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Research article

ASSESSING PLANT AVAILABLE POTASSIUM OF ILLITIC LOESS SOILS POSSESSING HIGH SPECIFIC SURFACE AREA AND WEAK AGGREGATION

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ABSTRACT: Although Quantities of potassium extractable by NH_4OAc in some illitic Loess slowly Swelling Soils possessing high specific surface area is high, potassium has been identified as the limiting plant growth factor in this areas. Due to potassium deficiency Golestan provincesoils, taking advantages of theNH_4OAc method was not feasible and what has been proposed was sodium tetra phenyl boron (K_{Nabph4}) method with 1minute extraction. The aim of this study was soil potassium assessment (K_{Nabph4}), specifying whether status of aggregation (SOA) and soil specific surface area (SSA) can effect onK_{Nabph4}, and feasibility studies for prediction of the K_{Nabph4}. 183 soil samples from 0-30 centimeter depth with varied physicochemical properties were obtained. Linear regression stepwise (LRS) models were established between the measured 17 parameters. Figures were tested via genetic algorithm (GA) solver and artificial neural network (ANN). MLP, RBF and ELMAN were used in ANN. By investigation of the interactions, it was specified that SOA (0.52^{**}), surface charge excess of potassium (0.69^{**}) and SSA (0.72^{**}) were highly correlated with K_{Nabph4}. Therefore, with ascending of the SSA amount, further surfaces of soil particles will be weathered and this process certainly ascends the K release. If the weak aggregation does not reduce the ascending trend of K release, the quantities of potassium availability will be increased. About predicting soil potassium, results indicated the produced models via ANN were much accurate than the LRS and GA. The best model was obtained in MLP network by selecting SOA and SSA as the inputs parameters and K_{Nabph4} as the output of model while the RMSE= 59.36, MEF= 84.06, AEP= 15.46, R_{Test}= 0.99, R^2= 0.84 was.
Key words: ANN, NaBPh4, Potassium, Soil aggregates, Golestan province

INTRODUCTION

The title "illite" is allocated to a group of mica-type minerals, which is widely distributed in marine shales and related sediments. Illite as the consequence of potassium depletion, has less potassium and contains more water molecules in comparison to true micas resembling muscovite, but anyhow it has mica-like sheet structure, moreover, it possesses interlayer micro pores and is poorly crystallized. Illite is categorized as an expandable 2:1 clay mineral and is identified as the source of soil potassium minerals [1]. The illite group of minerals has the same structural arrangement as the montmorillonite group, but the presence of potassium as the bonding materials between units makes the illite minerals swell less [2]. Thedominant mineral type of Golestan province locating in north-east of Iran besides Caspian sea, is illite mineral[3]. This zone is one of the most important agricultural areas in Iran. Golestan district contains loess soils with illite minerals superabundantly and is well-known for its loess and fertile soils [4].
The quantity of measured SSA through these illitic loess soils is usually over 100 m^2/gr alsoquantity of illite external SSA is high [5].External and total SSA were 112 versus 117 m^2/gr for illitc clay and 66 versus 732 m^2/gr for montmorillonite [6].Like the soils containing montmorillonite minerals (Vertisols), these sort of soils(illitic loess soil) also face with swelling and shrinkage process frequently. But in comparison with the rate of this process for the first type soils (Vertisol), shrinkage and swelling rate in the illitic soils are much lower [6]. Internal specific surface does not control swelling because interlayer swelling is minimal relative to inter-micellar swelling [7]. This swelling phenomenon results in releasing elements like K, moreover, cation deficiency for growth [3, 8]. Potassium is a macro nutrient which is accounted as an essential and extremely effective nutrient in plant root and crop yield [9].

Absorbable form of potassium for plant root is solution form. There is a dynamic equation between varied forms of potassium. K Transmission process in illitic loess slowly swelling soils of Golestan province is under influence of precipitated transitive micro-particle. The high specific surface property of these micro-particle effects on that process. It makes nonexchangeable potassium transforms to exchangeable one in a relatively rapid rate but for the forthcoming stage, transformation from exchangeable stage to soluble potassium, this high specific surface area descend that increasing trends extremely into a nadir[8]. Limiting plant growth factors varies with regional and temporal variation. As an outstanding result of a series of sequential researches by different researchers [10,11,12,13,8] potassium was determined as the Limiting plant growth factor of Golestan province lands. It maybe hypothesized that increased diffuse double layer truncation with high specific surface in slowly swelling-shrinking soils (SSSS's) may affect ion diffusion and availability for plants (e.g. Potassium) despite ample quantities present in diffuse double layer, therefor alternate wetting and drying of illitic minerals may aid to slow release of fixed potassium. It has been proven, plant available potassium assessment via NH_4OAc method in arable lands consisting illite mineral is not a suitable method [14,15,16,17]. The amount of measured potassium with NH_4OAc extractor is so high usually because it measures diffusion double layer (DDL) and soluble potassium which are not correlated to what plant absorbs in reality and Golestan province is of no exception from this affair.The high amount of potassium obtained via NH_4OAc method indicates there is no need to apply any fertilizers for the land but that potassium is the limiting plant growth factor in Golestan zone. Therefore, the appropriate method for evaluating soil potassium is sodium tetraphenylboron ($NaBPh_4$) method with one minute extraction [18].Although following from $NaBPh_4$ method procedure drives the researchers to a reliable amount of plant available potassium, through this procedure lots of cautions and complicated dilemma exists that not only are not negligible, but also following of those cautions is severely essential.

Herethe artificial neural network (ANN) can be used, positively to present various pre-determined neural network models to make the experiment cost and time efficient. The alternative approaches such as artificial neural networks (ANNs) have been recently used [19]. They are also becoming increasingly important in all engineering areas as a result of rapid development of information and computer technology [20, 21]. In this field, [5] used surface charge excess of potassium as the single input for predicting extracted potassium via $NaBPh_4$ and found ANN performs much accurate than regression stepwise model. [13] used extracted potassium by $NaBPh_4$ as the single input for predicting wheat crop yield and found ANN was much accurate than regression stepwise model.

The aim of this study was plant available potassium assessment with an alternative method via $NaBPh_4$ extractor, evaluating factors controlling plant available potassium and feasibility studies for estimating plant available potassium from easily accessible or measurable parameters by taking advantages of stepwise regression plus employing intelligent techniques.

MATERIALS AND METHODS

Study area *description*

From different zones of Golestan province, 183 soil samples from 0-30 centimeter depth with a wide range of physicochemical properties, were obtained. In figure 1, the sample sites are shown with different symbols, each of which will be explained below. The presented thin white film in figure 1,was the pathway of the sample site. The interval between each two samples was 2 kilometres. Vegetation covertype of Tuskestan, Shah-Koh Shah-roud regions were varied, including jungle, arable land and pasture.

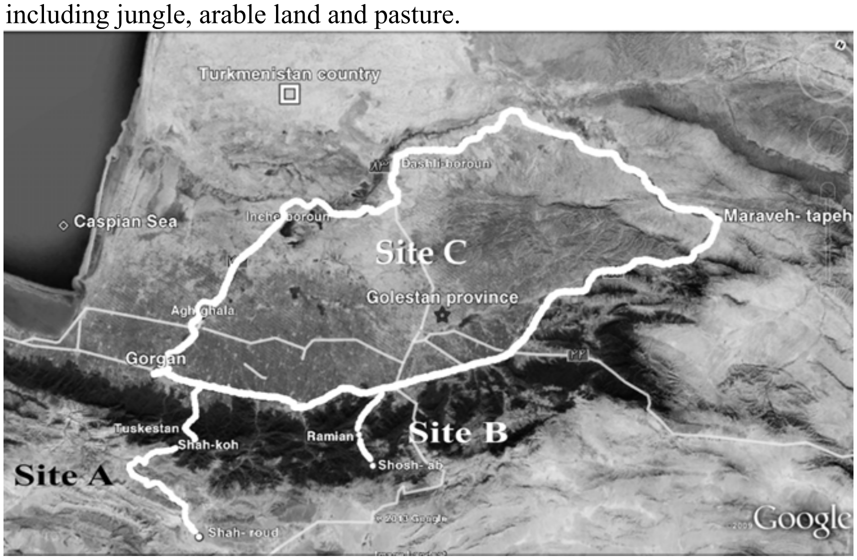

Fig1- Map of soil samples sites

This site was named as Site A. The site B including Ramian and shosh-ab, possessed jungle vegetation cover. The main roadway from the Gorgan city toward the Maraveh-tape, Dashli-born, Inche-born and final point Agh-ghala city was named as Site C. This site was full of arable lands and as the consequence of the massive production of this zone, it has been carrying for decades the main responsibility of cultivation and agriculture industry of Golestan province on its shoulders.

Physical and chemical soil properties.

2 types of samples were taken from each site. The series that was air-dried, gently crushed and passed through a 2-mm sieve, used for evaluating soil parameters. The second one remained undisturbed for the aggregation stability experiment.

Soil texture was evaluated via hydrometer methods [22]. Organic matter (O.M) was determined [23]. Cation exchange capacity (CEC) at pH 8.2 was measured [24].Aggregate stability including mean weight diameter (MWD), geometric mean diameter (GMD), status and degree of aggregation (SOA and DOA), dispersion ratio (DR), was measured using wet-sieving method [25]. Exactly 50gr of soil was sieved through 8 mm, was sprayed with water as a pretreatment and was oscillated in distilled water for 30 min using a set of sieves with 4.76, 2, 1, 0.5, 0.25 and 0.1 mm diameter. One more time the same procedure was done, but before using of wet sieving apparatus hydrogen peroxide and Calgon were used to specify the mechanical particles [26]. Specific surface area (SSA) was measured by the ethylene glycolmono ethyl ether (EGME) method [27].Potassium was measured in 3 different methods. Sodium tetraphenylboron ($NaBPh_4$) extractor [28], bulk solution potassium [22] and surface charge excessof potassium [29].

Statistical analysis and modelling

In order to find whether there was a relationship between measured variables, the Correlations (Spss.No.20) and regression stepwise models (Sas.No.9.3) were established between the 17 parameters. The prevalent form of the linear regression stepwise (LRS) function was as follows (one-order equation):

$$Y_i = aX_1 \pm bX_2 + \varepsilon \qquad (1)$$

Where *Yi* was the dependent output that was predictable by selecting two autonomous variables as the X_1 and X_2inputs. (a)and(b)were coefficients of these inputs that could be be positive or negative. ε, was the random error of models. Genetic Algorithm (G.A) Solver, a time-honored technique going back to Pearson’s 1908 use of it, was employed here to show a more precise equation than linear regression stepwise. The general purpose of G.A solver was to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The G.A solver equation took the form below:

$$Y = a(x_1)^z \pm b(x_2)^v \pm \ldots \pm b_n(x_n)^m \pm C \qquad (2)$$

(b) and (a) were the G.A solver coefficients, representing the dependent variable amount. C was a constantfor the intercept and when all the independent variables were 0, (Y) would be equal to C. Whole Results of the G.A solver and regression models were indicated in table 4.

Figures were trained, tested and verified with artificial neural network (ANN) system, by taking advantage of the MATLAB R2011b.The main purpose of ANN was similar to polynomial regression; however its function type for the mathematical process was different from the classical regression analyses. In order to obtain the optimal multidimensional surface for the prediction of a dependent variable, any composite functions was fitted to the data presented to the ANN model [30]. The most widely-used training algorithm was the feed-forward, multilayer perceptron trained by back-propagation algorithms based on the gradient descent method (FFBP). FFBP based on supervised rule worked by sending inputs forward and then propagating errors backwards. A feed-forward network configuration with two layers (one hidden layer and output layer) was plotted in Fig.2.

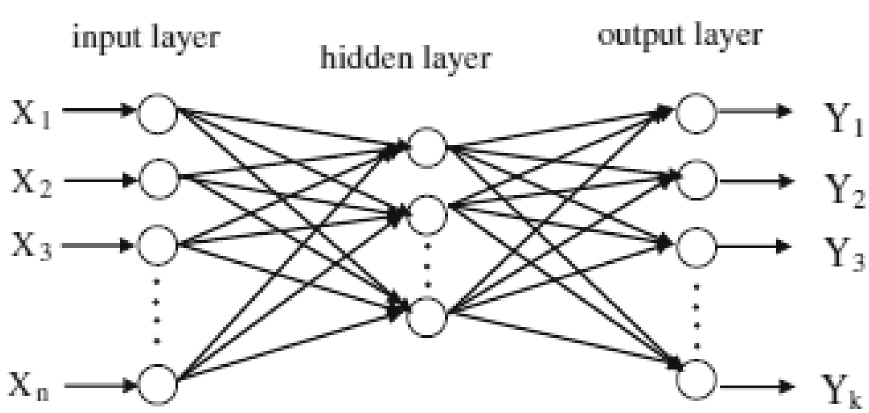

Fig. 2- multilayer ANN configuration.

In this research, the network was designed in MLP, RBF and ELMAN networks, with all of the factors influencing on measured K_{NaBPh4}. Also, all data were first normalized and divided into three data sets such as; training (60% of all data), test (20% of all data) and verification (20% of all data).

Statistical parameters

For evaluation of obtained result of LRS, G.A Solver and ANN models, various standard as the statistical performance evaluation criteria were used between the measured and predicted K_{NaBPh4}, including model efficiency factor (MEF), absolute error percentage (AEP), root mean square error (RMSE) and coefficient of determination (R^2). The MEF, AEP and RMSE were defined as:

$$MEF - 1 - \frac{\sum_{i=1}^{n}(Y_i^* - Y_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2} \times 100 \quad (3)$$

$$AEP = \frac{\sum_{i=1}^{n}|Y_i^* - Y_i|}{\sum_{i=1}^{n} Y_i} \times 100 \quad (4)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i^* - Y_i)^2}{n}} \quad (5)$$

(Y^*) was the predicted value of observation, by function for each sample, the measured value of observation was ($Y_{i)}$ and ($_i$) were the average of the measured value of observation. (n) was the number of total measured samples. R^2

obtained via following equation:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(X_1 - \bar{X}_1)(X_2 - \bar{X}_2)(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_1 - \bar{X}_1)}\sqrt{\sum_{i=1}^{n}(X_2 - \bar{X}_2)}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})}}\right]^2 \quad (6)$$

X and Y were two measured variables also and were the average of those variables.To reach a conceptual conclusion about the kind of relationship between selected variables.

Descriptive statistics of chemical properties

Quantities of measured chemical properties including soil reaction, soil electrical conductivity, organic matter, soil paste saturated water percentage, cation exchange capacity, soil potassium measured by sodium tetraphenylboron, surface excess, and saturated soil extract were mentioned in table 1.

Table 1- Descriptive statistics of chemical factors

Parameters	Unite	N	Minimum	Maximum	Mean	Std. Deviation
pH^a	$-\log(H^+)$	183	5.98	8.41	7.58	0.39
EC^b	$\frac{ds}{m}$	183	0.228	6.37	1.43	1.30
$O.M^c$	%	183	0.224	7.28	2.61	1.45
$S.P^d$	%	183	29.33	72.92	49.10	11.215
CEC^e	$\frac{\mathrm{Meq}}{\mathrm{100\ gr\ soil}}$	183	5.96	44.35	19.49	7.85
$K_{NaBPh4}{}^f$	$\frac{\mathrm{Mg\ k}}{\mathrm{kg\ soil}}$	183	51.03	680.25	225.27	156.15
$K_{sce}{}^g$	$\frac{\mathrm{meq\ K}}{\mathrm{100gr\ soil}}$	183	0.06	1.61	0.69	0.39
$K_{sol}{}^h$	$\frac{\mathrm{Mg}}{\mathrm{L}}$	183	1.95	103.20	18.83	18.62

[a]) Soil reaction, [b]) Soil electrical conductivity, [c]) Organic matter, [d]) Soil paste saturated water percentage, [e])Cation Exchange Capacity, [f]) Soil potassium measured by sodium tetra phenyl boron ($NaBPh_4$), [g]) Surface charge excess of soil potassium, [h]) Measured potassium of saturated soil extract.

Descriptive statistics of physical properties

In table 2 the obtained amounts physical variables were mentioned, including soil texture, specific surface area and aggregation stability.

Table 2- Descriptive statistics of physical factors

Parameters	Unite	N	Minimum	Maximum	Mean	Std. Deviation
Clay	%	183	15.60	48.32	30.72	8.03
Sand	%	183	11.68	69.68	38.20	13.68
Silt	%	183	4.0	52.00	31.06	10.43
MWD[a]	mm	183	0.18	5.31	1.61	1.27
GMD[b]	mm	183	0.61	1.72	0.97	0.194
SOA[c]	%	183	0.37	95.40	41.55	27.08
DOA[d]	%	183	0.011	99.25	17.67	22.72
DR[e]	-	183	3.48	99.45	55.13	28.54
SSA[f]	m^2/gr	183	49.72	237.18	116.67	40.40

[a]) mean weight diameter, [b]) geometric mean diameter, [c]) status of aggregation, [d]) degree of aggregation, [e]) dispersion ratio, [f]) specific surface area

Relationships between soil properties

In table (Table 3) the correlation analysis of the soil measured parameters was demonstrated.

Table 3- Pearson correlation coefficients among measured soil properties

Variables	O.m	S.p	Cec	K_{nabph4}	K_{sce}	K_{sol}	Clay	Sand	Silt	Ssa	Mwd	Gmd	Soa	Dr	Doa
O.m[a]	1														
S.p[b]	.59**	1													
Cec[c]	.47**	.48**	1												
K_{nabph4}[d]	.40**	.68**	.23	1											
K_{sce}[e]	.44**	.56**	.19	.69**	1										
K_{sol}[f]	.24	.1	-.03	.30*	0.02	1									
Clay	.28*	.6**	.14	.61**	.53**	-.14	1								
Sand	-.31*	-.5**	-.3**	-.5**	-.4**	.06	-.6**	1							
Silt	.19	.23	.33*	.22	.16	.04	.08	-.8**	1						
Ssa[g]	.25	.6**	.29*	.73**	.63**	.04	.58**	-.5**	.27*	1					
Mwd[h]	.63**	.4**	.16	.37*	.34**	.19	.24	-.21	.09	.22	1				
Gmd[i]	.58**	.5**	.17	.42**	.29**	.33**	.18	-.16	.08	.20	.79**	1			
Soa[j]	.62**	.61**	.4**	.51**	.53**	.03	.42**	-.2*	.06	.36**	.4**	.48**	1		
Dr[k]	-.6**	-.6**	-.4**	-.5**	-.5**	-.04	-.4**	.27*	-.04	-.3**	-.4**	-.5**	-.9**	1	
Doa[l]	.09	.16	.19	-.04	-.09	-.12	.17	-.24	.18	-.03	-.17	-.03	.31*	-.2	1

**. Correlation is significant at the 0.01 level. *. Correlation is significant at the 0.05 level.

[a]) organic matter, [b]) soil paste saturated water percentage, [c]) Cation Exchange Capacity, [d]) soil potassium measured by sodium tetra phenyl boron ($NaBPh_4$), [e]) Surface charge excess of soil potassium, [f]) measured potassium of saturated soil extract, [g])specific surface area, [h]) mean weight diameter, [i]) geometric mean diameter, [j]) status of aggregation, [k]) dispersion ratio, [l]) degree of aggregation.

Modeling soil potassium via LRS, G.A and ANN

After verification of the parameters that can effect on plant available potassium, the single chosen output (K_{NaBPh4})was predicted via the appropriate inputs in different models by using LRS, GA and ANN (Table 4).

The best obtained model was model No.1. In this model status of aggregation and specific surface area play the inputs roles and with a relative high precision and accuracy K extractable with $NaBPh_4$ can be predicted. In Fig.3 the spatial dispersion of the K extraction value via $NaBPh_4$ for soils, against the respective SSA and SOA quantities was demonstrated.

LRS Model

In figure 4 prediction Precision of potassium via LRS model was exhibited. Equation 5 presented the type of relationship between inputs and output of LRS model.

$f(x,y) = p10*x + p01*y$ (5)

$X= SSA,\ Y= SOA,\ f(x,y)= K_{NaBPh4},\ p10 = 2.48, p01 =1.64,\ RMSE= 158.10,\ MEF= -4.21,\ AEP= 62.48,\ R^2= 0.59.$

(K_{NaBPh4}) means soil measured potassium by sodium tetra phenyl boron ($NaBPh_4$), SOA means status of aggregation of soil and SSA mean Specific surface area.

G.A Model

In figure 5 prediction Precision of potassium via genetic algorithm model method was presented. Equation 6 implied on the type of relationship between inputs and output of G.A model.

Table 4: Produced models for prediction of K_{NaBPh4} via ANN (MLP, RBF and ELMAN) LRS and G.A

Model No.	Input numbers		ANN(RBF)				ANN(ELMAN)				ANN (MLP)							
	1	2	RMSE	AEP	MEF	R^2	RMSE	AEP	MEF	R^2	R train	R test	R valid	R all	RMSE	AEP	MEF	R^2
1	SOA	SSA	67.32	21.49	79.01	0.79	70.32	22.38	82.46	0.75	0.93	0.99	0.94	0.92	59.36	15.46	84.06	0.84
2	SOA	CLAY	102.36	39.97	59.12	0.61	106.36	42.31	55.48	0.59	0.81	0.98	0.71	0.82	87.12	27.61	68.10	0.68
3	K_{SCE}	CEC	91.03	34.12	62.21	0.64	97.94	36.12	60.12	0.61	0.90	0.91	0.89	0.89	79.35	22.63	71.36	0.72
4	O.M	SSA	102.36	41.02	54.71	0.61	104.13	44.34	50.12	0.58	0.89	0.94	0.81	0.85	80.4	26.31	70.12	0.69
5	SSA	MWD	109.25	30.1	64.01	0.65	112.78	32.14	61.21	0.60	0.85	0.94	0.91	0.88	85	24.85	70.45	0.71
6	ROD	SSA	73.25	22.6	74.21	0.74	70.15	19.4	70.35	0.70	0.81	0.96	0.93	0.89	69.25	19.69	79.98	0.78

Model No.	Input numbers		LRS				G.A			
	1	2	RMSE	AEP	MEF	R^2	RMSE	AEP	MEF	R^2
1	SOA	SSA	158.1	62.48	-4.21	0.59	98.48	29.1	63.56	0.63
2	SOA	CLAY	180.59	71.61	-35.2	0.49	113.12	38.3	48.50	0.47
3	K_{SCE}	CEC	143.36	52.63	41.79	0.54	126.36	39.64	41.66	0.56
4	O.M	SSA	172.36	67.81	-24.5	0.57	151.2	63.94	-9.43	0.52
5	MWD	SSA	160.01	67.44	-79.5	0.57	126.03	44.00	33.78	0.51
6	ROD	SSA	102.36	34.85	56.20	0.59	105.43	36.33	53.64	0.60

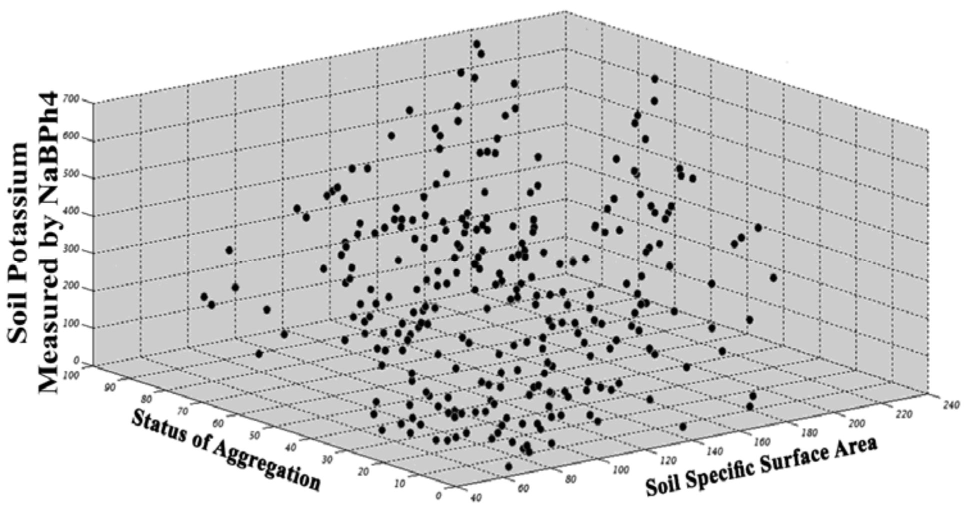

Fig. 3- Spatial dispersal of the K extraction value via $NaBPh_4$ against the respective SSA and SOA quantities

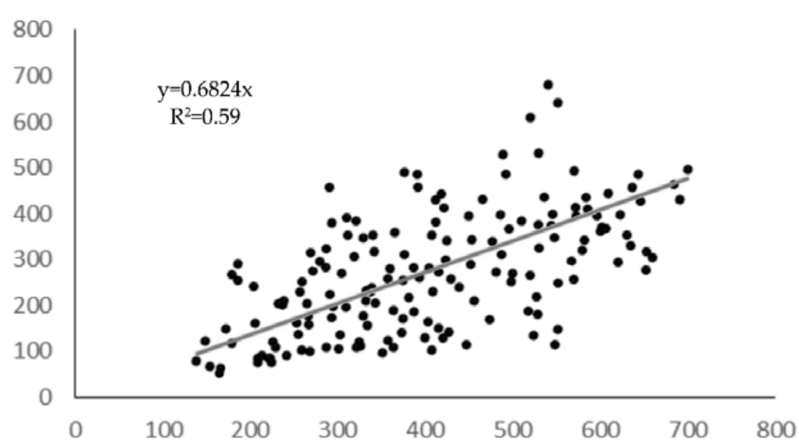

Fig. 4- relationship between measured and estimated (LRS) amount of potassium

$f(x,y) = p10*x^{\wedge(a)} + p01*y^{\wedge(b)}$ (6)

X= SSA, Y= SOA, f(x,y)= K_{NaBPh4}, *p10 = 0.023, a= 1.39,p01 =0.06, b=1.68, RMSE= 98.48, MEF= 63.56, AEP= 29.1,* R^2 *= 0.63.*

By a comparison between the obtained statistical indexes (RMSE, R^2, MEF and AEP) of the predicted amount of the models output, it was found that G.A solver can predict the soil measured potassium via sodium tetra phenyl boron much precise than LRS (Table, 4).

ANN models

MLP model

ANN simulation via MLP network was performed and soil K_{NaBPh4} was the output of the model. The extent of RMSE in this procedure was the lowest among the other models and possessed the highest capability in predicting soil potassium extractable by $NaBPh_4$precisely. This network (RMSE= 59.36, MEF= 84.06, AEP= 15.46, R_{train}= 0.93, R_{test}= 0.99, R_{valid}= 0.94, R_{all}= 0.92, R^2= 0.84) was identified as the best model for predicting amount of soil measured potassium by sodium tetra phenyl boron.

ELMAN model

Via simulations inELMAN network, it was proved that the lowest power and precision in predicting the amount of soil potassium through the ANN models, was for this (ELMAN) network with following result (RMSE= 70.32, MEF= 82.46, AEP= 22.38, R^2= 0.75). This model differed a little with the RBF model in RMSE, R^2, MEF and AEP but is was still functioning better than LRS and G.A.

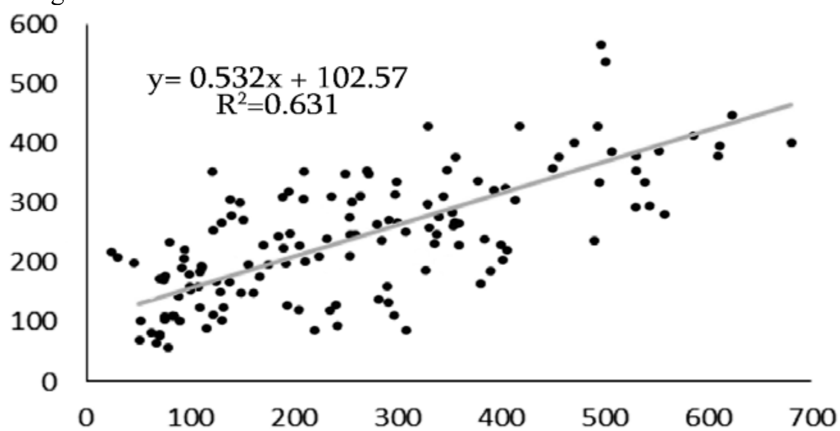

Fig. 5- relationship between measured and estimated (G.A) amount of potassium

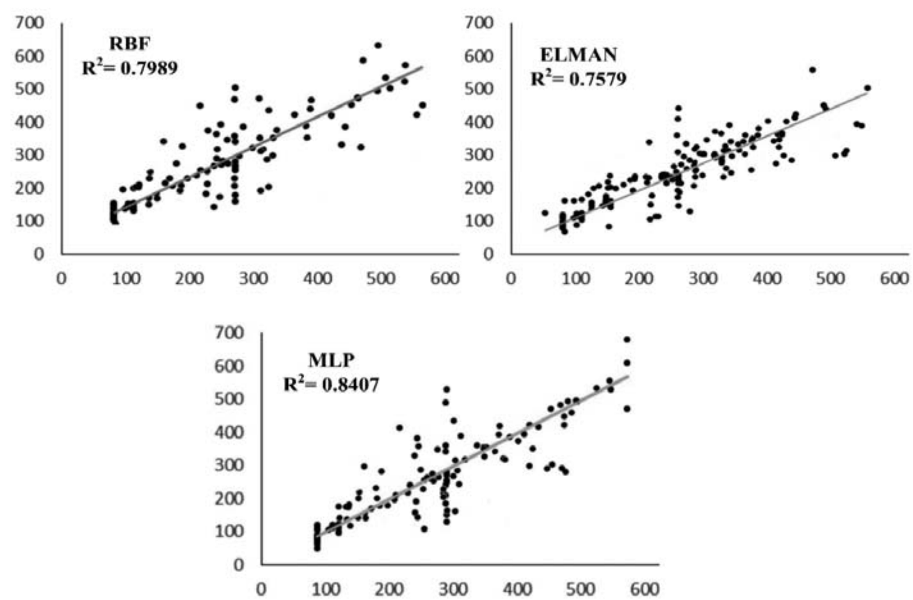

Fig. 6- Comparison of the function of MLP, RBF, ELMAN networks about the precision of potassium prediction capability

RBF model

RBF and MLP usually are considered as the best simulation networks in artificial neural network. The RBF model with the following characteristics RMSE= 67.32, MEF= 79.01, AEP= 21.49, R^2= 0.79, was more successful than the Elman models in predicting soil potassium. In figure 6 the relationship between soil measured potassium (K_{NaBPh4}) and estimated amount via MLP, RBF and ELMAN networks was presented.
Figure 6 and table 4 presented that if there was a ranking for the manner of developed model function, it would be as follows (Fig.5 and Table 4):*MLP>RBF>ELMAN*

DISCUSSION

In agreement with [3] research, our study proved that a positive interaction was between available potassium and soil water content also O.M and K followed the immediate structure. The better aggregation and aeration, the more available potassium will exist in soil. Managements which increase SOA such as organic matter additions and increasing tillage intensity may improve yield an it seems No-tillage was not a right method for increasing SOA [31]. Soilspossessing High SSA and fine clay particles may impose significant mechanical resistance to the root growth by cementing various sizes of soil particles. Soil mechanical resistance which is controlled by combined effect of dry bulk density and soil water content, impacts root extension, plant water and nutrients availability [32]. In sub humid climate of north of Iran in addition to cementing effects of high quantity fine clays in high specific surface soils, slow imbibition and incomplete swelling of soils may induce greater cohesion and mechanical resistance.
Limited truncated DDL-soil solution interfacing with specific surface area SSSS's limits rapid diffusion rendering nutrient slowly available [33]. Lack of strong correlation (0.41; P=0.0135) between soil potassium concentration and plant potassium uptake suggests NH_4OAc soil test is not reliable for extracting potassium from swelling soils characterized by high specific surface area and illite dominance in clay fraction [3]. 1 N NH_4OAc extracts unavailable K from soils possessing high K release and has retention properties of illitic nature [17,34,35]. Sodium tetraphenylboron mimics root potassium uptakes by plants [28] and hence the diffusion rate (important in swelling soil possessing high SSA) whereas 1 N NH_4OAc extracts soil exchangeable and bulk solution potassium. [36]research results implied on a founded Correlation between $NaBPh_4$ soil test and grain yield, which were 0.91 and 0.74 before heading and at harvest, respectively. Similar values for NH_4OAc soil test were 0.54 and 0.65, respectively. With a different experiment correlation between $NaBPh_4$soil test and grain yield were 0.84 and 0.73 before heading and at harvest respectively. Similar values for NH_4OAc soil test were 0.53 and 0.54, respectively.

CONCLUSIONS

Obtaining perfect knowledge about our surrounding environment is of high priority for researchers and agriculture policy makers. In soils comprising silt clay loam texture, illite minerals and with high SSA, moreover, presence of swelling property, the limiting plant growth factor of this would be properly potassium and application of K fertilizers should be essential. Our study proved that potassium measured by $NaBPh_4$ is in a positive relation with SSA and SOA. The more SSA and well-aggregated soil, the more quantity of potassium can be absorbed by plants. The better aggregation and SOA, the more potassium will be absorbed.Status of aggregation (SOA) affects swelling-shrinkage rate in soils with high specific surface and hence potassium availability. Therefore, In high specific surface soils with illite dominance in clay fraction, potential of potassium deficiency could be a function of SSA, potential of swelling with the ambient climatic conditions (as affect root zone soil wetness) and the SOA.
Furthermore, using ANN for making the cost and time of experiments efficient is totally necessary.The best model by using artificial neural network, for estimating plant available potassium was obtained by using soil specific surface area and status of aggregation in MLP network with 5 neurons. The inputs parameters and result were RMSE=59.36, MEF=84.06, AEP= 15.46, R_{test}=0.99, R^2=0.84. So by taking advantages of these easily accessible parameters, prediction of the aim which was potassium extractable by $NaBPh_4$ would be possible. In addition, among the different ways of modelling procedures, ANN with MLP network operated much precisely and accurately in comparison to other networks, classical statistical methods and genetic algorithm solver.

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