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Employing of regression analysis for prediction of sodium adsorption ratio of a soil

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Abstract

For practical soil management, indirect estimation of soil sodium adsorption ration (SAR, dimensionless) may be a good tool due to its important role in estimating of both the amount requirements of amendments and gypsum for soil reclamation. SAR is calculated from sodium, calcium and magnesium concentrations which are often determined with high costs. Therefore, developing of a simple tool to estimate SAR indirectly is more economical. Input data of the present study were collected from literature. The validation data were collected from actual laboratory soil analysis. Different regression models were developed to predict soil SAR based on soil electric conductivity (EC, dSm^{-1}), soil pH (pH) and soil texture index (STI, dimensionless). The best regression model for estimating SAR was selected based on higher coefficient of determination (R^2), lower both root mean square error (RMSE) and mean absolute error (MAE). The best regression model had the following form:

$$Soil \quad SAR = 78.554 - 2.764 \times EC - 10.785 \times pH - 625.819 \times STI + 0.436 \times EC \times pH - 32.244 \times EC \times STI$$

$$+ 90.086 \times pH \times STI + 4.237 \times EC \times pH \times STI \qquad R^2 = 0.789 \quad RMSE = 20.651 \quad MAE = 12.061$$

The performance of the best developed regression model was evaluated using an independent test data set. In order to evaluate the model, R^2 was used. The value of R^2 derived by the model for testing data was 0.9927. The proposed model is simple to be used by soil scientists and agricultural engineers to have a rapid check on sodium adsorption ratio at wide range of soil conditions within the studied range without the necessity of any time consuming and laboratory tests.

Keywords: Soil properties, SAR, modeling

1. Introduction

Soil is considered to be the major base of agricultural production and very important multifunctional medium for crop growth, crop productivity and maintaining the environmental quality (Jordanoska *et al.*, 2014) [8]. On the other hand, salt-affected soils, as they are called, are either saline or sodic (Allotey *et al.*, 2008) [4]. Saline soils refer to soils with electrical conductivity above 4 dSm^{-1} and usually contain sufficient soluble salts that adversely affect the growth of most crops (Allotey *et al.*, 2008) [4]. Sodicity is one of the most important types of salinity which occurs when Na^+ is more than 15% of the exchangeable cation (Rozema and Flowers, 2008) [18]. Sodicity changes soil physical properties by destroying soil structure, reducing the permeability and porosity of soils (Rengasamy *et al.*, 2003) [14]. Besides, sodic soils are unsuitable for many plants because of their high sodium concentration, which may cause plant rooting problems, and because of their high pH, which generally ranges from 8.5 to 12.0 (Alharbi, 2015) [3]. These two main groups of salt-affected soils differ (physically, chemically, biologically, as well as their geographical and geochemical distribution) and therefore, require different approaches for their reclamation and agricultural utilization (Allotey *et al.*, 2008) [4].

Most common process to evaluate the effect of sodium in the soil on plant…etc is by defining value of sodium adsorption ratio (SAR). However, the formula for defining sodium adsorption ratio (Suarez *et al.*, 2008) [21] is as follows:

$$SAR = \frac{Na^+}{\sqrt{\frac{1}{2}\left(Ca^{++} + Mg^{++}\right)}} \qquad (1)$$

Where sodium (Na^+), calcium (Ca^{++}) and magnesium (Mg^{++}) represent concentrations expressed in (meq L^{-1}).

Soil SAR differs based on soil textures (Kahlon *et al.*, 2013) [9]. However, SAR < 13 indicates non sodicity soils and SAR >13 indicates sodic soils (Richards, 1954) [15]. As shown in equation 1, for determining soil SAR, it is necessary to have concentrations of Na, Ca and Mg. But, these parameters are often determined in soil laboratories with high costs. So, it may be more appropriate and economical to develop a tool which determines soil SAR indirectly. However, several attempts have been made to estimate indirectly soil properties from more easily measurable and more readily available soil properties (Lake *et al.,* 2009; Zare *et al.,* 2014) [10, 23]. Furthermore, for practical soil management, indirect estimation of soil SAR may be a good tool due to different reasons. The first reason is belonged to its important role in estimating of both the amount requirements of amendments and gypsum for soil reclamation (Zia *et al.*, 2006) [25]. The second reason is attributable to both high cost and time consumed for monitoring changes of SAR in the soils. Consequently, developing of a simple tool to estimate SAR indirectly is more economical.

A number of investigators have performed experiments which focused on the development of prediction models of soil SAR by the help of soil parameters using different techniques. In their work, Robbins and Meyer (1990) [17] developed a model for estimating SAR from pH and EC data. The model has the following form:

$$SAR = \left[\frac{(pH - A)\times(1 + C\times EC)}{B}\right]^2 \quad \text{(2)}$$

They reported that when the coefficients A, B, and C are known for a particular soil, this method has the potential to economically and rapidly estimate SAR changes from more easily obtainable pH and EC data. Additionally, they showed the coefficients A, B, and C differed for different soil types. Rashidi and Seilsepour (2011) [13] presented a linear regression model for predicting soil SAR from soil electrical conductivity. The statistical results of the study indicated that in order to predict soil SAR based on soil electrical conductivity (EC) the linear regression model with R^2 = 0.69 was as follows:

$$SAR = 1.91 + 0.68\times EC(dSm^{-1}) \quad \text{(3)}$$

Previously researches report a relationship between soil SAR and soil EC (Robbins, 1993; Seilsepour and Rashidi, 2008) [16, 20]. Al-Busaidi and Cookson (2003) suggested linear regression model with R^2 = 0.83 based on soil EC for saline soil in Oman area as follows:

$$SAR = 7.077 + 0.464\times EC(dSm^{-1}) \quad \text{(4)}$$

Sarani *et al.* (2015) [19] proposed a relationship with R^2=0.63 among SAR and both soil EC and soil pH to be

$$SAR = 3.8\times LN(EC, dSm^{-1}) + 22.83\times LN(pH) - 44.37 \quad \text{(5)}$$

Despite there is considerable amount of research done, which shows the relationship between soil SAR with other soil properties, specific to a region or area and confined to only a few soil types. Therefore, the specific objective of the study was to develop a regression model to predict soil SAR considering soil components of sand, silt and clay in it to be more general. The model also is depended on soil pH and soil electrical conductivity as they are rapidly gathered by simple devices (Yegul *et al.*, 2011) [22].

2. Materials and Methods

2.1. Collecting the required data

Literatures collected data on soil SAR related to soil EC, pH and texture was reviewed to compile a database of soil SAR. Those variables were measured by laboratory tests. The database covered wide range of soil EC, soil pH and soil texture. Statistical description for the literature data of the soil SAR, soil EC, soil pH, sand, silt, clay% and STI are presented in Table (1).

Building any mathematical model more universal in the soil field, it is better to add to such model a variable describing the soil type as reported by Altendorf *et al.* (1999) [5]. By browsing through literatures, different formulas were found to represent soil components (sand, silt, and clay) in numeric value to be used in mathematical models (Elbanna and Witney, 1987; Oskoui and Harvey, 1992; Zein Eldin, 1995; Ismail, 2002; Aboukarima and Saad, 2006) [6, 12, 24, 7, 1]. In this study soil texture index (STI) which developed by Oskoui and Harvey (1992) [12] was selected due to it produces unique numbers for every combination of sand, silt and clay contents. This soil texture index represents soil components and it calculated as follows:

$$STI = \frac{log\,(S_i^{CC_a})}{100} \quad \text{(6)}$$

Where S_i and CC_a are % of silt and clay fractions in the soil, respectively. Meanwhile, the sand fraction is represented implicitly since the sum of sand, silt and clay fractions is always constant. Oskoui and Harvey (1992) [12] showed that the STI reflects the effects of all three of the soil fractions.

Table 1: Statistical description for the literature data of the soil SAR, soil EC, soil pH, sand, silt, clay% and STI.

Statistical criteria	Soil SAR*	Soil EC dSm^{-1}	Soil pH	Sand (%)	Silt (%)	Clay (%)	STI+
Mean	23.6	11.4	7.96	51.9	31.2	16.4	0.248
Standard Error	4.45	1.72	0.05	2.86	2.00	1.36	0.022
Median	6.36	6.70	8.00	56.0	29.0	9.00	0.139
Mode	0.50	0.96	8.10	70.0	35.0	7.00	0.139
Standard Deviation	45.13	17.4	0.50	29.0	20.3	13.8	0.231
Sample Variance	2036	303	0.25	844	413	191	0.053
Kurtosis	12.4	15.9	1.00	-1.23	-0.87	0.29	-0.098
Skewness	3.30	3.48	0.07	-0.24	0.39	1.19	1.106
Range	270	119	2.81	96.0	77.7	58.0	0.839
Minimum	0.30	0.43	6.50	1.00	2.00	1.00	0.003
Maximum	271	120	9.31	97.0	79.7	59.0	0.842
Count	103	103	103	103	103	103	103

*Calculated using Eq. (1). +Calculated using Eq. (6).

2.2. Laboratory measurements
In this study, actual laboratory data were collected to validate the best regression equation generated from the literature data. Laboratory measurements were performed for 4 soils which collected from different locations in Saudi Arabia and subjected to laboratory analysis to get soil EC, soil pH and components of sand, silt, clay%, chemical analysis for (Na^+), (Ca^{++}) and (Mg^{++}) to calculate SAR. Table (2) shows characteristics of the soil used to test the best regression model for prediction of soil SAR.

Table 2: Characteristics of the soil used to test the best regression model.

Soil No.	Soil SAR	Soil EC	Soil pH	Sand	Silt	Clay	STI
	(----)	dSm^{-1}	(----)	(%)	(%)	(%)	(----)
Soil1	8.20	10.8	9.10	80	13	7	0.077
Soil2	7.60	5.60	9.00	67	26	7	0.099
Soil3	7.60	3.84	8.15	60	7	33	0.278
Soil4	57.6	91.1	8.20	52	9	39	0.372

2.3. Data analysis
Data from the literature were analyzed. First, variations of soil SAR with soil EC, soil pH and STI were investigated separately. Secondly, multiple linear regression procedures were performed on the entire data to obtain the relationship between the dependent variable (SAR) and the independent variables (soil EC, soil pH and STI). The tested regression models are shown in Table (3).

Table 3: The tested regression models.

Model No.	Model form*
1	$SAR = \alpha_0 + \alpha_1 \times EC$
2	$SAR = \alpha_0 + \alpha_1 \times pH$
3	$SAR = \alpha_0 + \alpha_1 \times STI$
4	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times pH$
5	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times STI$
6	$SAR = \alpha_0 + \alpha_1 \times pH + \alpha_2 \times STI$
7	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times pH + \alpha_3 \times STI$
8	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times EC^2 + \alpha_3 \times pH + \alpha_4 \times STI$
9	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times EC^2 + \alpha_3 \times pH + \alpha 4 \times pH^2 + \alpha_5 \times STI$
10	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times EC^2 + \alpha_3 \times pH + \alpha_4 \times pH^2 + \alpha_5 \times STI + \alpha_6 \times STI^2$
11	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times \ln EC + \alpha_3 \times pH + \alpha_4 \times \ln pH + \alpha_5 \times STI + \alpha_6 \times \ln STI$
12	$SAR = \alpha_0 + \alpha_1 \times EC + \alpha_2 \times pH + \alpha_3 \times STI + \alpha_4 \times EC \times pH + \alpha_5 \times EC \times STI + \alpha_6 \times pH \times STI + \alpha_7 \times EC \times pH \times STI$

*$\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6$ and α_7 are regression constants.

The degree of fitness of the 12 models was compared on the basis of coefficient of determination (R^2), root means square error (RMSE) and mean absolute error (MAE). However, (R^2) was selected to be a criterion to measure the linear correlation between the calculated and the predicted values. The closer the R^2 value is to 1, the better the model fits to the actual data. However, RMSE and MAE could be calculated as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| SAR_{iobs} - SAR_{ipre} \right| \quad \text{..........................} \ (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left(SAR_{iobs} - SAR_{pre} \right)^2}{N}} \quad \text{..........................} \ (8)$$

Where SAR_{iobs} and SAR_{ipre} are actual and predicted soil sodium adsorption ratio, respectively, N is number of observations.

3. Results and Discussion
3.1. Data summary
Data summary of different soil properties used to develop regression models to predict SRA are presented in Table (1). The variation in soil SAR is very high as standard deviation is equal 45.1. Furthermore, standard deviation of soil EC had high value of 17.4 dSm^{-1} as illustrated in Table (1). Additionally, standard deviation of soil texture index had value of 0.232. The reason of this high standard deviation is due to that the data collection is from different regions and countries which have different soil chemical properties. Simple correlation coefficients that were computed between different pairs of characters for all data (103 points) are presented in Table (4). There were positive correlation between soil SAR and soil EC, soil pH and STI. However the correlation was weak between soil SAR and soil EC (r=0.147) as shown in Table (4). Negative correlation is seen between soil EC and soil pH (r = -0.182) and the same trend for correlation between STI and soil pH (r = -0.089).

Table 4: Correlation matrix among the studied characteristics of the soils based on data from literature.

	Soil SAR	Soil EC	Soil pH	STI
Soil SAR	1			
Soil EC	0.147	1		
Soil pH	0.576	-0.182	1	
STI	0.403	-0.022	-0.089	1

3.2. The proposed models for soil SAR calculation

The study is proposing a regression model to predict soil SAR based on soil EC, soil pH and STI. Single relationship between soil SAR and each variable is drawn and presented in Fig. (1). The best fit was selected between different pairs of the variables and it was differed from liner to exponential function with coefficient of determination (R^2) rang of 0.1327 to 0.3321 as illustrated in Fig. (1). However, Table (5) illustrates regression constants, R^2, RMSE and MAE for the tested 12 models to predict soil SAR.

Table (5): Regression constants, R^2, RMSE and MAE for the tested 12 models to predict soil SAR.

Model No.	Regression constants								R^2	RMSE	MAE
	α_0	α_1	α_2	α_3	α_4	α_5	α_6	α_7			
1	19.290	0.380							0.022	44.422	26.003
2	-392.433	52.254							0.332	36.701	27.001
3	4.171	78.424							0.162	41.109	25.697
4	-434.211	0.673	56.538						0.398	34.858	24.450
5	-0.589	0.403	79.092						0.186	40.510	23.631
6	-443.794	55.930	89.078						0.540	30.473	22.575
7	-489.735	0.721	60.603	91.161					0.614	27.884	18.832
8	-501.886	1.953	-0.015	61.137	92.357				0.668	25.870	16.718
9	1143.957	1.691	-0.013	-349.084	25.602	64.142			0.702	24.499	15.777
10	1148.348	1.711	-0.013	-350.321	25.673	72.997	-11.954		0.703	24.494	15.749
11	1904.362	0.228	7.495	349.934	-2281.715	114.232	-10.486		0.713	24.072	16.534
12	78.554	-2.764	-10.785	-625.819	0.436	-32.244	90.086	4.237	0.789	20.651	12.061

The results from Table (5) indicated that R^2 ranged from (0.022 to 0.789), MAE (12.061 to 27.001) and RMSE (20.6 to 44.4) for all models. This indicated that all models could not be used for predict soil SAR. However, the best model was belonged to model No.12. According to these results, soil SAR based on soil EC, soil pH and STI and other variables resulting from them contribute to accurately determine soil SAR. The best regression model (model No. 12) form was as follows:

$$Soil \quad SAR = 78.554 - 2.764 \times EC - 10.785 \times pH - 625.819 \times STI + 0.436 \times EC \times pH - 32.244 \times EC \times STI + 90.086 \times pH \times STI + 4.237 \times EC \times pH \times STI \qquad R^2 = 0.789 \tag{9}$$

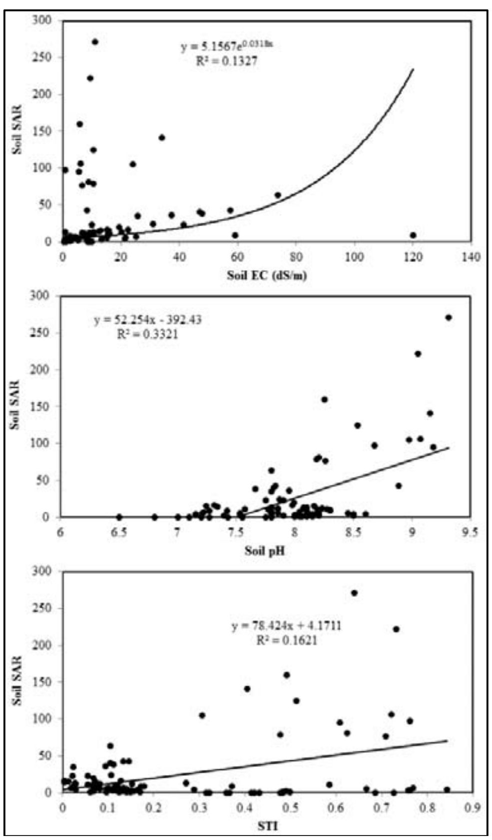

Fig 1: Relationship among soil SAR and soil EC, soil pH and STI for literature data.

The proposed regression model can be a good tool for soil scientists and agricultural engineers to have a rapid check on SAR at wide range of soil conditions within the studied range without the necessity of any time consuming and laboratory tests. The performance of the best developed regression model (model No. 12) was evaluated using an independent test data set. In order to evaluate the model, R^2 was selected to measure the linear correlation between the calculated and the predicted values. However, R^2 reflects the degree of fit for the mathematical model (Nath and Chattopadhyay, 2007) [11]. The value of R^2 derived by the model was 0.9927 as shown in Fig. (2).

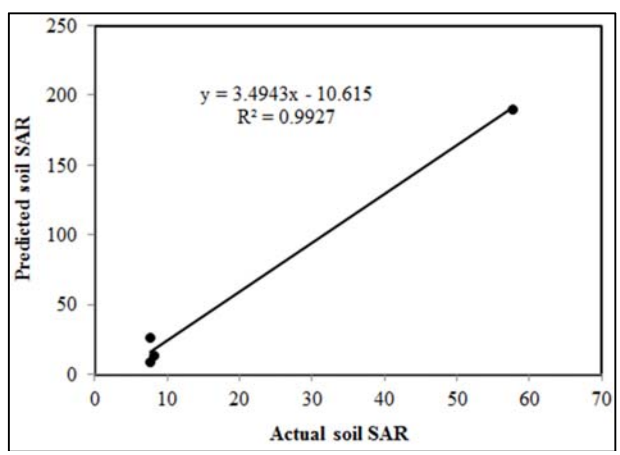

Fig 2: Comparison between the actual and predicted soil SAR using validation data and model No.12.

4. Conclusion

Regression models based on soil pH, soil EC and soil texture index were developed by the help of literature data to predict soil Sodium Adsorption Ratio (SAR). The best regression model form was:

$$\begin{aligned} Soil \quad SAR &= 78.554 - 2.764 \times EC - 10.785 \times pH - 625.819 \times STI + 0.436 \times EC \times pH - 32.244 \times EC \times STI \\ &+ 90.086 \times pH \times STI + 4.237 \times EC \times pH \times STI \qquad R^2 = 0.789 \end{aligned} \tag{9}$$

Where EC, is soil electric conductivity (dSm^{-1}), pH is soil pH and STI is soil texture index which calculated from sand, silt and clay percentage in the soil. The soil SAR values predicted using the best model was compared to the soil SAR values measured by actual laboratory tests and coefficient of determination (R^2) was 0.9927. Therefore, the soil SAR model can provide an easy, economic and brief methodology to estimate soil SAR.

5. References

1. Aboukarima AM, Saad AF. Assessment of different indices depicting soil texture for predicting chisel plow draft using neural networks. Alexandria Science Exchange Journal. 2006; 27(2):170-180.
2. Al-Busaidi AS, Cookson P. Salinity-pH relationships in calcareous soils. Agricultural and Marine Sciences. 2006; 8:41-46.
3. Alharbi A. Impact of soil salinity on agriculture in arid regions. Journal of Agricultural and Veterinary Sciences Qassim University. 2015; 8(1):71-81.
4. Allotey DFK, Asiamah RD, Dedzoe CD, Nyamekye AL. Physico-chemical properties of three salt-affected soils in the lower Volta basin and management strategies for their sustainable utilization. West African Journal of Applied Ecology. 2008; 12:163-182.
5. Altendorf CT, Elliott RL, Stevens EW, Stone ML. Development and validation of a neural network model for soil water content prediction with comparison to regression techniques. Trans. ASAE. 1999; 42(3):691-699.
6. Elbanna EB, Witney B. Cone penetration resistance equation as a function of the clay ratio, soil moisture content and specific weight. Journal of Terramechanics. 1987; 24(1):41-56.
7. Ismail KM. Statistical treatment of disk tool data for predicting soil draft. Misr J Ag Eng. 2002; 19(2):455-466.
8. Jordanoska B, Stafilov T, Pelivanoska V, Bacheva K. Assessment of the content of chemical elements in soil and its properties used for tobacco cultivation in the republic of Macedonia. Bulgarian Journal of Agricultural Science. 2014; 20(2):255-266.
9. Kahlon UZ, Murtaza G, Murtaza B, Hussain A. Response of soil texture for leaching of salts receiving different pore volumes of water in saline-sodic soil column. Pak J Agri Sci. 2013; 50(2):191-198.
10. Lake HR, Akbarzadeh A, Mehrjardi RT. Development of pedo transfer functions (PTFs) to predict soil physico-chemical and hydrological characteristics in southern coastal zones of the Caspian Sea. Journal of Ecology and the Natural Environment. 2009; 1(7):160-172.
11. Nath A, Chattopadhyay PK. Optimization of oven toasting for improving crispness and other quality attributes of ready to eat potato-soy snack using response surface methodology. Journal of Food Engineering. 2007; 80(4):1282-1292.
12. Oskoui KE, Harvey SJ. Predicting cone index from soil physical properties and organic matter content. ASAE Paper No. 92-1056, ASAE, St. Joseph, Michigan, USA. 1992, 1-16.
13. Rashidi M, Seilsepour M. Prediction of soil sodium adsorption ratio based on soil electrical conductivity. Middle-East Journal of Scientific Research. 2011; 8(2):379-383.
14. Rengasamy P, Chittleborough D, Helyar K. Root-zone constraints and plant based solutions for dry land salinity. Plant Soil. 2003; 257:249-260.
15. Richards LA. Diagnosis and Improvement of Saline and Alkali Soils, L.A. Richards (eds). Handbook of U.S. Dept. of Agriculture, Washington, 1954.
16. Robbins CW. Coefficients for estimating SAR from soil pH and EC data and calculating pH from SAR and EC values in salinity models. Arid Soil Research and Rehabilitation. 1993; 7:29-38.
17. Robbins CW, Meyer WS. Calculating pH from EC and SAR values in salinity models and SAR from soil and bore water pH and EC data. Australian Journal of Soil Research. 1990; 28:1001-1011.
18. Rozema J, Flowers TJ. Crops for a salinized world. Science. 2008; 322(5907):1478-1480.
19. Sarani FA, Ahangar G, Shabani A. Predicting ESP and SAR by artificial neural network and regression models using soil pH and EC data (Miankangi region, Sistan and Baluchestan province, Iran). Archive of Agronomy and soil Science. 2015; 4:1-12.
20. Seilsepour M, Rashidi M. Modeling of soil sodium adsorption ratio based on soil electrical conductivity. ARPN Journal of Agricultural and Biological Science. 2008; 3(5&6):27-31.
21. Suarez DL, Wood JD, Lesch SM. Infiltration into cropped soils: effect of rain and sodium adsorption ratio–impacted irrigation water. Journal of Environmental Quality. 2008; 37(5)Supplement:169-179.
22. Yegul U, Turker U, Talebpour B. Determination of some soil properties with electromagnetic induction sensor. Journal of Agricultural Machinery Science. 2011; 7(1):19-25.
23. Zare M, Ordookhani K, Emadi A, Azarpanah A. Relationship between soil exchangeable sodium percentage and soil sodium adsorption ratio in Marvdasht Plain, Iran. Int. J Adv Biol Biom Res. 2014; 2(12):2934-2939.
24. Zein Eldin AM. Predicting soil bulk density from cone index data. Misr J Agr Eng. 1995; 12(1):179-194.
25. Zia MH, Ghafoor A, Murtaza G, Saifullah, Basra SMA. Growth response of rice and wheat crops during reclamation of saline-sodic soils. Pak J Bot. 2006; 38(2):249-266.