APPLICATION OF SOFT COMPUTING METHODS AND SPECTRAL REFLECTANCE DATA FOR WHEAT GROWTH MONITORING

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ABSTRACT

Technology of precision agriculture has caused to the remote sensors development that compute Normalized Difference Vegetation Index (NDVI) parameters. Vegetation indices obtained from remote sensing data can help to summarize climate conditions. Artificial Neural Networks (ANNs), as a soft computing methods, are one of the most efficient methods for computing as compared to the statistical and analytical techniques for spectral data. This study was employed experimental radial basis function (RBF) of ANN models and adaptive neural-fuzzy inference system (ANFIS) to design the network in order to predict the soil plant analysis development (SPAD), protein content and grain yield of wheat plant based on spectral reflectance value and to compare two models. Results indicated that the obtained results of RBF method with high average correlation coefficient (0.984, 0.981 and 0.9807 in 2015 for SPAD, yield and protein, respectively and 0.979, 0.9805 and 0.984 in 2016) and low RMSE (0.271, 103.315 and 0.111 in 2015 for SPAD, yield and protein, respectively and 0.407, 105.482 and 0.121 in 2016) has the high accuracy and high performance compared to ANFIS models.

Keywords: remote sensing; spectral data analysis; ANFIS; artificial neural networks
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تطبيق طرائق البرامجيات وبيانات الانعكاس الطيفي لرصد نمو محصول الحنطه

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المستخلص

تقنية الزراعة الدقيقة قد تسببت في تطوير أجهزة الاستشعار عن بُعد التي تحسب صفات مؤشر اختلاف الغطاء النباتي .(NDVI) يمكن أن تساعد مؤشرات الغطاء النباتي التي يتم الحصول عليها من بيانات الاستشعار عن بُعد في تلخيص الظروف المناخية. تعد الشبكات العصبية (ANNs) ، مثل طرائق البرامجيات ا، واحدة من أكثر الطرائق الفعالة للحوسبة مقارنةً بالتقنيات الإحصائية والتحليلية للبيانات الطيفية. استعملت هذه الدراسة وظيفة أساس شعاعي تجريبي (RBF) لنماذج ANN ونظام الاستدلال العصبي الغامض التكيفي (ANFIS)لتصميم الشبكة من أجل التنبؤ بتطوير تحليل نبات التربة (SPAD) ، ومحتوى البروتين وإنتاجية محصول الحنطه على قيمة الانعكاس الطيفي ولمقارنة نموذجين. أشارت النتائج التي تم الحصول عليها من طريقة RBF بوجود معامل الارتباط عالي (0.984 ، 0.981 و 0.9807) لسنة 2015 و (0.979 ، 0.9805 و 0.984 لسنة 2016) لكل من SPAD   والحاصل والبروتين على التوالي. وانخفاض لجذرمتوسط مربع الخطا RMSE 0.271 و 103.315 و 0.111 لسنة 2015 كذلك 0.407 ، 105.482 و 0.121 لسنة 2016 لكل من SPAD و الحاصل والبروتين على التوالي باعلى دقه واداء مقارنة مع نموذجANFIS

الكلمات المفتاحيه: الاستشعار عن بعد؛ تحليل البيانات الطيفية ؛ ANFIS. الشبكات العصبيه

INTRODUCTION

The crops monitoring can be performed for ground survey at a local scale. But remote sensing can be appropriated for both in terms of spatial and temporal coverage at the regional scale (19, 24, 29). Recent development in the field of precision agriculture technology had caused the improvement of crop canopy sensors (ground-based active remote sensors). One of the important topics in the section of remote sensing is classification. The advantages of application of remote sensing techniques are: 1) The lower cost and the covering of large areas (2) The easier classifications (21,24). The remote sensors be able to calculate NDVI, and vegetation indices can find climate conditions (14,19,26). The plant characteristics can be measured indirectly and frequently by waveband (Red wavelengths (R) and Near Infrared (NIR)) (31).

Chemical composition, status of physiological and biomass plant were detected using spectral reflectance (22). Card et al. (2) accurately predicted the amount of nitrogen (N) of ground and dried tree leaves using a spectrometer. They used the Stepwise Multiple Linear Regression (SMLR) and suggested the wave length of 480 nm and 580 nm for prediction of nitrogen value (R^2=0.90). Hansen et al. (11) used multi-way Partial Least Squares regression (N-PLSR) to calculate the protein and yield value of grain. It was indicated that reflectance amount can be able to predict the protein content (11). Researchers can be able to predict the N value of corn ear leaves using SPAD (chlorophyll meter) at the wavelength of 659 and 940 nm (R^2= 0.962) (17). They advanced the prediction models using MLR, PLSR and principal component regression (PCR). The results showed that PLSR and PCR were the best models. While, Rasooli Sharabian et al. (27) used the multivariate analysis including of PLSR and SMLR to select the best wavelengths for growth characteristics of winter wheat. The results showed strong relationships between predicted and actual crop variables. They suggested the SMLR as the best model, because it had the highest R^2 value (0.85, 0.89 and 0.84 for SPAD, grain protein and yield,

respectively) (16,27). Tumbo et al. (30) applied the model of back-propagation neural network for prediction of corn nitrogen. 201 of spectral bands were used as input of the developed model (at range of 407-940 nm). They reported, the neural network model could correlate the amount of chlorophyll well (R^2= 0.91) (30).

Development of an alternative technique for determination of crop growth status is an urgent proceeding. Mathematical models had been applied to find the best relationships between data of inputs and outputs. ANNs is a efficient techniques as compared to analytical methods (20). Neural network are able to predict and approximate any nonlinear function (6). ANNs do not require any awareness of fitting function. Therefore, this is one of the main advantage of ANNs. Also, ANNs is very popular due to its ability in estimating and less consuming of time in complex systems modelling compared to another mathematical models such as regression method (9). The ANNs can be used for modelling due to complication of agricultural systems.

The main aim of this study was deployment of experimental Radial Basis Function (RBF) of ANNs models in comparison to adaptive neural-fuzzy inference (ANFIS) system to design a network in order to predict the SPAD, protein content and grain yield of wheat plant based on spectral reflectance value. This work contains 3 steps: 1) processing the requirement data, 2) developing the prediction methods and 3) suggesting and comparing the obtained results.

MATERIAL AND METHODS

Data processing

The reflectance spectral data was obtained with four growth stages (GS36, GS37, GS45 and GS60) of wheat (triticum aestivum L) in each year on two different date (2015, 2016) using a portable spectral diameter (Analytical Spectral Devices, Inc., USA). The value of SPAD and canopy reflectance was measured in 2015 at the stage of flag leaf (GS 37) and anthesis (GS 60) in 56 target points as well as in the 2016 (40 target points) after the elongation of stem (GS 36) and anthesis stage (GS 60) growth investigations. The value of

protein and yield of grain were evaluated after threshing and harvesting at area of 1 m × 3 m in each target point both two years. The value of SPAD was measured the chlorophyll concentration amount in leaves of plant with determining the leaf absorbance at two regions of red wavelength (650 nm) and NIR (940 nm) by a SPAD instrument (MINOLTA Co. LTD.). As shown in SPAD 502 catalogue (24) there is a strong relationship ($R^2 > 0.9$) between nitrogen concentration of leaf and SPAD value .Also, SPAD value has been applied to estimate the nitrogen contents, crop chlorophyll , health status of plant (35). In this research, the value of SPAD had been used as an index for prediction of content of actual nitrogen in leave of crops. Wheat canopy reflectance determines in the 350-2500 nm

wavebands (1 nm interval) were made under cloudless positions and as near to solar noon (27). The first 50 wavelengths (from 350 nm to 400 nm) at the lower visible and last the 1150 readings (from 1350 nm to 2500 nm) at the shortwave infrared (SWIR) were omitted because of their low signal to amount of noise; so, the revised spectra started from 400 nm (Figure 1).The reflectance on wavelength range of 400-1350 was considered as independent variable and SPAD, Yield and Protein were considered as dependent variables. According to Figure1, Generally, the reflectance of 2016 in green and red visible (VIS) and middle infrared waveband (MIR) was higher, while this reflectance in infrared (NIR) region was lower than reflectance of 2015 on average.
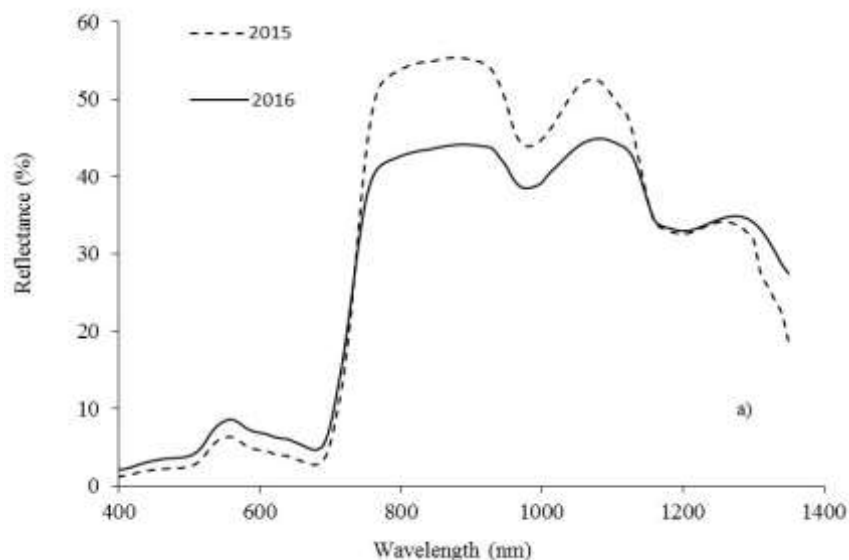

Figure 1. Average of reflectance spectrum of the different experimental treatments for years (n= 56 + 40).

RBF Modelling

ANNs is used to simulate the system performance, when simulation is needed and restricted experimental data value is available. ANNs includes a large number of neurons or processing elements connected using synaptic weights. In this research, RBF network study is used. RBF is a learning feed forward network and local type which responds just to a restricted portion of input space. In a hidden layer of RBF network, hidden node maps measure the distances between input to outputs vectors by means of a radial function or nonlinear kernel (33). RBF networks were suggested by other researchers to increase

training procedures, and to produce precise approximations with simpler network architecture and an alternative population of RBF networks is then compared to the other neural networks (7). RBF neural networks are used for nonlinear function approximation, data classification, systems modelling, and control (15). They have feed-forward architecture composed of an input layer, a hidden layer with a non-linear RBF function, and a linear output layer. One of the most important characteristic of RBF networks is the hidden layer neurons in the centre of the basis function that produce only local reactions for the input function. This is the reason that

the basic function can produce a significant nonzero response although the input space falls only in a local area. In other words, the

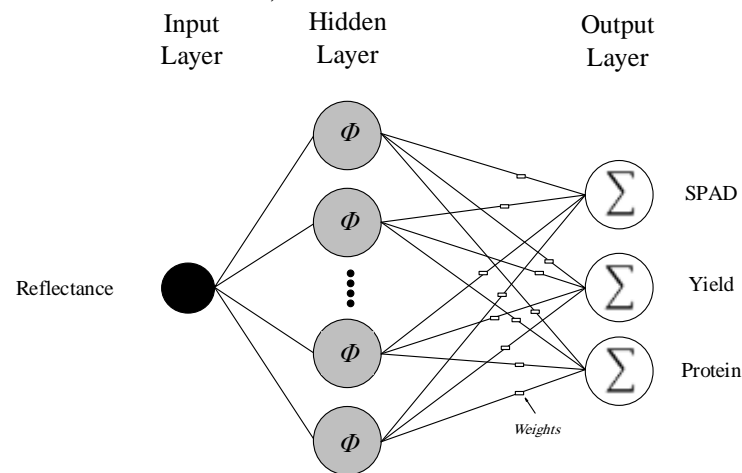basic functions output may be small (32). The RBF network structure is presented in Figure2.

Figure 2. RBF neural network structure.

The output of network is:

$$y_k = \sum_{j=1}^{M} w_{kj} \phi_j(x) + w_{k0} \qquad (1)$$

Where M: the number of basic functions, x: the input data vector ,w_{kj}: weighted connection between the basic function and output layer, and φ_j: the nonlinear function of the jth unit, which is typically a Gaussian function:

$$\phi_j(x) = \exp\left(-\frac{\|x - \mu_j\|^2}{2\sigma_j^2}\right) \qquad (2)$$

where x and µ are the input and the centre unit of RBF, respectively, and σ_j is the spread of the Gaussian basis function (8).
A least mean square (LMS) algorithm had been applied to optimize the weights once of the RBF centres units have been specified. There were two ways to choose the centres: randomly or by clustering algorithms. In this research, centres were selected randomly from a data set.
Percentages of reflectance of each wavelength were the inputs of network and SPAD, Yield and Protein were the outputs of network. In order to train network, after

defining the inputs and outputs to the network, there was a need to define the optimum neurons of in the hidden layer. For this purpose, 5 numbers of neurons defined as an initial number of neurons. After running the network with 5 neurons, 5 neurons added to primary neurons and training process was repeated. It was observed that during the network training process with increase of neuron numbers on hidden layer, the error of network decreases, based on performance plot of network. After each repetition 5 neurons were added to the previous neurons number. This action continued until the error reduction was converted into a horizontal line. This number of neurons selected as the optimum neurons on hidden layer.

ANFIS Modelling
ANFIS is a hybrid of ANN and fuzzy inference system (FIS) that was introduced to overcome the disadvantages of ANN and FIS (9). The ANFIS structure consists of five layers. The ANFIS model was considered with two inputs and one output (Figure 3).
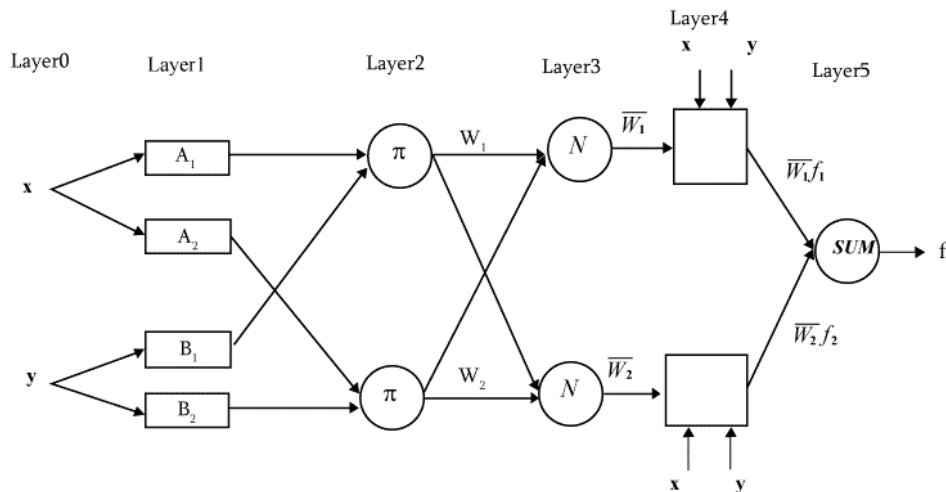
Figure 3. ANFIS structure.

For a first order Sugeno fuzzy model, two fuzzy if–then rules are consumed:

Rule 1: If x is A_1 and y is B_1; then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2; then $f_2 = p_2x + q_2y + r_2$

where A_1, A_2 and B_1, B_2 are the fuzzy sets for inputs x and y ,respectively, p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function that are specified during the training of ANFIS (12,23,28).

The parameters in the first layer (input layer) are called premise parameters. The rules second layer generates and holds the fuzzy roles. Every node in this layer is a fixed node labelled π, whose output is the product of all the incoming signals. Every node in third layer is a fixed node labelled N. The ith node calculates the ratio of the ith rules' firing strength. The output of this layer can be called normalized firing strengths. Every node i in forth layer is an adaptive node. Parameters in this layer are referred to as consequent parameters .And the last layer (Layer 5) calculates the overall output as the summation of all incoming signals (1, 3, 9, 20).

In this study, in order to test and train the ANFIS network, modelling was conducted by ANFIS toolbox in MATLAB R2012a. Also, Sugeno-type fuzzy inference systems had been applied for modelling process. In order to categorize the input data and make the rules, grid partition method is utilized, because of a few input variables. Two various types of input member functions (MFs) consist the trapezoidal (Trap MF) and Gaussian (Gauss MF) were used to model the

network (Figure 3). A linear function was applied as output MFs and the combined learning algorithm was used to model the predicted values.

The validation and comparing performance of RBF and ANFIS models were checked out using the comparing parameters such as correlation coefficient (r) and the root mean square error (RMSE) as follow.

$$R = \left(1 - \left(\frac{\sum_{i=1}^{n}(z-z')^2}{\sum_{i=1}^{n}z_i^2}\right)\right)^{1/2} \qquad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(z-z')^2} \qquad (4)$$

Where z is the target value and z' is the predicted value by ANFIS network (34)

The root mean square error (RMSE) is applied to measure the differences between predicted values and actually values (target values). Pearson correlation (r) is used to measure the linear correlation between two parameters (here are predicted and target variables).

RESULTS AND DISCUSSION

Primary results of data

This section shows the results of experimental treatments on trial data. This result includes different years, different levels of nitrogen application and strategies with a wide range of variation within the investigated crop according to Table 1. This wide range in the investigated crop variables was investigated in order to make the relationship between plant performance and reflectance values. Based on the Figure1, reflectance in the

visible region for 2015 increased as compared to 2016, it might be the difference in soil background (15) or this difference can be for higher SPAD value (hence, nitrogen concentrations of leaves and stems) in 2015. As shown in Table 1, an increasing in chlorophyll concentration causes increased reflectance in the visible regions and movement of the red edge to longer wavelengths (4), the position of the red edge in 2015 (around 720) was different from that in other years (around 700 nm).

Table 1. Selected property of the investigated crop variables.

Crop variables	Year	n^a	Mean	S.D.	Min	Max
SPAD (-)	2015	56	43.1	1.38	39.4	45.3
	2016	40	42.6	1.62	38.2	46
Yield (Kg ha^{-1})	2015	56	6864	966	5516	8549
	2016	40	6708	615	5450	8154
Protein (%)	2015	56	11.4	0.99	8.86	12.1
	2016	40	11.6	1.55	9.62	14.0
[a] n is the number of samples						

As shown in Table. 1, the mean and standard deviation value for SPAD in 2015 is respectively the highest and lowest as compared to 2016, for yield variable 2015 had the highest mean value and standard deviation. While the lowest standard deviation and mean value protein variable was related to 2015. These results can be effected on prediction model performance.

Evaluation of RBF model

In this study, the RBF method of artificial neural network was developed for modelling a network to predict the growth status of winter wheat based on reflectance measurements. 20 and 25 number of neurons was the optimum number of neurons on hidden layer for 2015 and 2016 data sets, respectively. 70 percent of data was randomly selected as training data and the rest of data selected as testing data by network. The outputs of network was extracted and performance of network was calculated on predicting growth statues on two years for four growth stage (GS36, GS37, GS45 and GS60) using presented comparing parameters on materials and methods. As an initial result, Figure 4 indicates the results of RBF network on the modelling dataset for two years on GS36, the predicted values of crop variables were plotted against the actual data.The plots show high determination coefficient and high correlation coefficient of predicted values against actual values for 2015 and 2016 datasets. These results represent proximity of predicted and actual values. In order to display the results statistically, the calculated results tabulated on Table. 2. High R-value and low RMSE value increases the accuracy of network. As shown on Table 2, for each two years from GS36 to GS60, there is a relative decreasing on predicting accuracy and correlation due to decreasing correlation coefficient and increasing RMSE value for SPAD, yield and protein except GS 37 on 2016.
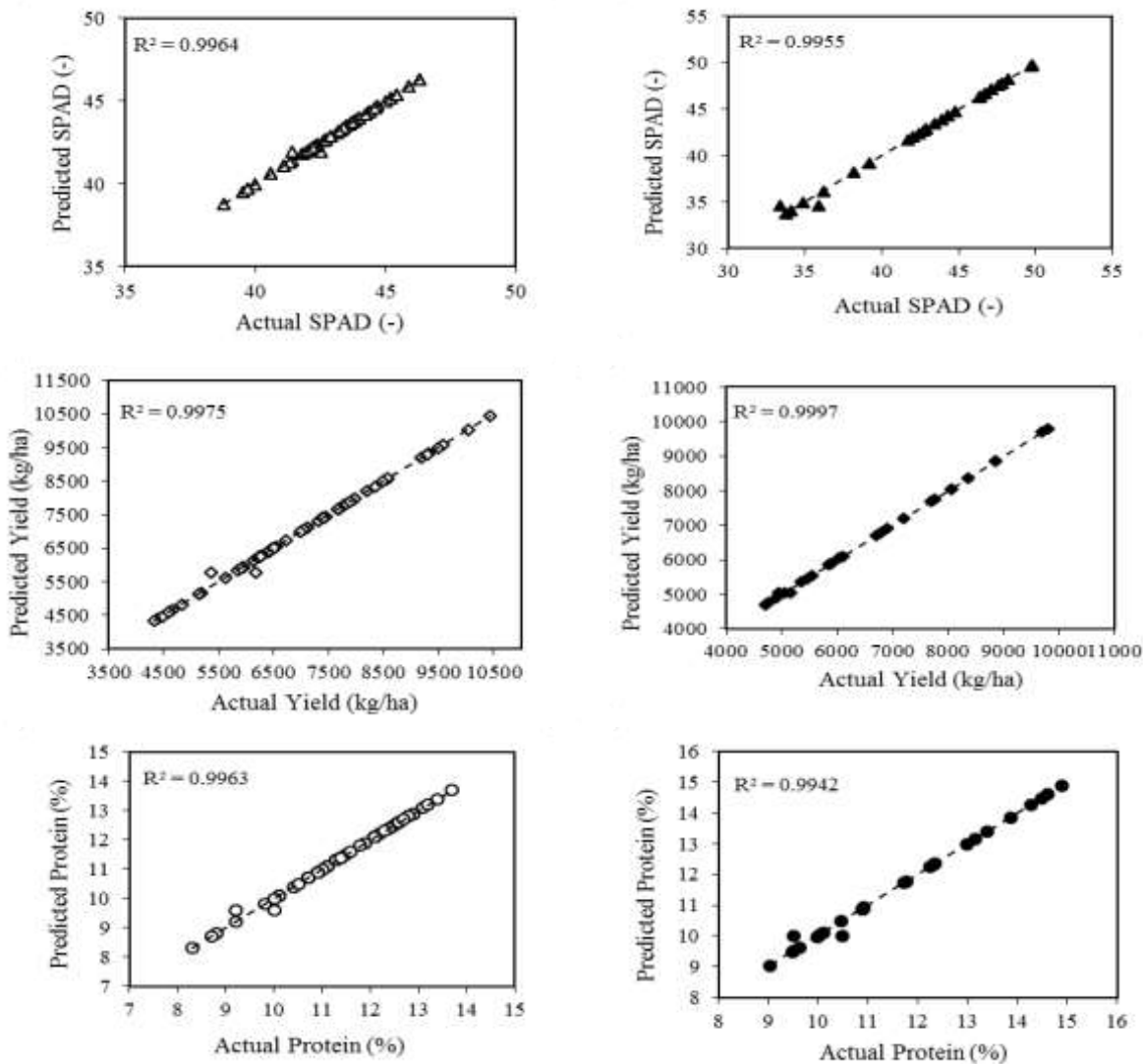
Figure 4. Plots for predicted and actual values of growth status. Left plots indicates 2015 datasets and right plots indicates 2016 datasets.

Based on Table 2, due to proximity of the results of correlation coefficient, the factor of RMSE will be better than correlation coefficient to compare the results. The results show a good relationship between actual crop variables and predicted values for validation datasets. Based on Table. 2, GS36 of 2015 has high correlation coefficient (0.998, 0.998 and 0.998 for SPAD, Yield and Protein, respectively) and low RMSE (0.104, 75.59 and 0.075 for SPAD, Yield and Protein, respectively) compared to other growth stages and on 2016, GS37 has high correlation (0.999 and

0.997) and low RMSE (0.072 and 0.046) for SPAD and Protein, respectively and GS36 with correlation value of 0.999 and RMSE value of 27.22 has the best resubliming the other growth stages. These results of prediction model were obtained without pre-processing operations on data sets.

Evaluating of ANFIS model
70% of the data were used to generate the model, and the remaining (30%) were used for prediction. The initial ANFIS model was generated by grid partition method.

Table 2. Performance indices (R and RMSE) for RBF models.

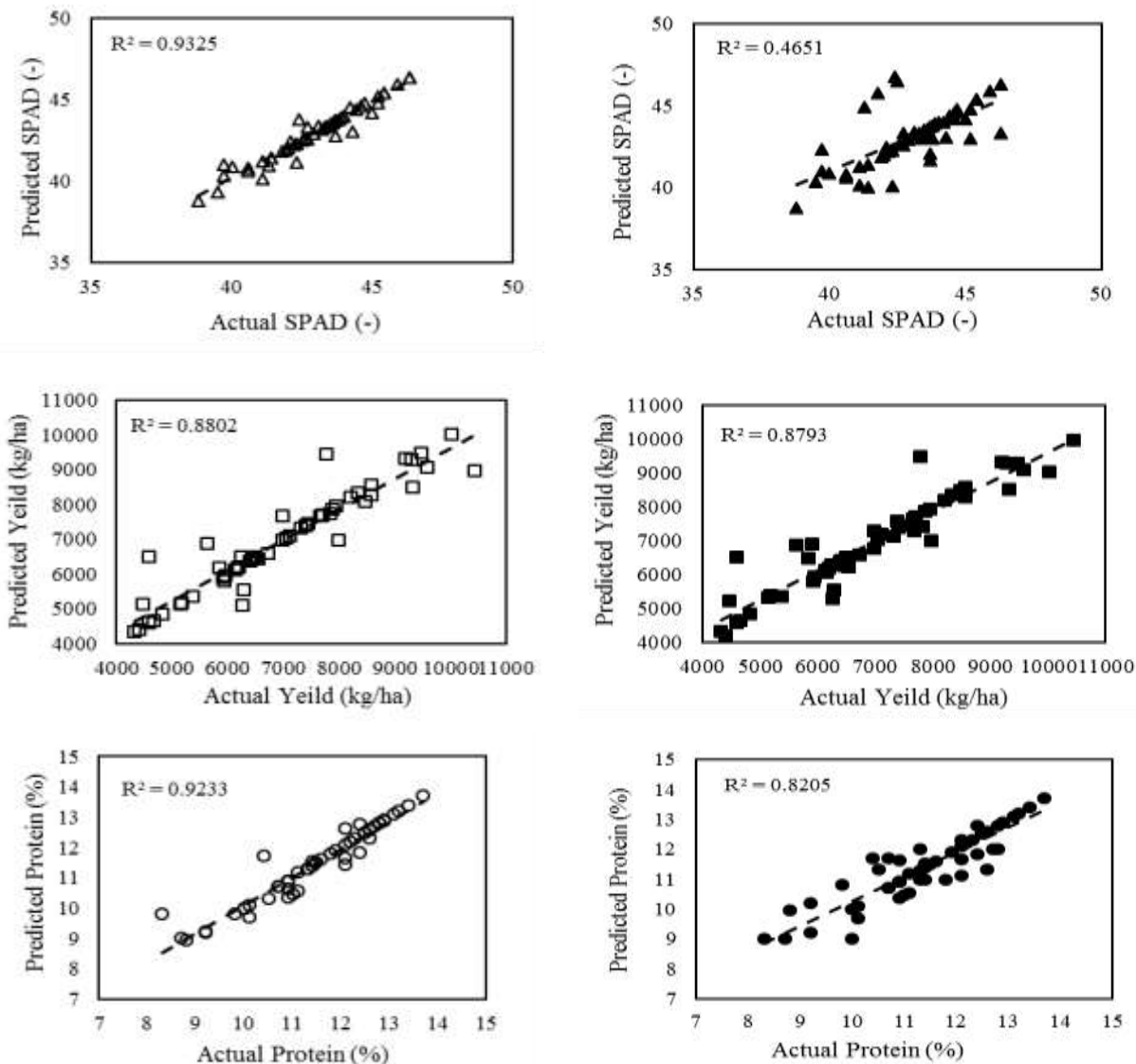| Year		SPAD (-)		Yield (kg/ha)		Protein (%)	
		r	RMSE	r	RMSE	r	RMSE
2015	GS36	0.998	0.104	0.998	75.59	0.998	0.075
	GS37	0.988	0.142	0.977	111.49	0.975	0.123
	GS45	0.978	0.170	0.977	111.50	0.975	0.123
	GS60	0.975	0.669	0.975	114.68	0.975	0.123
2016	GS36	0.998	0.340	0.999	27.22	0.997	0.135
	GS37	0.979	0.072	0.967	244.10	0.977	0.146
	GS45	0.965	0.809	0.977	123.39	0.974	0.188
	GS60	0.977	0.408	0.979	27.22	0.989	0.016

Figure 5. Plots for predicted and actual values of growth status for 2015 datasets. Left plots indicates results of Gaussian MFs and right plots indicates results of Trap MFs.

The fuzzification of input data was performed by two different types of MFs. After training process the ANFIS models were tested using independent data set. The outputs of network was extracted and performance of network was calculated on predicting growth statues on two years for four growth stage (GS36, GS37, GS45 and GS60) using presented comparing parameters on materials and methods. As an initial result, Figure 5 indicates the results of ANFIS on the modelling dataset for two years.
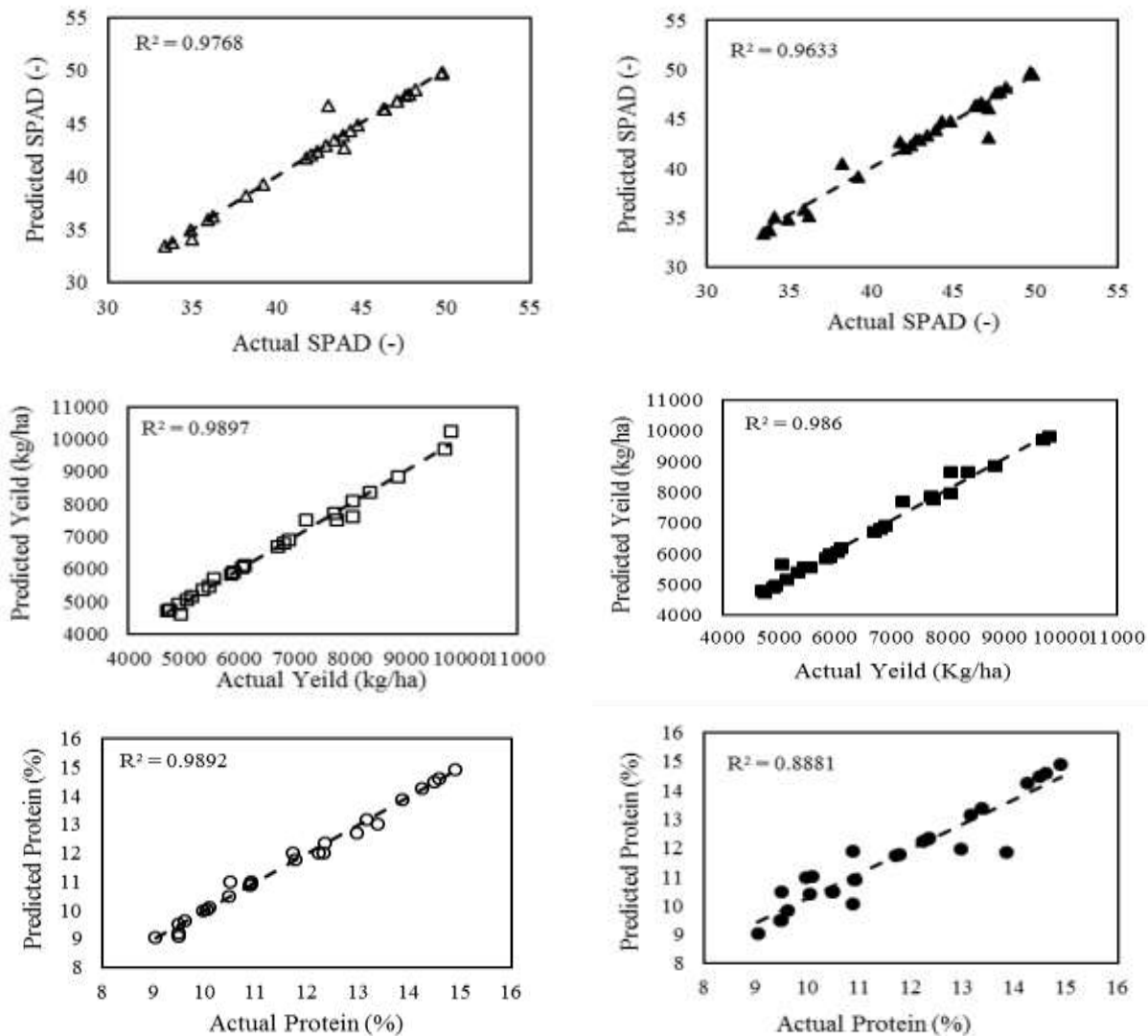
Figure 6. Plots for predicted and actual values of growth status for 2016 datasets. Left plots indicates results of Gaussian MFs and right plots indicates results of Trap MFs.

The relationship between target and predicted values by using two different types of MFs was indicated on Figure 5 and Figure 6 as an initial and schematic result, the predicted values of crop variables were plotted against the actual data.Based on the results of Figure 5 and Figure 6 , the obtained results of Gaussian membership functions have the high correlation and linear relationship compared to the obtained results from trap membership functions which reflects the high ability and high accuracy of Gaussian MFs for learning compared to Trap MFs. Table 3 presents the statically results of ANFIS performance.Based on the results of table 3, Gaussian MFs has the high correlation coefficient and low RMSE values compared to Trap MFs, it means that the output of ANFIS network on Gaussian MFs has the high accuracy and low difference with target values compared to Trap MFs. This claim is true for each two years (2015 and 2016) on each four stages (GS36, GS37, GS45 and GS60) for all dependent variables (SPAD, Yield and Protein). For example, the results of GS36 on 2015 are as follow. For SPAD, yield and protein, Gaussian MFs has high correlation (0.9657, 0.9382 and 0.9609, respectively) and low difference between output and target values based on the RMSE values (0.4523, 525.685 and 0.3464, respectively) compared to Trap MFs.

Table 3. Performance indices (R) and (RMSE) for ANFIS models.

Year	MF Type		SPAD (-)		Yield (kg/ha)		Protein (%)	
			r	RMSE	r	RMSE	r	RMSE
2015	Gauss	GS36	0.9657	0.4523	0.9382	525.685	0.9609	0.3464
	Trap		0.6819	1.0887	0.8977	588.1	0.9058	0.5300
	Gauss	GS37	0.9287	0.832	0.9473	486.58	0.9730	0.2887
	Trap		0.7929	1.5669	0.9258	580.715	0.9053	0.5480
	Gauss	GS45	0.98	0.091	0.9998	300.28	0.989	0.0213
	Trap		0.9079	1.4751	0.9891	229.362	0.6086	1.3707
	Gauss	GS60	0.9952	0.652	0.9998	260.81	0.998	0.0099
	Trap		0.982	1.2762	0.9927	183.775	0.9252	0.5007
2016	Gauss	GS36	0.988	0.0021	0.995	49.5	0.98	0.0094
	Trap		0.9815	0.0750	0.9930	204.836	0.9424	0.5969
	Gauss	GS37	0.9426	0.144	0.985	140.646	0.976	0.0137
	Trap		0.9276	1.7632	0.9788	180.644	0.9653	0.4734
	Gauss	GS45	0.969	1.2126	0.9705	375.555	0.9798	0.3578
	Trap		0.9002	2.1393	0.9580	388.765	0.9438	0.5923
	Gauss	GS60	0.9851	0.9926	0.9898	222.608	0.9909	0.2643
	Trap		0.9626	1.5212	0.9888	231.908	0.9199	0.6996

This result is also true for the rest of the year and growth stages, without exception, but in some cases has high intensity (GS36 on 2015) and in some cases has low intensity (GS60 on 2015 and 2016). Therefore, due to the best results of Gaussian MFs compared to Trap MFs, it was chosen as the best type of membership function and the network was trained with Gaussian function.

Comparing ANFIS and RBF models

In order to compare the results of two networks we need statics and attributable information. Figure 4 and Figure 5 take a graphically, initial and simple result of comparing two methods. Based on the results of Figure 4, Figure 5 and Figure 6, it can be taken that the linear relationship of RBF results is stranger than ANFIS results due to its high values of determination coefficient and correlation coefficient and also about ANFIS results, Gaussian MFs showed high linear relationship between target and output values compared to Trap MFs. To prove this claim, the static results extracted and tabulated on Table 4 Because of the extent of output and the impossibility of comparing parameters one by one, these results tabulated in terms of the average value of comparative parameters for each network separately on table 4.

Table 4. Average amount of performance indices (R and RMSE) for predictor models.

Year	Net		SPAD		Yield		Protein	
			r	RMSE	r	RMSE	r	RMSE
2015	ANFIS	Gauss	0.967	0.507	0.971	393.338	0.98	0.166
		Trap	0.841	1.352	0.951	395.488	0.836	0.737
	RBF	-	0.984	0.271	0.981	103.315	0.9807	0.111
2016	ANFIS	Gauss	0.971	0.587	0.98	197.076	0.981	0.161
		Trap	0.943	1.374	0.979	251.538	0.943	0.591
	RBF	-	0.979	0.407	0.9805	105.482	0.984	0.121

As shown on Table 4, RBF network with high correlation coefficient (0.984, 0.981 and 0.9807 in 2015 for SPAD, yield and protein, respectively and 0.979, 0.9805 and 0.984 in 2016) and low RMSE (0.271, 103.315 and 0.111 in 2015 for SPAD, yield and protein, respectively and 0.407, 105.482 and 0.121 in 2016) shows high accuracy, high linear relationship and high performance, compared to ANFIS. Between two types of membership functions of ANFIS model developing, based on Table 4, Gaussian MFs with high correlation coefficient (0.967, 0.971 and 0.98 in 2015 for SPAD, yield and protein, respectively and 0.971, 0.98 and 0.981 in 2016) and low RMSE (0.507, 393.388 and 0.166 in 2015 for SPAD, yield and protein, respectively and 0.587, 197.076 and 0.161 in 2016) has high performance an high accuracy compared to Trap MFs. On the other hand, based on the results of Table 3, due to the gap in the numbers of Table 3 for ANFIS output, the results show significant instability in the provision and unlike ANFIS, RBF in addition to high performance (Table 4) shows instability in presenting the results (Table 2). According to the results, the final decision is to select and to recommend the RBF method among three learning methods (RBF, ANFIS with gauss MFs and ANFIS with Trap MFs) as the best and precise predictor method of SPAD, Yield and protein using wavelength as the only independent input of network. Rasooli sharabian et al. (25) on a study about determining the important wavelength using multivariate analysis including of PLSR and SMLR procedures for prediction of grain yield and winter wheat growth status, reported strong relationships between predicted and actual crop variables (Sharabian et al., 2014). The best prediction model selected by SMLR on maximum data normalization for R^2 and RMSR were 0.84, 1.94 for SPAD, 0.87, 301 for grain yield, and 0.80, 0.786 for protein content. On a study by Gupta et al. (10). Evaluation of rice crop growth situation was performed using two types of feed forward back propagation neural network (FFBPANN) models namely FFBPANN-I and FFBPANN-II model. The FFBPANN-I model was expanded using a input neuron (VV - or HH -

polarized scattering coefficient) and a output neuron (leaf area or biomass index, chlorophyll content or plant height), while the FFBPANN-II model was expanded using two input neurons (VV and HH polarized scattering coefficient) and four output neurons (leaf area index, biomass , chlorophyll content and plant height). Results indicated a good estimating performance for HH- and VV polarized scattering. In general, R^2 and RMS error between observed and FFBPANN predicted values of crop parameters was reported as 0.993 and 0.118 for HH-Polarization, 0.982 and 0.157 for VV-polarization and 0997 and 0.057 for combination of HH and VV polarizations. On a other study by Liu et al. (18) a back propagation (BP) neural-network model was applied to predict the concentration of rice chlorophyll under heavy stress of metal on three experiment farms placed in Changchun, Jilin Province, China with level II pollution, I pollution and with safe level. The value of R^2 and RMSE for prediction of chlorophyll concentration was obtained 0.9014 and 2.58, respectively. The obtained results of present study is following the previous researches. The positive point of this study is to use different methods (RBF and ANFIS) for predicting growth status of winter wheat. Based on the results of the other predicting methods that was conducted in predicting winter wheat status, it can be said the present methods have high ability in prediction of variables. This is due to the nature of soft computing techniques. Important wavelengths were obtained using regression analysis on SPSS software using the output values of the best predictor (RBF network). Some wavelengths [(580, 660, 665, 720, 740, 800, 930, 990, 1010, 1110, 1120, 1150, 1240 and 1340 nm), (580, 660, 720, 740, 800, 930, 990, 1010, 1110, 1120, 1150, 1240 and 1340 nm) and (580, 660, 720, 740, 800, 930, 990 and 1010)] were identified by RBF as significant wavelengths for SPAD, grain yield and protein content, respectively for 2016 and [(590, 640, 680, 690, 710, 730, 750, 770, 780, 940, 1000, 1010, 1070, 1170, 1130, 1290 and 1350), (590, 640, 680, 690, 710, 730, 750, 770, 780, 940, 1000, 1010, 1070, 1130, 1170, 1290 and 1350) and (590, 640, 680, 690, 710,

730, 750, 770, 1010, 1070, 1170, 1290 and 1350)] were identified for the value of SPAD, grain yield and protein, respectively for 2015.The goal of this study was to model the SPAD, yield and protein of plant using wavelength using soft computing methods. ANFIS and RBF were selected as the predictor of system and were trained and tested. Results indicated that the obtained results of RBF method with high average correlation coefficient (0.984, 0.981 and 0.9807 in 2015 for SPAD, yield and protein, respectively and 0.979, 0.9805 and 0.984 in 2016) and low RMSE (0.271, 103.315 and 0.111 in 2015 for SPAD, yield and protein, respectively and 0.407, 105.482 and 0.121 in 2016) has the high accuracy and high performance compared to ANFIS models, then it was selected as the best predictor. Eventually, RBF network was proposed as the estimator network for studied outputs based on related input and was used to obtain the important wavelength.

Conflict of interest
There is no conflict of interest.

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