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ASSESSMENT CHEMICAL PROPERTIES OF SOIL IN INTERCROPPING USING ANN AND ANFIS MODELS

MEHDI DAHMARDEH[*1]; BEHROOZ KESHTEGAR[2]; JAMSHID PIRI[3]
[1] *University of Zabol, Departments of Agronomy, Faculty of Agriculture, Zabol, 98615-538 Iran*
[2] *University of Zabol, Deptartments of Civil Engineering, Zabol, 98615-538 Iran*
[3] *Departments of irrigation, Faculty of Water and Soil Sciences, Zabol, 98615-538 Iran*

Abstract

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Intercropping as an example of sustainable agricultural systems follows objectives, such as the ecological balance, more exploitation of resources and increase in soil fertility. Evaluation of soil nutrients in intercropping is a basic criterion for selecting the type of cultivation and increasing the productivity of the soil. Based on experimental study, evaluation of soil needs time and cost too much. However the soil parameters can be rapidly estimated using predicted meteorology and can be appropriately assessed. Linear estimation methods are less accurate than non-linear methods, but non-linear methods for modeling of soil elements are difficult due to highly computing times. The artificial intelligence is a powerful tool for fast modeling, more accurately. In this paper, artificial intelligence method such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used to estimate soil chemical properties (carbon and nitrogen). Four input parameters including the soil temperature, type of intercropping (different ratios of Roselle – green gram), type of tillage (no-tillage, minimum tillage, conventional tillage) and sodium have been used in ANN and ANFIS prediction. ANFIS and ANN modeling have been compared using several statistics (root mean square error (RMSE) and Mean Absolute Error (MAE). The results indicate that the artificial intelligences can be successful applied for estimating soil carbon and nitrogen. ANFIS is found to be more accurate than the ANN. A sensitivity analysis has conducted based on ANFIS estimate. It is shown that increased percent of green gram in intercropping can reduce the percentage of carbon to nitrogen (C/N).

Key words: Intercropping; ANN; ANFIS; soil nutrients; tillage
Abbreviations: ANN – Artificial Neural Networks, ANFIS – Adaptive Neuro – Fuzzy Inference System, MAE – Mean Absolute Error, RMSE – Root Mean Square Error

Introduction

Several studies conducted on agricultural management practices such as tillage type (Clapp et al., 2000; Holubik et al., 2016), fertilizer (Huang et al., 2010), the return of plant residues (Blaeir et al., 2006; Burhan and Bekir, 2013; Deibert and Utter, 2002; Thonnissen et al., 2000) and crop rotation (Koocheki et al., 2004) showed a significant effect on the amount of soil organic carbon. One aspect of sustainable agriculture is intercropping that is suggested as a solution for increasing advanced agricultural production, after increasing in number of species per unit area (Bodner et al., 2013; Ress, 2003). The use of nitrogen-fixing legumes in intercropping makes back much of the material absorbed by plants; soil and increases soil fertility (Hauggaard-Nielsen et al., 2003; Schipanski et al., 2010; Dahmardeh and Hodiani, 2016; Hung et al., 2010; Rees, 2003). Increased levels of nitrate in groundwater are attributed to inappropriate utilization of

**Corresponding author*: dahmard@gmail.com

nitrogen (MengBo and Yost, 2000). Achievement of the correct management of irrigation, desirable moisture storage of soil in dry areas, acceptable crop yields and soil conservation system depends on considering the stable system permeability (Ghorbani Dashtaki et al., 2002; Munz et al., 2014; Kasper et al., 2009). Energy consumption in agriculture is one of the most effective factors in sustainable agricultural production, because it reduces the costs, conserves natural resources and reduces the amount of air pollution and emissions of greenhouse gases (Ulhin, 1998). Soils provided with crop residues or Biodiesel Co-Product showed statistically significant increases in soil N and C compared to the control (no incorporation). These results indicate that field-scale incorporation of Biodiesel Co-Product may be an effective method to reduce nitrogen loss from agricultural soils, prevent nitrate pollution of groundwater and augment the soil microbial biomass (Redmile –Gordon et al., 2014). Any increase in agricultural production depends on the amount of energy and farm management that, tillage systems and management elements such as chemical fertilizers is an important factor in corn production (Gowdy et al., 1987; Dahmardeh and Hodiani, 2016). Ibrahimi and Naeblooyi (2003) in examination of 40 samples in triplicate in prediction of soil infiltration rates using several physical and chemical factors such as pH, density, specific gravity genuine, sodium, porosity, organic matter, electrical conductivity and total calcium and magnesium came to the conclusion that the artificial neural network model, to estimate the permeability has also high potential, even with a few data. Sarmadian and colleagues (2004) by comparing the methods of neuro-fuzzy, neural network and multiple regression predicted some soil properties such as wilting point, field capacity, cation exchange capacity and bulk density paid and their results showed high-performance of artificial neural network (ANN) and neuro-fuzzy (ANFIS) model rather than the linear regression analysis. Sorangi et al. (2006) predicted the soil salinity and drainage outlet in a pilot area in India using ANN. The results showed that the ANN was better to predict salinity of drains output. Noorani et al. (2009) used intelligent neural network, fuzzy inference systems and ANFIS to predict the monthly and daily runoff in the catchment area of Lighvanchai, located in East Azerbaijan province. Their results showed that fuzzy modeling (comparative and inductive) is more accurate than other models and had the lowest error. Irmak et al. (2006) predicted spatial patterns of soybean yield at the farm level using ANN and studied the role of factors such as topography and the spatial variability of soil fertility. Khashei et al. (2011) investigated the performance of wheat by ANFIS using meteorological data in Khorasan province. The obtained results showed that the predicted performance using ANFIS trained with temperature data (maximum, minimum and dew point) has a correlation coefficient of 0.67. Astetkiz et al. (2006) compared ANFIS and ANN in different soil conditions and farm management to predict crop yield. Artificial intelligence (AI) as a powerful tool and easy to estimate and predict natural phenomena has been used by researchers. It is evident from the literature that, AI has not been used for estimating soil chemical properties in hot and dry regions before. In hot and dry regions, determination and evaluation of the changes in soil chemical properties can be used to provide a model of sustainable cultivation. According to data obtained from laboratory analysis of the nutrient medium for a period of two years in a warm, dry area (Case Study Sistan, Iran), artificial intelligence has been used to predict soil chemical parameters such as carbon and nitrogen. In this study, the effect of intercropping on soil nutrient changes is estimated using parameters, such as soil temperature, sodium of soil and tillage type. Results showed that tillage without plowing estimated the most soil nutrients for the study area, also the C/N ratio was decreased with increasing machine ratio.

Material and Methods

Zehak city's geographical position is 61° and 41 minutes east longitude and 30 degrees 54 minutes north latitude and it is at an altitude of 481 meters above sea level. The results of soil chemical analysis showed that the soil has the EC = 2.93 ds/m and pH = 7.80. This experiment is conducted with plots in a randomized complete block design with three replications. The main factor included tillage types of no-till, reduced tillage, conventional tillage plows and disk, sub-plot included, pure Roselle, pure green gram, 50% Roselle plus 50% green gram, 75% Roselle + 25% green gram, 25% Roselle plus 75% green gram. Preparing the ground according to the three types of plowing, with no-tillage (zero tillage), reduced tillage (disk), conventional tillage (disc and plow) were performed. Plants were planted in plots with dimensions of 2 × 3 spacing of 40 cm from each other's culture lines (all treatments were planted in a row of Roselle and a row of green gram). The distance between the rows was the same but density in each row was different. On the basis of three types of tillage and intercropping types in each cultivation unit, three samples were collected, that in accordance with the results of laboratory, average of three samples per culture medium is listed in Table 1. As can be seen, no-tillage system compared to other tillage systems has more carbon and nitrogen and less sodium (Table 2). The amount of carbon and nitrogen in pure cultures of green gram has been increased compared to pure cultures of Roselle. Walkley and Black

Table 1
Results of statistical variables nutrient and soil temperature

Depended variable	Mean	Standard deviation	Maximum	Minimum	Number of samples
Carbon (%)	1.07	0.35	1.8	0.34	90
Nitrogen (%)	0.22	0.03	0.16	0.0293	90
Na (ppm)	62.71	30.34	110.62	14.8	90
Soil temperature (Co)	20.4	2.1	24.6	16.2	90

Table 2
The statistical parameters of each data set

Period	Data set	Unit	x_{mean}	Sx	Cv (Sx/$x_m)_{ean}$)	x_{min}	x_{max}	Correlation with C	Correlationwith N
Training	Tillage		2	0.82		1	3	0.576	0.533
	Na		50.1	31.1	0.62	14.8	119.68	0.530	0.576
	T		19.23	2.3	0.12	14.9	25.8	0.501	0.470
	Inter Cropping		50	35.55	0.71	0	100	0.346	0.324
	C		0.887	0.35	0.39	0.33	1.83	1	-
	N		0.076	0.031	0.5	0.03	0.19	-	1
Test	Tillage		1.95	0.759		1	3	0.356	0.390
	Na		52.46	27.11	0.52	16.51	112.57	0.527	0.583
	T		18.7	1.85	0.1	16.19	22.53	0.281	0.312
	Inter Cropping		48.8	35.77	0.73	0	100	0.183	0.039
	C		0.93	0.38	0.41	0.33	1.83	1	-
	N		0.08	0.03	0.04	0.03	0.14	-	1
Validation	Tillage		2.24	0.831		1	3	0.588	0.630
	Na		66.92	35.74	0.53	15.32	119.67	0.495	0.495
	T		20	2.93	0.15	16.52	25.82	0.545	0.593
	Inter Cropping		50	36.27	0.73	0	100	0.328	0.24
	C		0.78	0.29	0.37	0.45	1.64	1	-
	N		0.07	0.035		0.03	0.19	-	1

In the table, the x_{mean}, Sx, Cv, x_{min} and x_{max} denote the mean, standard deviation, variation coefficient, minimum and maximum, respectively

(1934) method was used to measure carbon (%). Nitrogen (%) was measured using the Kjeldahl Method and sodium (ppm) was measured using the water-soluble method with a flame photometer type of Corning 405. Thermometers special for France were applied to measure the temperature of the soil (Thermometer Dial Deep Frying). In order to achieve this, the thermometer was placed between rows at a depth of 15 cm in the middle of day and the soil temperature was measured in the different treatments. These measurements are done for 90 sample points whose statistical properties are tabulated in Table 1 for test, train and variation periods. Date of planting was June 2, 2013 and harvest date November 17, 2013.

In this study, an evaluation method was used, in which data set was divided into 3 separate and non-overlapping parts, and in 3 stages in tandem, each time a part of this 3 sections as a test set, 3 parts are considered as a test set and 3 parts are considered as validation.

Artificial Neural Network (ANN)

Artificial neural network, in general, is a simulation of a natural nervous system and includes a set of neurological units, called neurons, which are connected by connections called axons. Each neuron receives the output signals of other neuron by dendrites. The junction of the output of a neuron (Exxon) and other input neurons (dendrites) called synapses. Signal transmission at synapses takes place through a chemical reaction (Menhaj, 2004). In ANN, we try to design a structure similar to biological structure of the human brain and nervous system so, it will have learning and decision-making power (Menhaj, 1997; Jang et al., 1997; Nurani et al., 2009). One of the specific features of neural networks is low sensitivity to errors in the input neurons. This issue comes true with parallel processing. This division of work, and parallel processing, result in a positive outcome, and it is that, because so many neurons are involved in activities, the contribution of each neuron is very important. Therefore, an error in one of neurons and its result does not significantly effect on the functional unit (Tammadon, 2001). An ANN usually consists of three layers: the input layer, middle layer and output layer. Input layer includes units (nodes) with the number of explanatory variables. For example, if the number of explanatory (independent) variables is five, the input layer will have five nodes. The layer that its output is the network output is called output layer. Input layer and output operate similar to the dependent and independent variables in regression models. Researchers usually design neural networks with one or two hidden layers (Juybarian et al., 2001). Because a neural network with intermediate layer has a higher potential than with two layers neural networks (Ghadimi and Moshiri, 2002). Neural network used in this article, is MLP (Multilayer Perceptron) (Piri et al., 2009). The number of MLP hidden layer, is considered one. The general structure of such a network is shown in Figure 1. This network enables approximate any continuous function with any desired accuracy, using non-linear functions in middle layer and linear function in output neurons and using sufficient neuron number in the middle layer. In Figure 1, input is $I \in R^n$ and output is $y \in R$. p is the number of neurons in the middle layer. In the learning phase, the network learning algorithm with marq method (Basic Levenbeng Marquardt Method) is used. In this method, an MSE (Mean Square Error) criterion is used and it has a fast and robust convergence property better than the standard BP algorithm (Back propagation). Primary weight of network is selected randomly (Moghadamnia et al., 2009).

Adaptive neuro-fuzzy inference system (ANFIS)

First, the theory of fuzzy sets was released in 1965 by Professor Lotfi Asgarzadeh, Iranian scientist and professor at the University of California at Berkeley. This theory has become more widespread after its introduction and has found various applications in different areas. In 1993, Jung by considering the abilities of neural network and fuzzy theory provided adaptive neuro-fuzzy inference model (Jung et al., 1993; Jang, 1993; Stathakis et al., 2006). The classic method of neuro-fuzzy system is Sugeno type of fuzzy inference system that uses hybrid learning algorithm for determining the parameters of the fuzzy system to train the model (Zhang et al., 1997; Jorabiyan and Hoshmand, 2002). ANFIS model is a model with a five-layer structure, emerged with a combination of fuzzy logic and artificial neural network model (Figure 2).

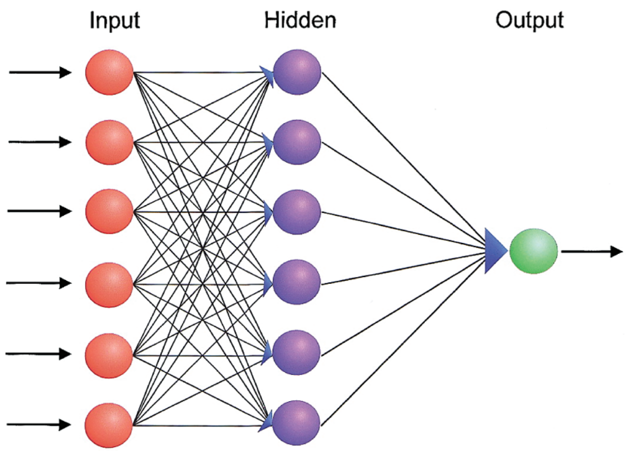

Fig. 1. The general structure of such a network

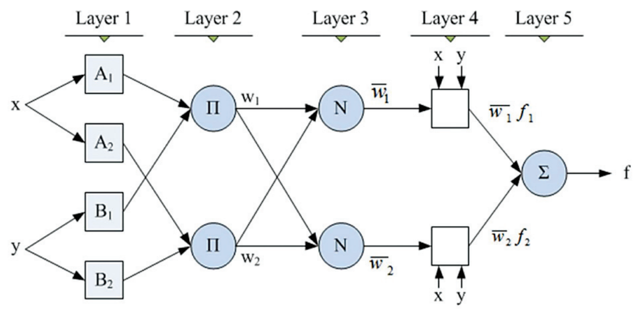

Fig. 2. A framework of ANFIS

The first layer or access layer, in which membership degree of input nodes to different periods is determined using membership functions. Membership functions have different kinds, including functions that can be trapezoidal, triangular, sigmoid, Gaussian and bell-shaped functions, which generally include more general case of them.

The second layer where the inputs to each node multiplied and the result that is the weight of rules is achieved.

In the third layer, nodes normalize the weight of rules.

The fourth layer is called rules layer and rules obtained in this layer.

The fifth and last layer of the network contains only a single node, which calculates the total output by summing all input values together.

Results and Discussion

The nutrients such as nitrogen and carbon have been estimated based on ANN and ANFIS using four input parameters including temperature (T), tillage, intercropping and sodium content in soil. The analysis obtained from any of the models with different architectures and algorithms have been compared with each other and the best result has been obtained. In this paper, the ratio of carbon to nitrogen in soil was simulated based on soil nutrient variables (carbon, than culture, sodium and soil temperature) with artificial intelligence models. In the structure of the neural network four input neurons (carbon, culture ratio, and sodium and soil temperature), 12 hidden neurons and an output neuron (C/N) has been used. Levenberg-Marquardt algorithm has been used in training and iteration has been set to 1000. Before applying ANN, data have been normalized. In ANFIS, hybrid learning algorithm and Gaussian membership functions have been used and 20 iterations have been employed. Models have been evaluated with respect to root mean square error (RMSE) and Mean Absolute Error (MAE) (Kisi, 2009). The RMSE and MAE can be expressed as:

$$RMSE = \left[\frac{\sum_{i=1}^{N}(\tilde{y}_i - y_i)^2}{N}\right]^{1/2} \times \frac{100}{\bar{y}} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^{N}\left|\tilde{y}_i - y_i\right|}{N}, \quad (2)$$

where $\tilde{y}_i$ and y_i are the prediction and observation of *i-th* data and N is number of sample. Lower bound of RMSE was zero and RMSE values indicate that how much the predicted values deviate from the observed values. Mean absolute error (MAE) indicates the average value of the error, and the less shows greater accuracy.

Table 3 and 4 respectively show the statistics of modeling errors related to training, testing and validation in estimating nitrogen. An appropriate degree of correlation is observed with regard to both ANN and ANFIS models (Figure 3, 4). The ANFIS represents a superior performance in predicting soil nitrogen in the test period. Furthermore, the model validation results indicate a higher level of efficiency of ANFIS method compared to ANNs. Tables 5 and 6 exhibit the results of carbon data estimation based on ANFIS and ANN methods (Figure 5, 6). The ANFIS provides more satisfactory results for adjustment (higher value of correlation coefficient) and lower rate of error compared to ANNs. Figures 3-6 respectively show the scatter diagram of observed and estimated data for soil nitrogen and carbon based on ANN and ANFIS modeling. It is clear that data scatter diagram is more inclined at 45 degree line making use of ANFIS modeling which expresses further adjustment of prediction data with observed data. On the other hand, we preface less dispersion for these data based on ANFIS modeling. So, we can state that ANFIS modeling exhibits higher level of accuracy compared to ANNs.

The ANFIS and ANN modeling show that the former method represents more satisfactory estimations than the

Table 3
Error statistics for each model in training and test for Nitrogen

Model	Input	Structure	Training			Test		
			RMSE	MAE	R^2	RMSE	MAE	R^2
ANN	Tillage, Na, T, Inter Cropping	4-12-1	0.013	0.009	0.88	0.014	0.009	0.75
ANFIS	Tillage, Na, T, Inter Cropping	4-20-1	0.011	0.008	0.87	0.010	0.008	0.87

Table 4
Error statistics for each model in validation for Nitrogen

Model	Input	Structure	RMSE	MAE	R^2
ANN	Tillage, Na, T, Inter Cropping	4-12-1	0.012	0.008	0.85
ANFIS	Tillage, Na, T, Inter Cropping	4-20-1	0.011	0.008	0.88

Table 5
Error statistics for each model in training and test for carbon

Model	Input	Structure	Training			Test		
			RMSE	MAE	R^2	RMSE	MAE	R^2
ANN	Tillage, Na, T, Inter Cropping	4-10-1	0.193	0.148	0.50	0.21	0.17	0.44
ANFIS	Tillage, Na, T, Inter Cropping	4-22-1	0.14	0.011	0.80	0.15	0.11	0.79

Table 6
Error statistics for each model in validation for carbon

Model	Input	Structure	RMSE	MAE	R^2
ANN	Tillage, Na, T, Inter Cropping	4-10-1	0.19	0.15	0.48
ANFIS	Tillage, Na, T, Inter Cropping	4-22-1	0.15	0.13	0.77

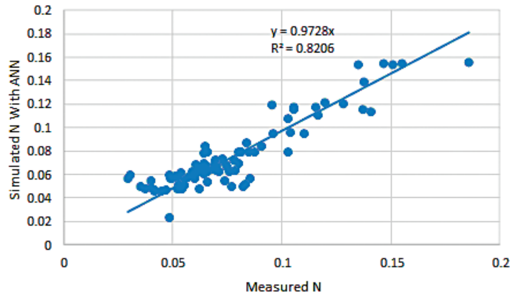

Fig. 3. Observed data dispersion compared to predicted data for soil nitrogen based on ANN modeling

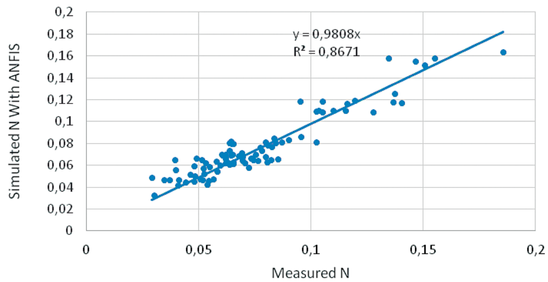

Fig. 4. Observed data dispersion compared to predicted data for soil nitrogen based on ANFIS modeling

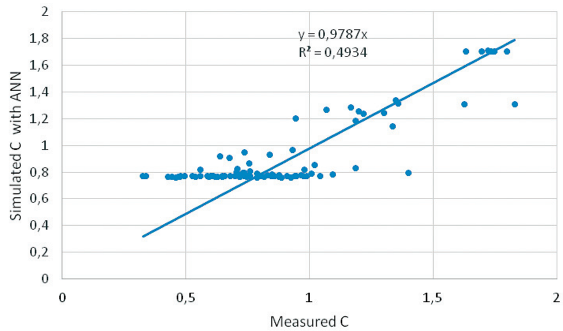

Fig. 5. Observed data dispersion compared to predicted data for soil Carbon based on ANN modeling

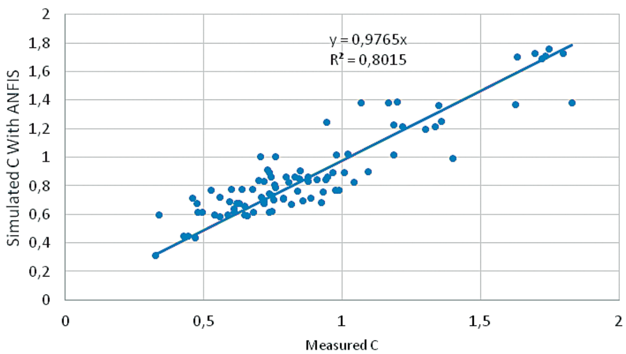

Fig. 6. Observed data dispersion compared to predicted data for soil Carbon based on ANFIS modeling

latter. Similarly, the evaluation of soil nutrient parameters is implemented by ANFIS method. To achieve a better examination of soil nutrient elements which includes both parameters of carbon and nitrogen, the related ratio has been established. The ratio reduction signifies soil fertility which consequently brings about more sustainable intercropping pattern. This paper evaluates the three parameters of temperature, sodium content in soil and type of tillage with respect to the impacts of intercropping on carbon-nitrogen ratio.

Types of Tillage

The type of tillage (no-tillage, minimum tillage and conventional tillage) is estimated for carbon-nitrogen ratio based on the changes in Roselle percentage in an intercropping system combined with green gram. The results are shown in Figure 7.

Figure 7 shows that the carbon-nitrogen ratio in conventional tillage system is less than the other two prevalent types. The nitrate leaching and rapid degradation of plant debris has apparently reduced the carbon-nitrogen ratio in conventional tillage. It is also found that increasing the Roselle percentage in intercropping similarly increases the carbon-nitrogen ratio in two kinds of minimum tillage and no-tillage systems. In other words, increasing the green gram ratio in intercropping, the carbon-nitrogen ratio in the aforementioned types of tillage will decrease.

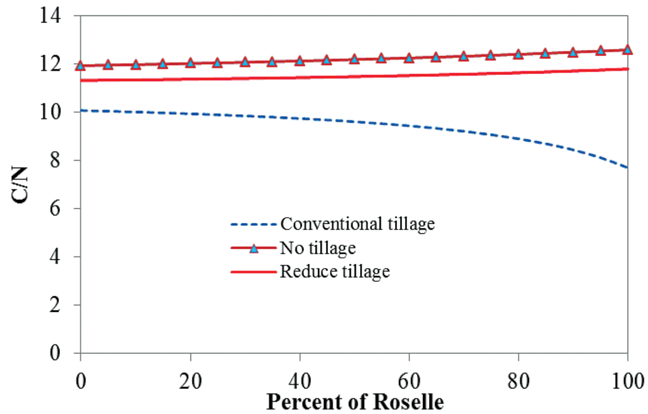

Fig. 7. The impact of tillage type on carbon-nitrogen ratio changes in Roselle intercropping combined with Roselle-green gram

Since the soil displacement does not take place in no-tillage systems and naturally there will be a significant decrease in the level of nitrate leaching, regarding the situation in which the remains of legume plants owns less carbon-nitrogen ratio, we come to the conclusion that the most desired estimate of carbon-nitrogen ratio is achieved when the ratio of green gram is increased in intercropping and the no-tillage system is applied simultaneously. Dibirt and Outer (2002) reported that no-tillage system increases the soil nutrient elements such as phosphor and potassium which however has no impact on soil pH. Casper et al. (2009) and Dahmardeh and Hodiani (2016) reported that organic carbon, total nitrogen and carbon-nitrogen ratio depend on tillage system. For example conservative tillage has less destructive impact on soil characteristics. So this kind of tillage possesses adequate potential to absorb carbon and nitrogen. As shown in Figure 7, the increase of Roselle ratio, which has less nitrogen than legumes, causes the nitrogen transfer from mineral to organic phase. The increment in plant debris enriched with nitrogen such as green gram also increases the soil organic nitrogen reserves. The poor hemicellulose and cellulose condition of legume plants makes the decomposition of debris occurs more rapidly which reduces the carbon-nitrogen ratio in soil. Therefore, the no-tillage system increases the soil nutrients and fertility. This impact is evaluated based on the two variables of temperature and sodium content in soil in no-tillage system.

Impact of soil temperature on carbon-nitrogen ratio

Figure 8 shows the impact of temperature on carbon-nitrogen ratio in intercropping. Increasing temperature from 15 C° to 24 C° decreases the carbon-nitrogen ratio in no-tillage system. Increasing Roselle percentage in intercropping also increases the carbon-nitrogen ratio in soil. It seems that temperature increment also increases the organic matter decomposition which finally decreases the carbon ratio in soil. The decomposition of organic matters happens more slowly in lower temperatures which leaves the biomasses of organic matters in soil. Toniston et al. (2000) reported that the efficiency of green fertilizer to increase nutrients depends on the type of soil, ambient temperature, acidity and soil management system. The mineralization of nitrogen depends on C/N ratio especially during the first beginning weeks of decomposition process.

Temperature and humidity are amongst the vital climate factors significantly affect the organic carbon ratio in soil. If the soil texture, vegetation and other factors are homogenous, increasing humidity also enlarges the soil carbon ratio (Post, 1993). The level of organic carbon ratio in hot soil is lower than cold soil. Therefore, the movement from cold to hot climate brings about a decrease of organic carbon. If the humidity condition and vegetation are both homogenous, the average organic carbon increases two to three times for every $10^{C°}$ degree drop of annual temperature (Franzluebbers, 2002). A drop in soil temperature also decreases the nutrient elements absorption especially nitrogen which consequently decreases the generation of photosynthesis pigments and decreases the light use efficiency (Pandey et al., 2010). Since the respective copping is implemented in a dry and semi-dry region with the average soil temperature equal to $22^{C°}$ at the time of cropping, it is evident that carbon-hydrogen variation range fluctuates from 11.85 to 12.5 degree. To achieve an appropriate quantity of nutrient fixation, the carbon-nitrogen ratio should be determined with the value equal to 12. The intercropping combined from 30% Roselle and 70% green gram is set to reach a proper ratio of carbon-nitrogen.

The impact of sodium on carbon-nitrogen ratio in soil

Figure 9 demonstrates the impact of sodium fluctuations occurring in intercropping and no-tillage systems on carbon-nitrogen ratio. This figure shows that the increase in sodium increases the carbon nitrogen ratio in soil. Besides the decrease, in sodium decreases this ratio. The changes in Roselle prove that sole cropping of green gram in low salin-

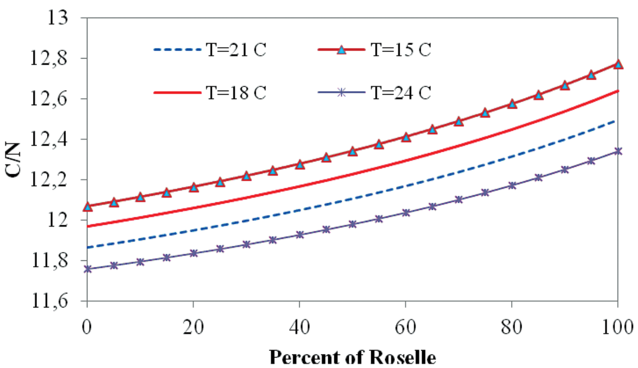

Fig. 8. The impact of soil temperature on carbon-nitrogen ratio changes in Roselle intercropping combined with Roselle-green gram

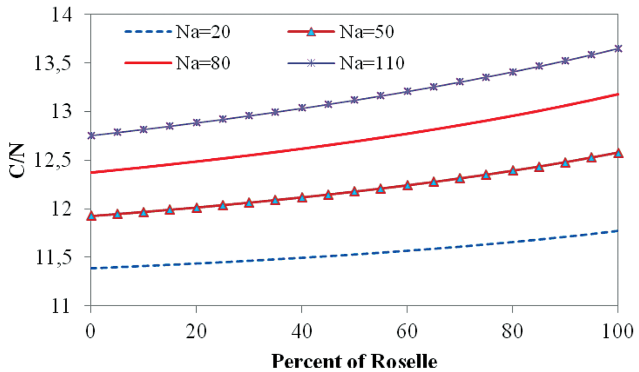

Fig. 9. The impact of soil temperature on carbon-nitrogen ratio changes in Roselle intercropping combined with Roselle-green gram

ity possesses lower carbon-nitrogen ratio compared to high salinity. In other words, the increase of salinity percentage causes an increase of carbon-nitrogen ratio either. Moreover, the increase of Roselle in intercropping increases the carbon-nitrogen ratio. The increase of green gram percentage decreases the carbon-nitrogen ratio.

Conclusions

● The accurate estimation of soil nutrients can be applied to forecast the patterns appropriate for sustainable cropping. On the other hand, the evaluation of effective parameters and their effects provide the ground for a beneficial decision making about type of cropping and tillage. The long-term cropping and implementation of experiments undertake long time and high costs. The modeling methods to estimate the nutrients are simple and provide appropriate estimation of soil nutrients to measurement parameters. This paper shows the application of artificial intelligence to predict the soil nutrients on the basis of two methods such as ANN and ANFIS methods. The ANN and ANFIS are implemented for the carbon and nitrogen estimates with respect to temperature input data, sodium, type of tillage and intercropping. The study distinguishes that the ANFIS is more accurate than the ANN method in estimating carbon-nitrogen ratio. The effects of three parameters of temperature, type of tillage and sodium are evaluated based on type of intercropping to carbon-nitrogen ratio. The results are conducted as follows:

● No-tillage is the most appropriate type of tillage.

● The increment of green gram percentage is led to decreasing the carbon-nitrogen ratio in intercropping system.

● The carbon-nitrogen ratio in soil is decreased with respect to increasing the temperature.

● The increase of sodium content in soil increases the carbon-nitrogen ratio.

● With regard to the presented modeling to achieve suitable carbon-nitrogen ratio estimation (12) in the observed region, the intercropping with 30 % Roselle (it is corresponding to 70% green gram) and no-tillage system are recommended.

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References

Blaier, N., R. D. Faulkner., A. R. Till., M. Korschens and E. Schulz, 2006. Long-term management impacts on soil C, N and physical fertility: Part II. Bad Lauchstadt static and extreme FYM experiments. *Soil & Tillage Research,* 91: 39-47.

Bodner, G., D. Leitner, A. Nakhforoosh., M. Sobotik., K. Moder and H. P. Kaul, 2013. A Statistical approach to root system classification. *Frontiers in Plant Science*, 4: 1-15.

Burhan, K. and A. Bekir, 2013. Effect of mulch practice on fresh ear yield and yield components of sweet corn. *Turkish Journal of Agriculture and Forestry,* 37: 281-287.

Clapp, C. E., R. R. Allmaras., M. F. Layese., D. R. Linden and R. H. Dowdy, 2000. Soil organic carbon and 13C abundance as related to tillage, crop residue, and nitrogen fertilization under continuous corn management in Minnesota. *Soil & Tillage Research*, 55: 127-142.

Dahmardeh, M. and A. Hodiani, 2016. Assessment of soil elements in intercropping based on mathematical model. Computers and Electronics in Agriculture, DOI information: 10.1016/j.compag.2016.01.036

Deibert, E. J and R. A. Utter, 2002. Edible dry bean plant growth and NPK uptake in response to different residue management systems. *Soil Science Plant Anal*, 33: 1959-1974.

Franzluebbers, A. J, 2002. Soil organic matter stratification ratio as an indicator of soil quality. *Soil and Tillage Research*, 66: 9 – 106.

Ghadimi, M. R and S. Moshiri, 2002. Modeling and predicting economic growth in Iran using artificial neural networks (ANN). *Quarterly Iranian Economic Research,* 12: 97-125.

Ghorbani Dashtaki, S. H and M. Homaie, 2002. Parametric estimation of unsaturated soil hydraulic functions using transfer functions. *Journal of Agricultural Engineering Research*, 12: 1-3.

Gowdy, J. M., J. I. Miller and H. Kherbachi, 1987. Energy use in us agriculture. *Southern Journal Agriculture Economics*, 19: 33-41.

Hauggaard-Nielsen, H., P. Ambus and E. S. Jensen, 2003. The comparison of nitrogen use and leaching in sole cropped versus intercropped pea and barley. *Nutrient Cycling in Agro Ecosystems,* 65: 289-300.

Holubík, O., M. Hrabalíková, P. Huislová and J. Vopravil, 2016. Soil wetting effects on fallow and cropland in three different soil types of the Czech Republic. *Plant Soil Environ,* **62** (6): 243-249.

Hung, S., W. Rui, X. Peng, Q. Huang and W. Zhang, 2010. Organic carbon fractions affected by long-term fertilization in a subtropical paddy soil. *Nutrient Cycling in Agro Ecosystems*, 86: 153-160.

Irmak, A., J. W. Jones., W. D. Batchelor., S. Irmak., K. J. Boote and J. O. Paz, 2006. Artificial neural network model as a data analysis tool in precision farming. *Transactions of the American Society of Agricultural and Biological Engineers*, 49: 2027-2037.

Jang, S., 1993. Adaptive network-based Fuzzy Inference System. *IEEE Journal*, **23** (3) .665-685, ISSN 0018-9472.

Jang, S., T. Sun and E. Mizutani, 1997. Neuro-Fuzzy and Soft Computing a Computational Approach to Learning and Machine intelligence, *Prentice Hall*, Inc. ISBN 0132610663

Jorabiyan, M. and R. Hoshmand, 2002. Fuzzy Logic and Neural Networks. 1st ed. *Institute of Shahid Chamran University Press*, 300 pp.

Kasper, M., G. D. Buchan, A. Mentler and W. E. H. Blum, 2009.

Influence of soil tillage systems on aggregate stability and the distribution of C and N in different aggregate fractions. *Soil Science Society of American Journal*, 105: 192-199.

Kisi, O. 2009. Daily pan evaporation modelling using multi-layer perceptron's and radial basis neural networks. *Hydrol. Process.*, **23** (2): 213-223.

Khashei, A., M. Kouchakzadeh and B. Ghahraman, 2011. Predicting dry land wheat yield from meteorological data using expert system, Khorasan province, Iran. *Journal of Agricultural Science and Technology,* 13: 627-640.

Koocheki, A., M. Nasiri Mohalati., A. Zarea Feizabadi and G. Jahanbin, 2004. Evaluation of variability in different cropping systems of Iran. *Pajouhesh-va- Sazandegi*, 63: 70-81.

MengBo, L. and R.S. Yost, 2000. Management-oriented modeling: optimizing nitrogen management with artiÆcial intelligence. *Agricultural Systems,* 65: 1-27.

Menhaj, M. 2007. Principles of Neural Networks. I volume, *Center Amir Kabir University Press*. 715 pp.

Munz, S., T. Feike., Q. Chen., W. Claupein and S. Graeff-HOnninger, 2014. Understanding interactions between cropping pattern, maize cultivar and the local environment in strip-intercropping systems. *Agricultural and Forest Meteorology,* 15: 152-164

Nurani, V., M. A. Kaynejad and L. Malekani, 2009. Application of neuro- fuzzy inference system in rainfall-runoff modeling. *Journal of Civil of Engineering & Environment,* **39** (4): 75-81 (Pers(.

Pandey, R. K., J. W. Maraville and M. M. Chetima, 2010. Tropical wheat response to irrigation and nitrogen in a shahelian environment, biomass accumulation nitrogen uptake and water extraction. *European Journal of Agronomy,* 15: 107-118.

Piri, J., S. Amin, A. Moghaddamnia, D. Han and D. Remesun, 2009. Daily pan evaporation modeling is hot and dry climate. *Journal of Hydrologic Engineering*, 14: 803-811.

Post, W. M, 1993. Organic carbon in soil and global carbon cycle, In: M. Heiman (Ed.) .The Global Carbon Cycle., NATO ASI Series 1: Global Environmental Change. *Springer*, New York, pp. 216-302.

Ulhin, H., 1998. Why energy production is increasing: an I-O analysis of Swedish agriculture. *Agriculture System*, 56: 443-465.

Redmile-Gordon, M. A., E. Armenise, P. R. Hirsch and P. C. Brookes, 2014. Biodiesel Co-Product (BCP) Decreases Soil Nitrogen (N) Losses to Groundwater. *Water Air Soil Pollut*ion (2014) 225:1831. DOI 10.1007/s11270-013-1831-7.

Rees, D. J., 2003. The effects of population density and intercropping with cowpea on the water use and growth of sorghum in semi-arid conditions in Botswana. *Agricultural and Forest Meteorology,* **37** (4): 293-308.

Sarmadiyan, F., R. A. Taghizadeh, H. M. Askari and A. Akbarzadeh, 2010. Comparison of neuro-fuzzy neural network and multiple regression. In anticipation of some soil properties (Case study: Golestan Province). *Journal of Water Research and Soil,* 41: 220-211.

Schipanski, M., L. Drinkwater and M. Russelle, 2010. Understanding the variability in soybean nitrogen fixation across agro ecosystems. *Plant and Soil*, 329: 379-397.

Stathakis, D., I. Savina and T. Nègrea, 2006. Neuro-fuzzy modeling for crop yield prediction. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* **34** (3).

Thonnissen, C., D. J. Midmore., J. K. Ladha, D. C. Olk and U. Schmidhalter, 2000. Legume decomposition and nitrogen release when applied as green manure to tropical vegetable production system. *Agronomy Journal*, 92: 253-260.

Walkley, A and I. A. Black, 1934. An examination of the Degtjareff method for determining organic carbon in soils: Effect of variations in digestion conditions and of inorganic soil constituents. *Soil Science,* 63: 251-263.

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