 117 soil samples in the Songnen Plain, Northeast China, and estimated ESP values using SAR_e and $SAR_{1:5}$. They reported high correlation coefficient ($R^2 = 0.76$, $p < 0.01$), between ESP, SAR_e and $SAR_{1:5}$ for saline soils and presented these logarithmic regression equations: ESP = 10.72 × ln (SAR_e) - 15.36 and ESP = 11.44 × ln ($SAR_{1:5}$) + 5.48.Farahmand et al. (2011) found out nonlinear relationship between ESP and SAR in 29 samples of salt-affected soils in Tabriz plain, north West of Iran. Mesquta et al. (2005) expressed an equation same as Freundlich equation [ESP = K × $(SAR)^m$] between ESP and SAR..

Increasing trend in soil salinity is a very important problem, globally and also in Iran. Approximately 44.5 million hectares of arid agricultural land in Iran are influenced by salinity and 18 million hectares (10%) of soils of Iran are sodic soils (Banai et al., 1383). Sistan is one of the interior plains of Iran plateau located in southeastern Iran, with elevation ranging from 475 to 500 meters above sea level and covered by alluvial delta of the Hirmand River and its surrounding floods. Considering dry climate, high groundwater levels, low annual rainfall, high evapotranspiration rate, and unsuitable water quality which utilized to irrigate agricultural farms,, salinity is a serious problem in this region and is expanding. Unfortunately due to vastness of Sistan plain and difficult conditions for field investigations, soil studies and findings in this area are very little. Planning for preventing and solving the problem of salinity in order to improve soil quality and sustainable agricultural development is necessary and inevitable in this area. The purpose of current study is investigating and suggesting relationships and models to predict the amount of soil ESP from SAR. Considering statistical regression methods that have been used in previous studies, computational-intelligence-based methods performance assessed. It was tried to present an accurate model with minimum input variables and acceptable precision that does not need to costly and time-consuming laboratory measurements for estimating ESP.

Material and Methods

Description of the study area

The study area is Sistan plain located in the southeast of Iran, one of the driest regions of Iran and famous for its "120 day winds", a highly persistent dust storm in the summer which blows from north to south with velocities of nearly 20 knots. The Sistan delta has a very hot and dry climate. In summer, the temperature exceeds 50^{o}C. Rainfall is about 55 mmyear^{-1} and occurs only in autumn and winter. Evapotranspiration of the area is 4500 to 5000 mm year^{-1}. Strong winds in the region are quite unique and are an important contributing factor for the high evaporation (fig. 1).

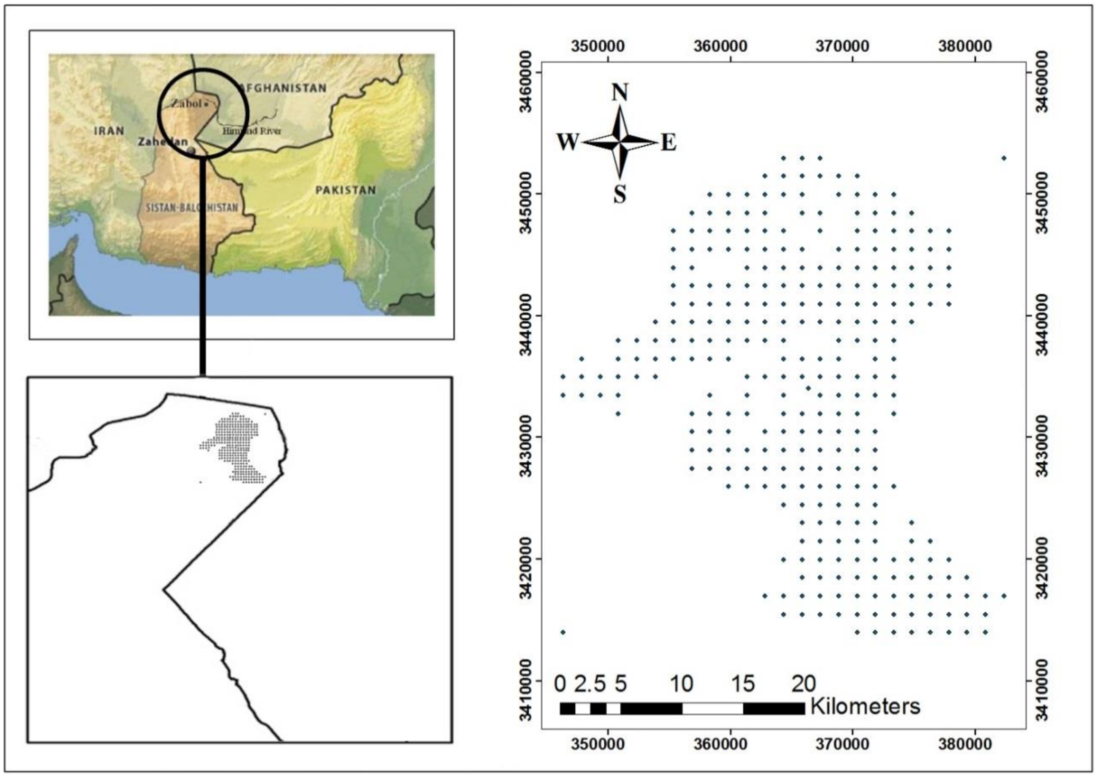


Figure 1: Map showing the geographical setting of the stady area, Zabol, Iran.

Field and Laboratory Analyses

Soil samples were collected from 301 points throughout study area. Every soil sample was taken in lands with a high risk of salinization and/or sodification. Air-dried soil samples were passed through a 2-mm sieve for selected chemical and physical measurements. The 1:5 and 1:1 soil to water extracts were prepared by adding 20 mL distilled water to 4g and 20g soil in a 100 mL bottles, respectively. The bottles were sealed with a stopper, agitated for 15 min on a mechanical shaker (100 r min^{-1}), allowed to stand for 1 h, and then agitated again for 5 min before a sample was obtained by filtration (Chi and Wang, 2010). Electrical Conductivity (EC), pH, concentrations of Na^{+}, Ca^{2+} and Mg^{2+}, CEC and soil texture were determined using hydrometric technique (USDA-NRCS, 1996). The ESP and SAR were determined according to eqs. 1and 2, respectively.

Table 1: The mean values, standard deviation (S.D.) and coefficient of variation (C.V.) for soil physical and chemical properties of the soil samples used to determine ESP-SAR

Parameter	Minimum	Maximum	Mean	S.D.	C.V. (%)
Clay (%)	7.10	49.50	23.2	9.22	39.3
Sand (%)	2.50	85.00	34.4	18.2	52.9
Silt (%)	0.00	82.00	42.6	14.6	34.3
pH (log[H^{+}])	7.66	10.26	8.84	0.53	6.00
$EC_{1:1}$ (dS m^{-1})	1.44	87.00	11.13	14.0	125.7
$EC_{1:5}$ (dS m^{-1})	0.20	29.90	3.50	5.03	144
$SAR_{1:1}$ (Cmol kg^{-1})	1.00	73.01	5.34	8.33	155.9
$SAR_{1:5}$ (Cmol kg^{-1})	0.56	46.08	4.85	6.69	137.3
ESP (%)	5.86	59.74	23.94	9.19	38.40
CEC (Cmol kg^{-1})	3.7	24.70	10.8	2.30	21.27

Linear and nonlinear regression model:
An example of a linear and nonlinear regression model is shown in the equation 3 and 4, respectively.

$$Y = aX + b \quad (3)$$

$$Y = a \times \ln x + c \quad (4)$$

Where:
Y: dependent variable, for example, ESP, soil samples
X: independent variables, for example the SAR of soil samples.
a : the regression coefficient, and
C: the intercept.
Order to estimate and modeling using sodium adsorption ratio of ESP, a linear Regression equation was suggested above.
Before modeling, 85% of data assigned to simulation and 15% to test the model. Coefficient of determination (R^2) and root mean square error (RMSE) were used for evaluating models. All linear and nonlinear regression equations were fitted to the data using the Datafit software and the best regression equations were selected.

Artificial neural networks modeling
The artificial neural network is a useful computational way for predicting and modeling abstruse relationships among parameters, especially when there is no explicit relation (Gallant, 1993; Smith, 1993). The structure of artificial neural network basically includes three layers, the input layer that all the data are imported to the network and calculation of the weights of variables are done, the hidden layer or : layers, that data are computed, and the output layer, that the artificial neural network results are obtained. Every single layer includes one or more fundamental section(s) called a node or a neuron (Dreyfus et al., 2011). The problem is the key factor can determined the number of neurons in the layers. The small number of hidden neurons is a limiting factor to learn the process carefully however too high number can be very time consuming and the network may over fit the data (Karunanithi et al., 1994).

Multilayer Perceptron (MLP) description
This network includes an input layer, hidden layer and an output layer (fig. 2). The scaled values have been passed into the input layer and after that propagated to the next layer which is called hidden layer, before reaching the output layer of the network (Hussain et al., 2002). Each node in both hidden or output layer in the first place will act as a summing junction with the use of the following equation inputs combine and modify from the previous layer (Jorjani et al., 2008).

$$Y_i = \sum_{j=1}^{i} X_i W_{ij} + b_j$$

which y_i is the net input to node j in hidden or output layer, the weight related to neuron i and neuron j are indicated as w_{ij}, x_i is the input of neuron j, b_j is the bias connected to node j (Razavi et al., 2003). Sigmoidal transfer function usually use for nonlinear relationship (Ghaffari et al., 2006; Torrecilla et al., 2007). The general form of this function is showed below (Jorjani et al., 2008)

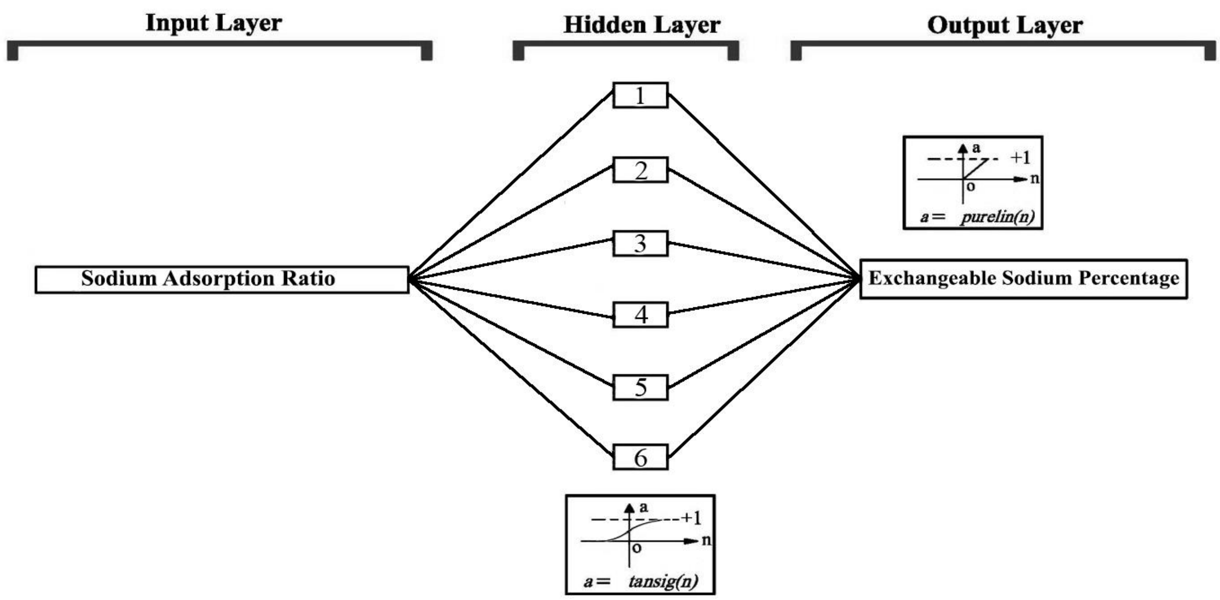


Figure 2: The MLP architecture of one inputs and six neurons

$$Z_i = \frac{1}{1+e^{-Y_y}}$$

where Z_j is the output of node j. To avoid reduction in network speed and accuracy and to make data values equal, it is necessary to normalize input data (Torrecilla et al., 2007). Normalization was done so that the mean of the data series became 0.5 (Kumar et al., 2002). The following equation is used for normalizing data:

$$x_n = 0.5\left[\frac{x-\bar{x}}{x_{max}-x_{min}}\right]+0.5$$

where x_n: normalized value, x: actual value, $\bar{x}$: mean value, x_{min}: minimum value and x_{max}: maximum value of parameter.

MLP network need sample series of input and output data for designing and training. In this study, SAR has been considered as network input and ESP as output data. Seventy (70), 15 and 15% of data were used to train, validate and test of MLP model, respectively.

MLP network applied for ANN modeling using MATLAB 7.6 software. Marquardt-Levenberg learning rule and hyperbolic tangent function were used for training (Haykin, 1994). Number of neurons in hidden layer was computed by trial-and-error method and finally the best structure for ESP was selected considering the greatest R^2 value and the least RMSE.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

The advantage of the fuzzy inference system is that it can deal with linguistic expressions and the advantage of a neural network is that it can be trained and also can self-learn and self-improve. Jang (1993) took both advantages, combining the two techniques, and proposed the Adaptive Neuro-Fuzzy Inference System (ANFIS). The idea behind neural network and fuzzy inference combination is to design a system that uses a fuzzy logic to represent knowledge in an interpretable manner and has the learning ability derived from a neural network that can adjust the membership functions parameters and linguistic rules directly from data in order to enhance the system performance (Wang et al., 2006). The ANFIS architecture contains a five-layer feed forward neural network as shown in figure 3. ANFIS is a hybrid intelligent system which implements a Sugeno fuzzy inference system for a systematic approach to generate fuzzy rules from a given input-output dataset (Negnevitsky, 2005).

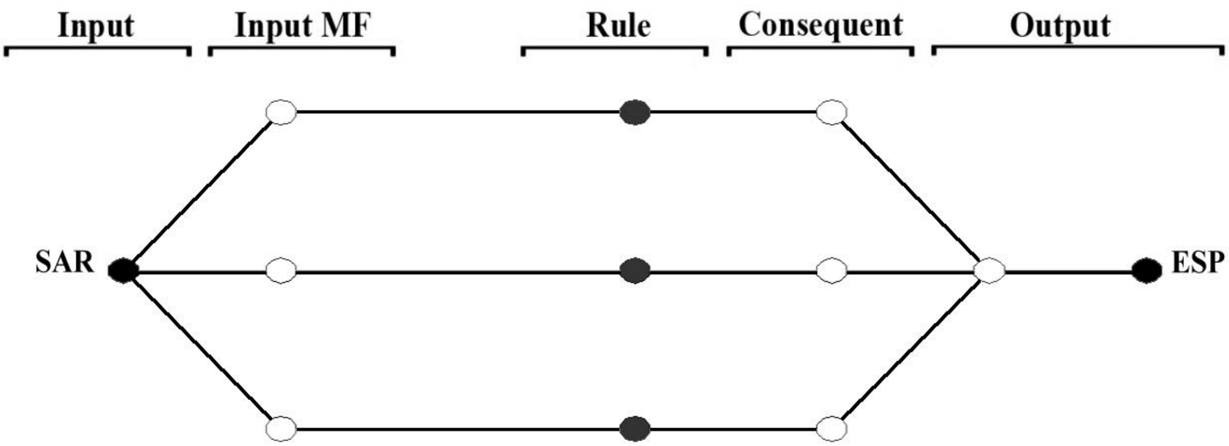


Figure 3: ANFIS architecture of one input and three rules

Analysis

The R^2 and RMSE values used to compare models predicted soil ESP and measured values and assess the performance of models.

$$R^2 = 1 - \sum_{i=1}^{n}(y_i + y_{di})^2 \Big/ \sum_{i=1}^{n}(y_{di} + y_m)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_{di})^2} \quad (6)$$

where n is the number of points, y_i is the output value got from the neural network model, y_{di} is the experimental value, and y_m is the average of the experimental values.

In this study in order to predict ESP using MLP and ANFIS, SAR considered as input. MLP had three layers (an input layer, one hidden layer and an output layer) and seven neurons in the hidden layer. Furthermore, ANFIS had five layers (input layer, input membership function layer, rules layer, consequent layer and output layer) with three triangular membership functions (TriMF) for input function.

Results and Discussion

Table 2 indicates various statistics of the best linear and nonlinear regression models for predicting ESP based on SAR in 1:1 and 1:5 extract soil to water.

Table 2: The RMSE of the independent variable, R^2 and Coefficient of Variation (C.V.) of the soil ESP pedotransfer function

Pedotransfer function	Independent var.	RMSE(%)	R^2	C.V. (%)	P value
$ESP = 0.92 \times SAR_{1:1} + 19.01$	$SAR_{1:1}$	5.47	0.77	21.11	< 0.0001
$ESP = 8.73 \times \ln(SAR_{1:1}) + 14.14$	$SAR_{1:1}$	3.79	0.87	18.12	< 0.0001
$ESP = 1.19 \times SAR_{1:5} + 18.18$	$SAR_{1:5}$	5.04	0.69	19.64	< 0.0001
$ESP = 8.68 \times \ln(SAR_{1:5}) + 14.78$	$SAR_{1:5}$	4.09	0.81	18.63	< 0.0001

The logarithmic regression which fitted to the data in DataFit has the higher accuracy among the nonlinear equations (Higher R^2 and lower RMSE). In addition, results presented in Table 2 shows better performance of nonlinear regression models comparing linear models.
.
Pedotransfer function of ESP from $SAR_{1:1}$ has R^2 and CV equal to 0.87 and 18.12%, respectively, and is the most effective regression model to estimate ESP.
Logarithmic relationship between ESP and SAR, $SAR_{1:1}$ and $SAR_{1:5}$, represents in figure 4

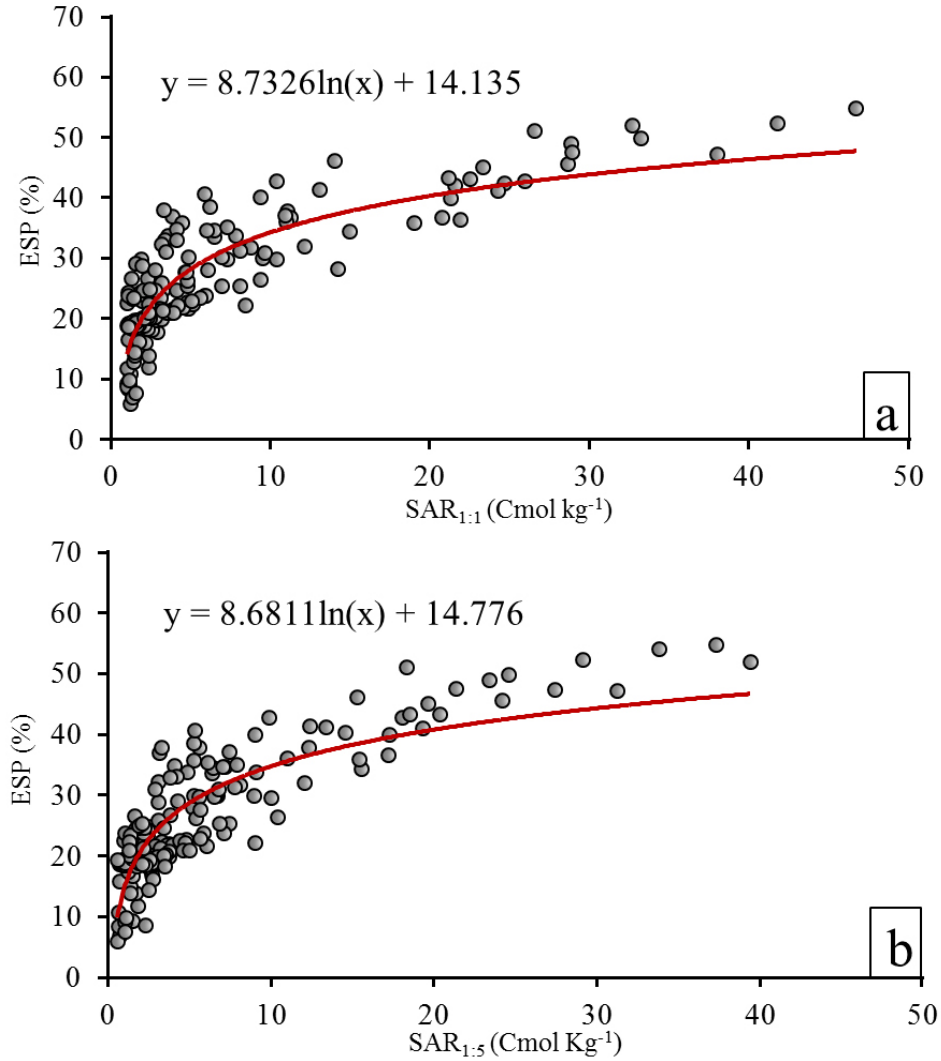


Figure 4: Relationships between ESP and (a) $SAR_{1:1}$, (b) $SAR_{1:5}$

Relationships between ESP and SAR

No significant difference observed between estimated ESP from $SAR_{1:1}$ and $SAR_{1:5}$ (ESP mean values were 23.932% and 23.929%, respectively) and its actual measured value (mean value: 23.941%) for 45 soil samples ($P > 0.01$). Figure 5 shows comparison between predicted and measured ESP data using logarithmic equations.

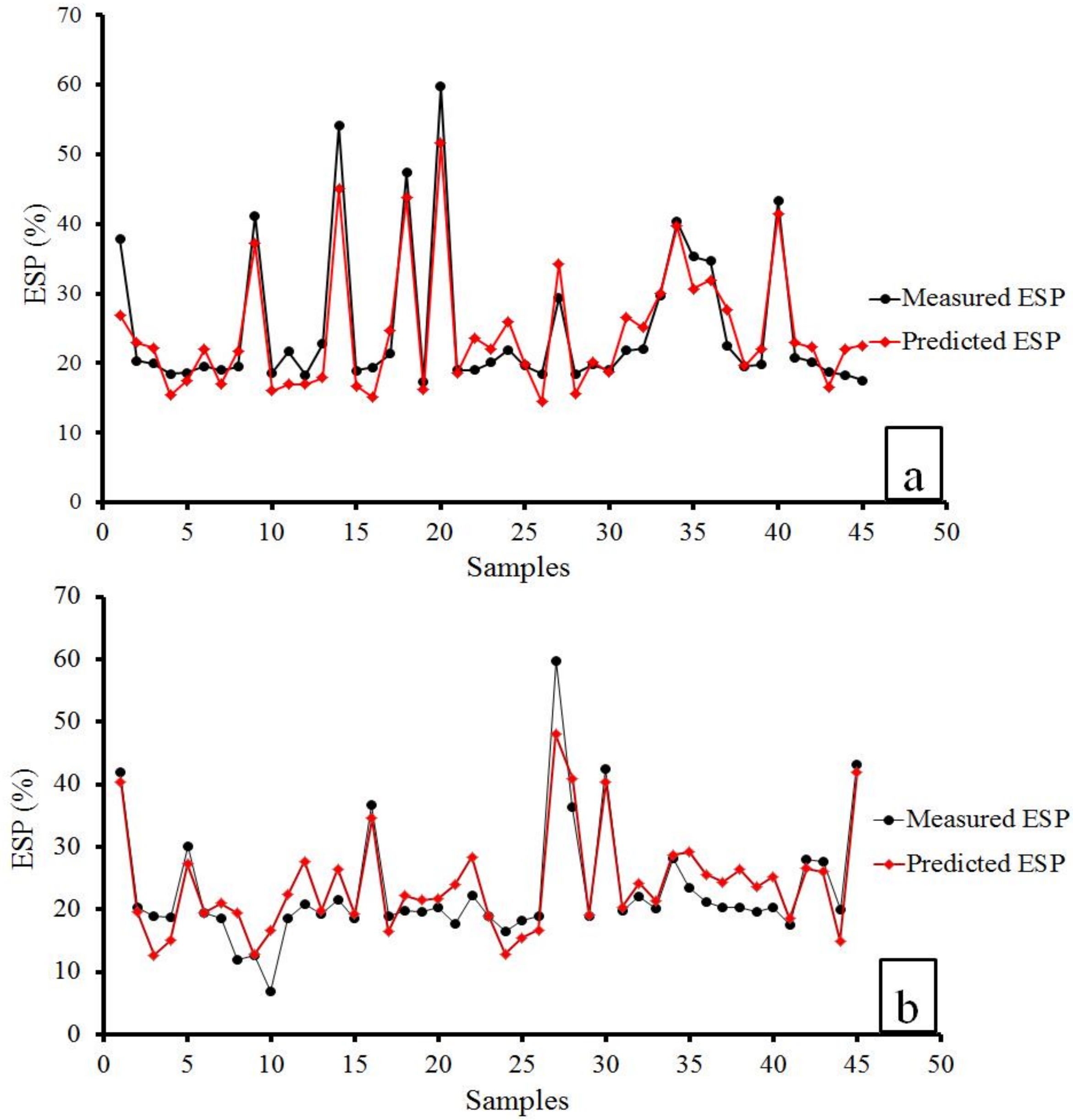
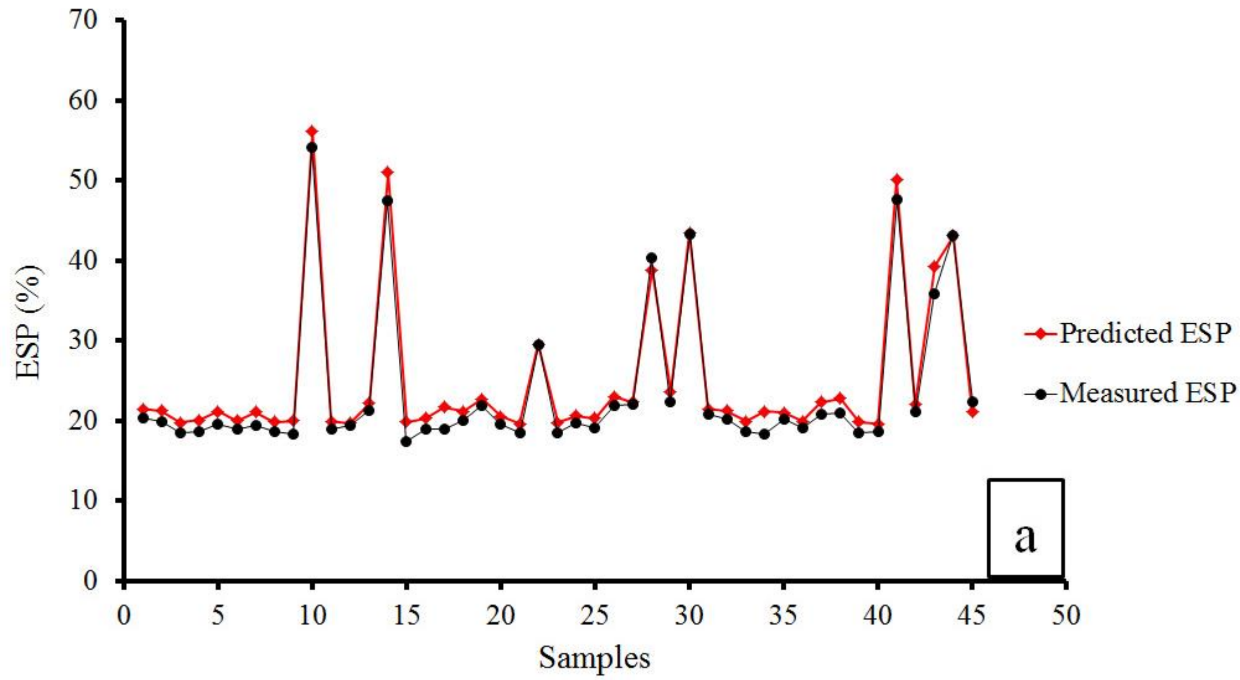


Figure 5: Comparing logaritmic regression equation output and experimental data for ESP (a) using $SAR_{1:1}$ and (b) using $SAR_{1:5}$

Developing MLP and ANFIS to estimate ESP

Values of R^2 and RMSE for ESP from $SAR_{1:1}$ and $SAR_{1:5}$ were 0.92, 0.038 and 0.88, 0.042, respectively by MLP. These values were 0.99, 0.014 and 0.94, 0.024 using ANFIS. Figure 6 compares observed and predicted ESP by ANFIS method for test data.



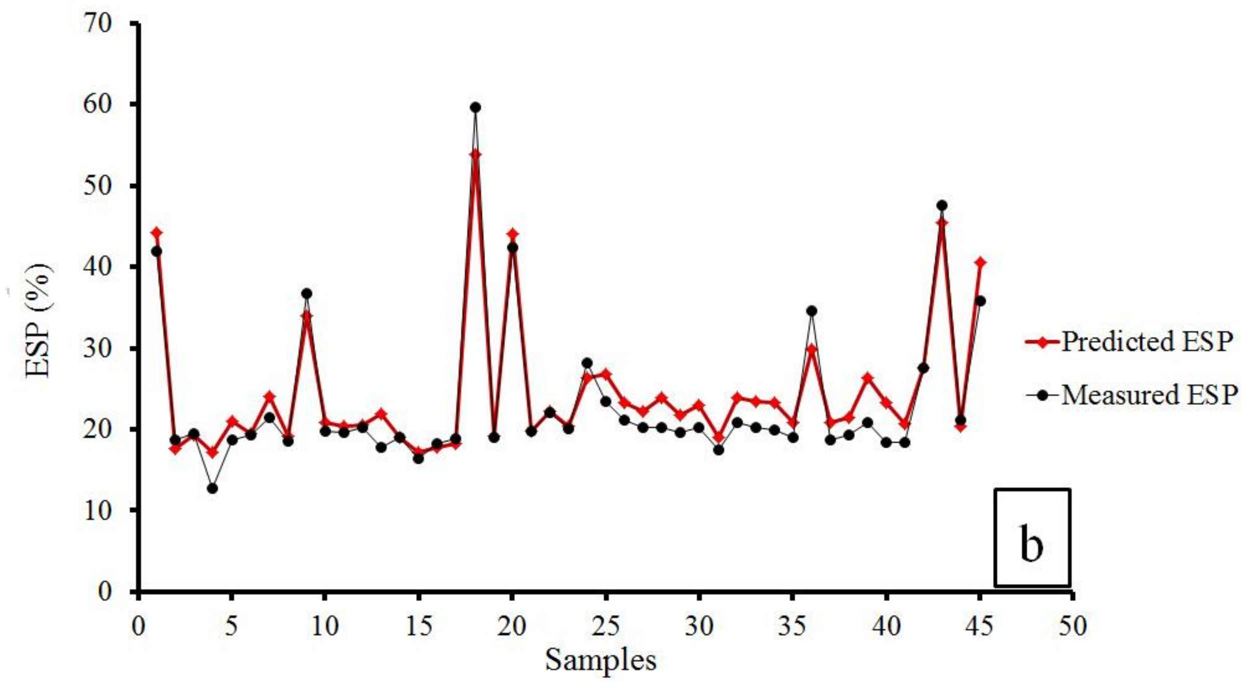


Figure 6: Comparing ANFIS output and experimental data for ESP (a) using SAR1:1 and (b) using SAR1:5

Comparing the results of used models

Fifteen percent of ESP data selected randomly and analyzed. Performance of obtained models (MLP, ANFIS and Regression models) evaluated and compared in estimating the ESP and results are shown in table 3.

Table 3: The values of R^2 and RMSE for predicted ESP from $SAR_{1:1}$ and $SAR_{1:5}$

Net.	output	Input	$SAR_{1:1}$		$SAR_{1:5}$	
			RMSE (%)	R^2	RMSE (%)	R^2
Liner Reg.	ESP	SAR	5.04	0.77	5.47	0.69
Logarithmic Reg.	ESP	SAR	3.79	0.87	4.09	0.81
MLP	ESP	SAR	0.04	0.92	0.04	0.88
ANFIS	ESP	SAR	0.01	0.99	0.02	0.94

The results showed that $SAR_{1:5}$ as model input in comparison with $SAR_{1:1}$ better explain ESP variation (table 3). The regression equations obtained in this study is different from what has shown in literatures (Rengasamy et al., 1984; Mesquta et al., 2005; Seilsepour et al., 2009; Chi et al., 2011, Farahmand et al., 2011). Thus, the ESP-SAR relationship is notconsistent, since these variables are affected by many factors such as ionic solution strength (Shainberg et al., 1980), Soil salinity (Frenkel and Alperovitch, 1983) and mineral clay content (Endo et al., 2002). Furthermore, the results in Table 3 indicate superiority of MLP and ANFIS models over regression models for estimatingESP. Perhaps it is due to complex and nonlinear relationships between soil characteristics such as ESP and SAR, that computational-artificial-intelligence-based methods are more successful in this regard.In the current study, the ANFIS showed a higher accuracy to predict ESP from $SAR_{1:1}$ (R^2 and RMSE values are 0.99 and 0.014, respectively) in comparison with other models. In other words, this model explains 99% of ESP variations and estimate this variable reasonably.

Conclusions

The results of this research indicate better performance of logarithmic regression comparing linear regression in order to estimate ESP Literature review showed that ESP has been estimated using readily available variables like SAR, only with statistical regression methods. Some of them applied and validated linear regression models and others, like current study, nonlinear models. Results of this study showed that the artificial intelligence models are able to estimate ESP, especially when conventional methods such as regression modeling are not acceptable. Of various methods used in this study, ANFIS -a hybrid of neural network and fuzzy logic-, showed the best performance to estimate ESP from $SAR_{1:1}$. MLP network was superior to logarithmic regression, too. This indicates better results of intelligent model compared to linear and nonlinear regression models to explain relationship between ESP and SAR. Consequently, these models are able to estimate ESP effectively and overcome problem of costly and time consuming direct measurement and calculation.

References

Agyare, W. A. and Park, S. J. (2007). Artificial neural network estimation of saturated hydraulic conductivity, Vadose Zone Journal, 6, 423-431.

Banaei M.H., Moameni A., Bybordi M. and Malakouti M.J. 2005. The soil of Iran: New Achievements in Perception, Management and Use. SANA Publishing, Tehran, Iran.

Bower, C. A., Reitemeier, R. F. and Fireman, M. (1952). Exchangeable cation analysis of saline and alkali soils. Soil Science, 73, 251-261.

Cetin, M. and Kirda, C. (2003). Spatial and temporal changes of soil salinity in a cotton

field irrigated with low-quality water. Journal of Hydrology, 272, 238-249.
Chi, C. M. and Wang, Z. C. 2010. Characterizing salt-affected soils of Songnen Plain using saturated paste and 1:5 soil-to-water extraction methods. Arid Land Res. Manage. 24(1): 1–11.
Chi, Ch. M., Zhao, Ch. W., Sun, X. J. and Wang, Z. C. 2011. Estimating exchangeable sodium percentage from sodium adsorption ratio of salt-affected soil in the Songnen plain of northeast China. Soil Science Society of China, Pedosphere, 21(2): 271–276.
Dreyfus G, Martinez JM, Samuelides M, Gordon MB, Badran F, Thiria S. Apprentissage statistique: Réseaux de neurones-Cartes topologiques-Machines à vecteurs supports: Eyrolles; 2011.
Endo, T., Yamamoto, S., Honna, T. and Eneji, A. E. 2002. Sodium-calcium exchange selectivity as influenced by clay minerals and composition. Soil Sci. 167(2): 117–125.
Evangelou, V. P. and Marsi, M. 2003. Influence of ionic strength on sodium-calcium exchange of two temperate climate soils. Plant and Soil, 250: 307–313.
Farahmand, A., Oustan, SH., Jafarzadeh, A. J. and Asgarzad, A. N. (2011). The parameters of sodium and salinity in some salt affected soils of the Tabriz Plain. Journal of Soil and Water, 22(1), 1-15. (In farsi)
Food and Agriculture Organization of the United Nations. (2008). Land Resources, Management, Planning and Use, from http://www.fao.org/ag/agl/agll/spush
Frenkel, H. and Alperovitch, N. (1983). Factors affecting the estimation of exchangeable sodium percentage in soils from Israel. Hassadeh, 63, 1291–1296.
Gallant SI. Neural network learning and expert systems: MIT press; 1993.
Ghaffari A, Abdollahi H, Khoshayand M, Bozchalooi IS, Dadgar A, Rafiee-Tehrani M. Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. International Journal of Pharmaceutics. 2006; 327(1): 126-38.
Haykin S, 1994. Neural Networks: A Comprehensive Foundation. Macmillan, New York. 696pp.
Hussain, M., Shafiur Rahman, M., Ng, C. 2002. Prediction of pores formation (porosity) in foods during drying: generic models by the use of hybrid neural network. Journal of Food Engineering. 51(3):239-48.
Jang, J. S. R. (1993). ANFIS-Adaptive-network-based fuzzy inference system, IEEE Transactions System Man Cybernetics, 23, 665-658.
Jorjani E, Chehreh Chelgani S, Mesroghli S. Application of artificial neural networks to predict chemical desulfurization of Tabas coal. Fuel. 2008; 87(12):2727-34.
Jurinak, J. J., Amrhein, C. and Wagenet, R. J. (1984). Sodic hazard: The effect of SAR and salinity in soils and overburden materials, Soil Science, 137, 152 -158.
Karunanithi N, Grenney WJ, Whitley D, Bovee K. Neural networks for river flow prediction. Journal of Computing in Civil Engineering. 1994; 8(2): 201-20.
Kopittke, P. M., So, H. B. And Menzies, N. W. 2006. Effect of ionic strength and clay mineralogy on Na-Ca exchange and the SAR-ESP relationship. European Journal of Soil Sciences, 57(5): 626–633.
Kumar M, Raghuwanshi NS, Singh R, Wallender WW, Pruitt WO, 2002. Estimating evapotranspiration using artificial neural network. J Irrig Drain Eng 128: 224-233.
Mesquta ME, Goncalves MC, Goncalves AR, and Neves MJ, 2005. Effect of electrolyte concentration on sodium adsorption: Application of competitive

extended Freundlich isotherms. Arid land Reserch and Managmet 19: 161-172.

Minasny, B., Hopman, J., Harter, W. T., Eching, S.O., Toli, A. and Denton, M. A. (2004). Neural networks prediction of soil hydraulic functions for alluvial soils using multistep outflow data, Soil science Society American Journal, 68: 417– 429.

Mohamadi J. and tahri S. M. (2005). Fitting the pedotransfer functions by using the fuzzy regression. Science and Technology of Agriculture and Natural Resources, 2, 51-60. (In farsi)

Negnevitsky, M. (2005). Artificial Intelligence: a guide to intelligent systems. Pearson Education Limited, Essex, England.

Quirk, J. P. 2001. The significance of the threshold and turbidity concentrations in relation to sodicity and microstructure. Australian Journal of Soil Research, 39: 1185-1217.

Razavi MA, Mortazavi A, Mousavi M. Dynamic modelling of milk ultrafiltration by artificial neural network. Journal of Membrane Science. 2003; 220(1): 47-58.

Rengasamy, P., Greene, R. S. B., Ford, G. W. and Mehanni, A. H. (1984). Identification of dispersive behaviour and the management of red-brown earths. Australian Journal of Soil Research, 22, 413-431.

Rhoades, J. D. (1982) Cation exchange capacity. In A. L. Page et al., (Ed.), Methods of Soil Analysis. Soil Science Society of American, Madison, WI.

Richards, L. A., (1954) Diagnosis and improvement of saline and alkali soils. In: USDA Handbook 60. U. S .Department of Agriculture, Washington, DC.

Seilsepour, M., Rashidi, M. And Khabbaz, B. G. (2009). Prediction of soil exchangeable sodium percentage based on soil sodium adsorption ratio. American-Eurasian Journal Agriculture Environment Sciences, 5(1), 1-4.

Shainberg, I., Oster, J. D. and Wood, J. D. 1980. Sodium calcium exchange in montmorillonite and illite suspensions. Soil Sci. Soc. Am. J. 44: 960-964.

Smith M. Neural networks for statistical modeling: Thomson Learning; 1993.

Soil Survey Staff. 1996. Soil survey laboratory methods manual. Soil Survey Investigations Rep. 42. Version 3.0. U.S. Gov. Print. Washington, DC.

Sumner, M. E. 1993. Sodic soils: New perspectives. Australian Journal of Soil Reserch, 31: 683-750.

Torrecilla J, Otero L, Sanz P. Optimization of an artificial neural network for thermal/pressure food processing: Evaluation of training algorithms. Computers and Electronics in Agriculture. 2007; 56(2): 101-10.

United States Salinity Laboratory Staff. 1954. Diagnosis and improvement of saline and alkali soils. USDA Handbook 60, 7-33.

Wang, Y.G., Xiao, D. N., Li, Y. and Li, X. Y. (2008). Soil salinity evolution and its relationship with dynamics of groundwater in the oasis of inland river basins: case study from the Fubei region of Xinjiang province, China Environmental Monitoring and Assessment, 140, 291-302.

Wang, Z., PALADE, V. and XU, Y. (2006). Neuro-fuzzy ensemble approach for microarray cancer gene expression data analysis. In Evolving Fuzzy Systems, 2006 International Symposium on, 241-246.