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Effect of soil chemical properties on bio-saline production of blue panic grass (*Panicum antidotale* Retz.) under water-deficit and salinity stress conditions

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ABSTRACT

An experiment comprising two irrigation regimes (110 and 160 mm cumulative evaporation from Class A pan) and four salinity levels of irrigation water (5, 10, 20 and 30 dS/m) was conducted on bio-saline production of *Panicum antidotale* Retz. Results showed that the artificial neural network model could predict dry matter yield variability by 99% using soil chemical properties. The sodium content of 30-60 cm depth had the most important factor affecting dry matter production of blue panic grass. And acidity, concentration of sodium and potassium in the depth of 90-60 cm, pH in the depth of 30-60 cm and organic matter in the depth of 0-30 cm were other important factors affecting the production of dry matter. Establishment of bio-saline system in this condition had a significant effect on soil chemical properties during short time and should be paid attention for productivity, profitability and sustainability of commercial in arid zones.

Key words : Artificial neural networks, forage yield, salinity, sodium chloride, soil depth, water deficit

INTRODUCTION

Today, in many countries of the Middle East and the Mediterranean region, including Iran, which has a arid and semi-arid climate, increasingly scarce water resources and salinization of cultural lands (Masters *et al.,* 2007; Kafi *et al.,* 2010b), biosaline production of salt tolerant plants such as halophytes may be logical alternative for salt-sensitive crops that have not suitable yield in this condition (Kafi and Khan, 2008). The successful domestication of halophytes needs to identify important factors that affect their production (Akhani, 2006; Masters *et al.,* 2007). Zandi Esfahan *et al.* (2007) evaluated 19 aspects of soil physical and chemical characteristics associated with *Haloxylon ammondendron* (C. A. Mey) growth in Segzi region of Isfahan Province, Central Iran, and expressed physical characteristics such as hard layer depth (constraining layer) and saturated moisture content and chemical properties such as salinity and alkalinity and total nitrogen content had the greatest influence on plant growth indices.

Blue panic grass (*Panicum antidotale* Retz.) is a native plant in temperate and tropical regions of Asia, the Middle East to India (Halvorson and Guertin, 2003), has a very deep root system and can absorb available water of deep soil layers (FAO, 2002; Esghizadeh *et al.,* 2011). In addition blue panic grass rapidly response to sudden environmental changes occurred during the summer, and so has high tolerance to drought and water-deficit conditions in the grasslands and deserts. *Panicum antidotale* (Retz.) is palatable forage especially for dairy cows (Ruyle and Young, 1997) and the sheep (Saini *et al.,* 2007). So, it can be considered as an option for production in arid and semi-arid regions that have both saline soil and water resources.

On the other hand, artificial neural networks (ANN) are the part of dynamic systems that can transmit the unknown

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science or knowledge of the experimental data processing to the network structure and therefore were called as smart systems (Lawrence, 1994; Liu *et al.,* 2001). Using optimum ANN, selecting the correct weights and activation functions can be simulated linear and non-linear processes. Network architecture, training algorithm and activation function (stimulation or transfer) are the main characteristics of ANN (Menhaj, 2000). Shukla *et al.* (2004) stated that ANN applications in agricultural production, included modelling of crop yield, measuring the effects of pesticide, nutrient losses, estimation of soil moisture curve and forecast damage by pests and diseases. In the United States, to predict the yield of soybean and corn back propagation was used-ANN (Kaul *et al.,* 2004). The properties of soil such as phosphorus, potassium, pH, organic matter, soil depth and magnesium levels were considered as input data and the results of this study were compared with results from statistical models. Although the network model needs some reforms to increase accuracy, obtained satisfactory results by ANN. Liu *et al.* (2001) in a study to predict the yield of corn and determine the factors affecting its performance found that back propagation-ANN models were able to predict corn yield with 80% accuracy. In addition, they found that predicted yield was more sensitive to amount of precipitation (especially latest rainfall in July), the amount of nitrogen fertilizer and soil phosphorus. This study was conducted under water-deficit and salt stress conditions, simultaneously, to identify some important soil chemical properties in bio-saline production systems of blue panic grass (*Panicum antidotale* Retz.) using ANN models.

MATERIALS AND METHODS

Experimental Site and Soil Properties

This experiment was conducted at Drainage and Land Reform of Rudasht Research Farm in Isfahan, 65 km East of Isfahan Province, Iran (32°30'N, 52°9'E, altitude 1500 m) in 2010. The average air temperature ranged from 15 to 33°C. Average relative humidity was 20.3%.

The field was fallow in the previous year. Based on soil tests, 100 kg/ha triple superphosphate (P_2O_5 : 46% min.) and 150 kg/ha urea (N : 46%) as basal fertilizer, then applied urea once as topdressing 200 kg/ha after first cutting. Land preparation practices were tillage and disk, respectively. Plot area was 5 m^2 with 50 cm row spacing.

The seeds of blue panic grass (*Panicum antidotale* L.) were obtained from the Agricultural and Natural Resource Research Center of Sabzevar, Khorasan Razavi, north-east of Iran. The germination test of seeds was performed in the sterilized Petri dishes. Results showed that germination percentage of seeds was 95. Seeds were planted in two rows on either sides of each furrow in 1-1.5 soil depth, approximately. The first furrow irrigation was applied on 20 May. Final plant density was 13/m^2 after thinning in the 4-3 leaf stage.

The irrigation levels were applied after 110 and 160 mm cumulative evaporation from class A evaporation pan during the whole period of plant growth as control (I_1) and water-deficit treatments (I_2), respectively. Salinity levels were achieved by different electrical conductivity of irrigation water averaging about 5, 10, 20 and 30 dS/m (Table 1).

First cutting was performed in panicle emergence stage (more than 90% of plants in each plot) from 15 cm above the soil surface or third node on the main stem, approximately, on 20 August. Then plants had improvement and second cutting was done on 14 October.

The plant harvesting was done by hand, plant samples were placed in the oven at a temperature of 70°C for 48 h and then dry weight of each plot was calculated. After the second cutting to evaluate the chemical properties of soil 0-30, 30-60 and 60-90 cm depths were sampled, separately. The soil acidity using pH meter and EC of soil saturation was measured using an electrical conductivity meter. Available P was extracted with a solution of sodium bicarbonate ($NaHCO_3$) and determined with ammonium molibidate in colorometric method. Available K was extracted with NH_4-OAc solution and determined by flame detector. Organic matter was measured on wet oxidation procedures (McLeod, 1973). The ions were measured by Flame Photometer method for sodium and titration method for chloride and calcium (Allison, 1965). Descriptive statistics were analyzed by using SPSS software version 16.

Table 1. Characteristics of the water used in irrigation water salinity levels in the different months of study

Sampling time	Salinity treatment	EC (dS/m)	pH	HCO_3^{-1}	CO_3^{-2}	Na^+	Cl^-	K^+
			-----	-----	-----	meq/l	-----	-----
May	-	6.39	7.62	1.1	7.0	39.6	6.5	3.40
June	Control	8.01	7.37	0.5	5.0	54.1	22.0	5.37
	10	10.2	8.35	2.10	11.0	58.8	26.5	11.28
	20	16.0	7.09	0.6	5.0	59.2	30.0	18.18
	30	32.2	7.55	1.0	7.0	62.9	97.5	27.0
August	Control	7.98	8.18	2.2	10.0	49.8	10.5	1.43
	10	15.7	7.45	0.5	6.0	64.3	35.5	10.3
	20	20.3	7.96	1.5	8.0	67.7	56.5	22.1
	30	29.5	7.41	0.5	6.0	80.5	90.5	30.0
September	Control	2.68	8.36	3.5	13.0	16.6	5.5	0.44
	10	7.47	8.01	2.30	11.0	47.3	27.5	4.39
	20	20.6	8.47	2.0	8.0	69.4	65.5	24.1
	30	30.0	8.05	1.5	8.0	76.1	95.0	27.0
October	Control	4.29	8.46	2.0	11.0	22.6	9.5	6.36
	10	16.4	8.10	2.0	10.0	57.5	18.5	7.34
	20	20.3	8.06	1.5	8.0	67.7	50.0	11.3
	30	28.6	8.90	4.0	14.0	79.6	85.0	31.9

Artificial Neural Network Modelling

Multilayer perceptron (MLP) with back-propagation learning rule was employed. The MLP network [also termed feed-forward back-propagation (BP) network] is a common architecture, probably the most popular network in engineering problems in the case of non-linear mapping that requires relatively little memory and is generally fast, is called the 'universal approximator' (Haykin, 1994; Lawrence, 1994). The learning process was performed using the well known BP algorithm, the standard BP algorithm based on the delta learning rule (Rumelhart and McClelland, 1986). In the forward pass, an output pattern was presented to the network and its effect was propagated through the network, layer by layer. For each neuron, the input value was calculated by the following Equation 1 (Haykin, 1994).

$$\mathrm{net}_i^n = \sum_{j=1}^{m} \mathrm{W}_{ji}^n \cdot \mathrm{O}_j^{n-1} \quad ...(1)$$

Where, net_i^n is the input value of *i*th neuron in *n*th layer; W_{ji}^n is the connection weight between *i*th neuron in *n*th layer and *j*th neuron in the (n-1)th layer

O_J^{n-1} is the output of *j*th neuron in the (n-1)th layer

n is the number of neurons in the (n-1) th layer

In each neuron, the value calculated from Equation 1 was transferred by an activation function.

The common function for this purpose is the sigmoid function, given by Equation 2.

$$\mathrm{Sig}\,(net_i^n)=1/[1+\mathrm{Exp}(-net_i^n)] \quad ...2$$

The output of each neuron was computed and propagated through the next layer until the last layer. Then, the final computed output of the network was prepared to compare with the target output. In this regard, an appropriate objective function such as the sum of square error (SSE) or the root mean square error (RMSE) was calculated following Equations 3 and 4 (Degroot, 1986) :

$$SSE = \sum_{i=1}^{n_p} \sum_{j=1}^{n_o} (T_{pj} - O_{pj})^2 \quad ...(3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n_p} \sum_{j=1}^{n_o} (T_{pj} - O_{pj})^2}{n_p . n_o}} \quad ...(4)$$

Where, Tpj is the *j*th element of the target output related to the *p*th pattern

Opj is the computed output of *j*th neuron related to the *p*th pattern

n_p is the number of patterns

n_o is the number of neurons in the output layer

After calculating the objective function, the second step of the BP algorithm i. e. the backward process was started by back propagation of the network error to the previous layers. Using the gradient-descent technique, the weights were adjusted to reduce the network error by performing Equation 5 (Rumelhart and McClelland, 1986) :

$$\Delta w_{ji}^{n}\big|_{(m+1)} = \eta \frac{\partial(E)}{\partial w_{ji}^{n}} + \alpha \Delta w_{ji}^{n}\big|_{(m)} \quad ...(5)$$

Where, ΔW^{n}_{ji} (m+1) is the weight increment at the (m-1) *th* iteration (Epoch)
η is the learning rate
α is the momentum term ($0 \leq j, \mu \leq 1$)

This process was continued until the allowable network error was obtained. For designing the ANN, the measured chemical soil properties were used. Sixty per cent of the data for model training, 20% for model validation and 20% were chosen as model test data, respectively. ANN models were performed using MATLAB software package (MATLAB, 2008). Various activation functions were tested for MLP neural networks and the tansigmoid function presented the best results.

Sensitivity Analysis

In order to identify the most important soil chemical charters affecting above ground biomass of blue panic grass, sensitivity analysis was performed using the StatSoft method (StatSoft Inc., 2004). A sensitivity ratio was calculated by dividing the total network error when the variable was treated as being not variable by the total network error when the actual values of the variable were used. A ratio greater than 1.0 implied that the variable made an important contribution to the variability in root morphological components. Variables with higher sensitivity ratio are more important (StatSoft Inc., 2004; Miao *et al.,* 2006).

RESULTS AND DISCUSSION

Some descriptive statistics of chemical properties in 0-90 cm soil depth under different quantity and quality of irrigation water are summarized in Tables 2, 3, 4 and 5. Mean values of soil electrical conductivity at three soil layers differed significantly and the highest electrical conductivity (14 dS/m) was observed at 30-60 cm soil layer that was 13 and 9% more than 0-30 and 60-90 cm layers, respectively (Table 2). Similarly, the highest soil pH 8.11 belonged to 30-60 cm soil layer and was about 0.175 units more than others in average (Table 2).

There were no significant differences in average values of sodium concentration at different soil depths (Table 3). Although the average concentration of Na^{+} was about 2 meq/l more in the 60-30 cm soil layer than other depths. The concentration of chlorine in the lower layer of the soil was more than surface especially in 30-60 cm.

Average amounts of available potassium at different depths had also significant differences with each other. Available potassium of 0-30 cm of soil layer with 272 mg/kg was more than 30-60 (5%, respectively) and 60-90 cm (21%) layers (Table 4). Averages of available phosphorus were similar in the different soil depths (Table 4).

The 0-30 and 60-90 cm soil depths had similar calcium concentration, but the value was higher (5 meq/l) in 30-60 cm soil layer (Table 5). The most soil organic matter was observed in the 0-30 cm soil depth (Table 5).

There were significant differences between maximum and minimum dry matter yield of blue panic grass by three-fold (Table 6)

Table 2. Descriptive statistics of pH and electrical conductivity for 0-90 cm soil depth under different quantity and quality of irrigation water

The statistics	Electrical conductivity (dS/m)			pH [-log(H^{+})]		
	Soil depth (cm)			Soil depth (cm)		
	0-30	30-60	60-90	0-30	30-60	60-90
Mean	11.2	14.0	12.8	7.97	8.11	7.90
Standard error	0.50	1.05	0.67	0.035	0.069	0.025
Median	10.8	11.8	13.3	7.98	7.99	7.93
Standard deviation	2.45	5.17	3.29	0.173	0.338	0.125
Minimum	8.32	9.52	7.60	7.67	7.75	7.60
Maximum	17.3	23.7	18.0	8.33	8.90	8.08
Range	9.01	14.2	10.4	0.66	1.15	0.480
C. V. (%)	21.8	36.9	25.7	2.17	4.16	1.57
Skewness	0.85	1.11	-0.26	0.596	1.67	-0.79

Table 3. Descriptive statistics of sodium and chloride concentrations for 0-90 cm soil depth under different quantity and quality of irrigation water

The statistics	Na^+ (meq/l)			Cl^- (meq/l)		
	Soil depth (cm)			Soil depth (cm)		
	0-30	30-60	60-90	0-30	30-60	60-90
Mean	71.1	73.1	71.5	33.5	36.4	35.6
Standard error	1.70	1.06	2.10	2.88	2.71	2.66
Median	72.8	73.7	71.5	28.5	33.2	31.7
Standard deviation	8.36	5.18	10.3	14.1	13.3	13.0
Minimum	53.5	62.6	50.7	19.0	15.0	18.5
Maximum	82.2	81.3	82.2	67	60	60
Range	28.7	18.7	31.5	48	45	41.5
C. V. (%)	11.7	7.07	14.4	60.0	50.4	50.8
Skewness	-0.345	-0.472	-0.555	1..27	0.484	0.480

Table 4. Descriptive statistics of available potassium and phosphorus concentrations for 0-90 cm soil depth under different quantity and quality of irrigation water

The statistics	Available potassium (mg/kg)			Available phosphorus (mg/kg)		
	Soil depth (cm)			Soil depth (cm)		
	0-30	30-60	60-90	0-30	30-60	60-90
Mean	272	259	225	11.9	11.6	11.5
Standard error	14.7	9.79	7.09	1.23	1.36	1.17
Median	242	258	221	10.7	11.4	9.97
Standard deviation	72.2	48.0	34.7	5.76	6.70	5.71
Minimum	168	168	151	3.71	3.36	2.47
Maximum	398	348	307	22.2	26.5	19.4
Range	230	181	156	18.5	23.1	16.9
C. V. (%)	26.5	18.5	15.4	48.4	57.7	49.6
Skewness	0.439	-0.204	0.525	3.13	0.996	0.127

Table 5. Descriptive statistics of calcium and organic matter concentrations for 0-90 cm soil depth under different quantity and quality of irrigation water

The statistics	Calcium concentration (meq/l)			Organic matter (%)		
	Soil depth (cm)			Soil depth (cm)		
	0-30	30-60	60-90	0-30	30-60	60-90
Mean	78.1	82.9	78.1	0.21	0.19	0.18
Standard error	4.17	3.70	3.94	0.008	0.009	0.012
Median	78.8	85.4	80.8	0.21	0.19	0.17
Standard deviation	20.5	18.1	19.3	0.041	0.048	0.059
Minimum	33.7	48.1	40.8	0.15	0.11	0.07
Maximum	124.8	118.6	109.5	0.29	0.29	0.29
Range	91.1	70.6	68.7	0.13	0.17	0.22
C. V. (%)	26.2	21.8	24.7	19.1	25.3	33.0
Skewness	-0.014	-0.183	-0.070	0.114	0.158	0.414

and showed the growth condition affected by different quality and quantity of irrigation water.

Between soil chemical properties, on an average, acidity and chloride content in the different soil layers had the lowest (2.5) and highest (53.7) coefficient of variation, respectively. The observed variation is justified because the concentration and composition of the dissolved salts vary depending on the source of the irrigation water between treatments.

The skewness coefficients, presented in Tables 2, 3 and 4 confirm that all of the variables except pH and electrical conductivity of 30-60 cm soil layers (Table 2), chlorine

Table 6. Descriptive statistics of the dry matter of blue panic grass (*Panicum antidotale* Retz.) under different quantity and quality of irrigation water

The statistics	Dry matter yield (g/m^2)		
	1st cutting	2nd cutting	Total
Mean	706.2	491.6	1197.7
Standard error	44.4	41.2	77.7
Median	762.4	452.4	1184.0
Standard deviation	217.7	201.8	380.5
Minimum	249.0	264.6	684.1
Maximum	1108.7	1163.4	2107.0
Range	859.7	898.8	1422.9
C. V. (%)	31.0	41.0	32.0
Skewness	-0.347	1.66	0.426

content (Table 3) and available P of 0-30 cm (Table 4) were normally distributed and their skewness coefficients were between +1 and -1.

Artificial Neural Networks (ANN) Analysis

For the chemical soil properties that affect dry matter production of blue panic grass, the best network structure was based on the lowest RMSE (158.8) and the highest R^2 (0.99^{**}) by try and error, respectively. Structure obtained by the ANN for chemical properties of soils, dry matter production had 24 nodes in input layer, one node in the output layer, 49 nodes in hidden layer, respectively. Tansig was used as the effective transfer function for all the structures of artificial neural networks. To calculate coefficients of determination (R^2) predicted data were plotted versus observed data (Fig. 1). The 99% of the observed variability in dry matter production was predicted by developed ANN model.

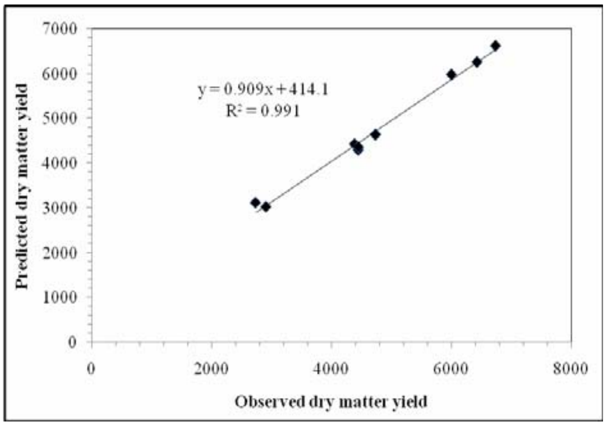

Fig. 1. Scatter plots displaying results of artificial neural network (ANN) predicted versus observed dry matter production for blue panic grass plant (*Panicum antidotale* Retz.) from the validation data set.

Sensitivity Analysis

The results of sensitivity analysis for soil properties are provided by StatSoft method as shown in Table 7 and Fig. 2. All of the chemical characters of soil had an effective attribute in growth, development and dry matter production of the blue panic base on the sensitivity coefficients. The electrical conductivity, pH and both potassium and calcium concentration of the 60-90 cm soil layer were more important, respectively.

Table 7. Sensitivity coefficients of some soil chemical properties used in the prediction of dry matter of blue panic grass (*Panicum antidotale* Retz.) under different quantity and quality of irrigation water in Stat Soft method

Variable	Sensitivity coefficients	Variable	Sensitivity coefficients
EC_{0-30}	4.65	Cl_{0-30}	6.84
EC_{30-60}	3.67	Cl_{30-60}	3.89
EC_{60-90}	7.10	Cl_{60-90}	5.67
pH_{0-30}	6.54	P_{0-30}	4.67
pH_{30-60}	11.4	P_{30-60}	4.94
pH_{60-90}	14.1	P_{60-90}	3.93
Na_{0-30}	8.16	OM_{0-30}	11.3
Na_{30-60}	14.3	OM_{30-60}	4.14
Na_{60-90}	13.2	OM_{60-90}	4.92
K_{0-30}	8.09	Ca_{0-30}	4.16
K_{30-60}	5.94	Ca_{30-60}	4.45
K_{60-90}	12.9	Ca_{60-90}	8.88

Knowledge of the spatial variability of soil chemical and physical properties is a key element in soil management and provides valuable information about the nature and characteristics of soil in the field (Ayoubi *et al.,* 2008) that can be used for designing management operations (Shukla *et al.,* 2004).

Usually the leaching of salt from the surface layers and accumulation of soluble salts increase electrical conductivity and acidity of deeper parts of the soil more than others (Zandi Esfahan *et al.,* 2007). These results are consistent with the findings of other researchers in the use of saline water only in the production of safflower (Kamali *et al.,* 2011) or combination of fresh and saline water (Kafi *et al.,* 2011). However, the wide range of sodium levels in each layer highlighted a significant difference between treatments. Similarly, Kamali *et al.* (2011) stated that sodium concentration in the lower

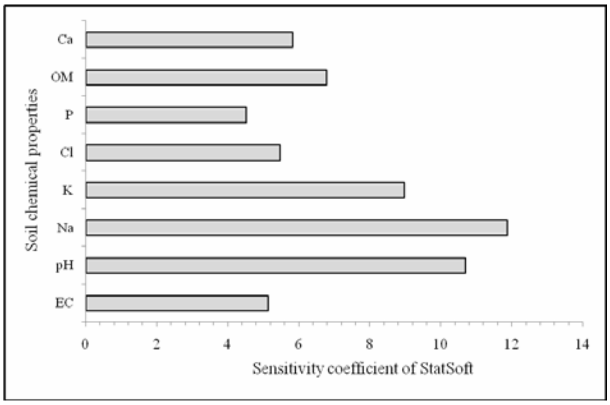

Fig. 2. Histogram coefficients of sensitivity of some soil chemical properties used in the prediction of dry matter are provided by Stat Soft method, EC : Electrical conductivity of soil saturation extract (dS/m), pH : The activity of hydrogen ions, Na : Sodium (meq/l), K : Available potassium (mg/kg), Cl : Chloride (meq/l), P : Available phosphorus (mg/kg), OM : Organic matter (%) and calcium (meq/l).

layers was more affected when the saline water was used for irrigation. It seems that the effect of leaching and the various permeabilities of different soil layers causing difference in the rate of water infiltration are as effective factors for this condition (Soltani *et al.,* 2009; Kafi *et al.,* 2011).

Variation between available potassium in different layers is acceptable due to the nature of the rock material and the oxidation (Akhavan-Ghalibaf *et al.,* 1994). In addition, the differences in potassium concentrations of saline water treatments and the difference of water consumption for water-deficit treatment (1540/m^3) could help for understanding the difference between minimum and maximum amount of available potassium in soil layers.

However, available phosphorus in the surface layer showed a slight increase for two main reasons (i) the surface area exposed to the air directly and (ii) tillage operations usually were conducted in 0-30 cm of soil. High calcium concentrations in the soil were predictable due to the nature of the soils and climatic conditions (hot and dry) prevailing in this region. Different quantity and quality of irrigation water consumption has been effective in wide range between minimum and maximum extent of the amount of calcium.

Usually the amount of organic matter in surface soil is more than the lower layers because growth and development of plant root system, root exudates and the possible interactions between root and soil microorganisms are mainly accorded in upper layers of soil (Jafari *et al.,* 2006). Wide range between minimum and maximum amount of soil organic matter, especially at a 60-90 cm depth (314%) showed the effectiveness of different treatments on depth and development of root system (Esghizadeh *et al.,* 2011).

In this experimental condition, the significant variation in dry matter was predictable due to difference between the least and highest level of water salinity in average 25 dS/m and different volume of irrigation water. These observations are consistent with the findings of other researchers on the effects of varying salinity on dry matter yield of safflower (Kamali *et al.,* 2011), canola (Soltani *et al.,* 2009), corn (Liaghat and Esmaili, 2003), blue panic grass (Esghizadeh *et al.,* 2011), kochia (Kafi *et al.,* 2010b) and the different effects of water-deficit stress on corn performance (Esghizadeh and Ehsanzadeh, 2009). Accumulation of salts affected plant growth by undesirable changes in physical and chemical soil properties because plant growth was under effect of excess concentration of soluble salts such as sodium and chloride ions and pH. In addition, the increased amount of sodium in the soil solution will result in degradation of soil aggregates, the swelling and dispersion of clay particles, and reduce porosity and permeability of soil (Kafi *et al.,* 2011).

In addition, different amounts of irrigation water have been implicated as the cause of diversity. However, the acidity of the soil is usually less affected by environmental factors, especially in the short term. Other researchers have acquired the lowest coefficient of variation in pH between the soil characteristics (Paz-Gonzalez *et al.,* 2000; Lopez-Granados *et al.,* 2002; Cox *et al.*, 2003; Mohammad Zamani *et al.,* 2007).

In the modelling yield components, the ANN model can be a good substitute for conventional regression models due to considering the non-linear relationship between environmental factors and key variables and subsequent increase in the estimated predictions (Menhaj, 2000). The results showed that the design of ANN model using the chemical properties of soil was an effective tool to predict plant dry matter production of blue panic grass. However, some of the difficulties associated with ANN models are the testing of various components of network structure such as law for synaptic neuron learning, transfer functions used in hidden and output layers, the number of hidden layer and number of neurons in the hidden layer base on try and error method. Notably, a poor correlation between the dependent variable in the regression models is not always indicative that there is not any relationship between them. The correlation coefficient does not reflect non-linear relationships between two variables (Norouzi *et al.,* 2009).

Esghizadeh *et al.* (2011) with studying the pattern of root development in blue panic grass reported that the root penetration was one of the main factors to tolerate salinity stress and uptake of water; however, it seems that the lower layers characters such as EC may play an important role in production. Unlikely, Na, Cl and organic matter in surface soil layers were more effective than other properties. Norouzi *et al.* (2009) also emphasized the importance of soil organic matter in the production of wheat grain yield.

CONCLUSION

Establishment of production system for blue panic grass had a significant effect on soil chemical properties during these five months that need to know for productivity, profitability and sustainability of commercial bio-saline system in arid zones. The concentrations of sodium, pH, potassium, calcium and organic matter in soil were more important in bio-saline production of blue panic grass, respectively. The effectiveness of chemical properties was highly correlated to soil depth for example in 60-90 cm soil layer : the electrical conductivity, pH, both potassium and calcium concentration and unlikely in surface soil layers : Na, Cl and organic matter were more, respectively. It seems likely that based on dry matter production, establishment of bio-saline system of blue panic grass is possible in similar condition but more intensive research is needed for establishment of a production system for this plant in dry and saline areas.

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