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Artificial intelligence applications in precision agriculture to predict the effect of Root-Knot nematodes and grafting on vegetable crop health from proximal remote sensing machines

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Abstract

In precision agriculture, the Normalized Difference Vegetative Index (NDVI) considers the spectral characteristics of healthy green vegetation. This index is an effective way of detecting the green state of plants. This is why we choose to use NDVI as a reference index to predict the effect of Root-Knot nematodes and grafting on vegetable crop health from proximal remote sensing machines. These machines were used to estimate different physiological, biochemical, and agronomic parameters as indicators of stress (GA, GGA, SPAD, and canopy temperature). Leaf level pigments were measured using a handheld sensor (SPAD). Canopy vigor and biomass were assessed using vegetation indices derived from RGB images and the NDVI was measured with a portable spectroradiometer (Greenseeker). The plant level water stress was assessed indirectly by plant temperature using an infrared thermometer. We conclude that the grafted plants were less stressed and more protected against nematode attack. The comparison of NDVI index predicted by AI models showed that artificial neural network MLP demonstrated the best prediction performance than the linear regression method. However, their R-squared decreased from 0.820 to 0.772, and NRMSE increased from 12.3% to 12.4%, respectively.

1. INTRODUCTION

The failure to adopt adequate management practices allows nematode populations to succeed at very high levels, causing yield losses that will exceed 50% (Blok et al. 2008; Kashaija et al. 2004). Once introduced in a neighborhood, it becomes very difficult to eradicate a nematode problem, and it is necessary to adopt practices of population reduction and minimization of potential damages (Expósito et al. 2019). The most important trial is the application of resistant or tolerant crop cultivars (Sorribas et al. 2005). Because of that, the primal view of the challenge and the adoption of practices to escape greater losses are of great significance (Guan et al. 2014). The below-mentioned control tools represent lead-ins for the use of precision farming, either as localized practices or through variable rate technologies (Abrougui et al. 2022a). The collection of root samplings and soil in high density for transferring to the laboratory can bring prohibitive, and indispensable styles are required to characterize the distribution of nematodes with the applicable resolution level (Abd-Elgawad. 2020). Remote sensing with the use of high-resolution multispectral images is one of the techniques that has been employed (Abrougui et al. 2022b). Therefore, it is necessary to take over that high populations of the nematode beget a meaningful reduction of the crop biomass, which allows the employment of vegetation indexes that offer a good correlation with the biomass to indicate places with a lesser probability of circumstance of nematodes. In this sense, the use of hyperspectral sensors associated with novel techniques of data analysis can allow the differentiation of the causes of variability and isolate the sites with nematode problems with greater accuracy (Hunt et al. 2013; Hamdane et al. 2022). In fact, with variable rate application, deductions of 40 in the volume of nematicide related have been observed, substantially in the areas of a field where the nematodes aren't yet extant and the product doesn't require to be applied. In addition to the benefit per hectare, the application of the site-specific application brings an environmental accrual not yet quantified, since the nematicides applied are largely poisonous and its operation in spots where it isn't imperative can contribute to the elimination of distinct organisms and beget natural imbalances (Silva-Sánchez et al. 2019). In fact, new methodologies have been brought to farming by advancements in precision farming and plant phenotyping that permit fast and non-destructive assessments of crop health. In order to better study the crop's physiological status and its nutrient or other operation conditions, leaf sensors, and proximal or remote sensing devices may be esteemed more productive (Araus and Kefauver, 2018). Non-destructive techniques to predict the chlorophyll content of vegetation (SPAD) are of significant importance to agricultural management operations, particularly in the area of precision agriculture (Gitelson et al. 2003; Kaufmann et al. 2010). The normalized difference vegetative index (NDVI) resulting from visible and near-infrared (NIR) reflectance is strictly related to vegetation presence or vigor (Tucker, 1979; Thenkabail et al. 2000; Thenkabail et al. 2002; Huang et al. 2021). Precision farming has also been approved by RGB (Red, Green, Blue) or multispectral cameras to capture several field images that may be combined via photogrammetric techniques to establish orthophotos covering large areas (Kefauver et al. 2017). The multispectral images contain many values per pixel apart the traditional red, green and blue values to analyze and process spectral vegetation indexes that may offer detailed information on plant health, including fungal infections and treatment needs (Kefauver et al. 2015). In this work, field sensors and fast assessment ways involving non-destructive, proximal, and remote sensing were exploited to collect information on plant physiological status in greenhouses to compare the impacts of nematodes on diverse vegetative crops. To emphasize the needfulness for quickly assessing nematode harm to crop development, comparisons were made between the growth and physiological status of various crops grafted to root stock resistant to root-knot nematodes (RKNs) and those without grafting (non-grafted). There is an absence of a comprehensive and detailed assessment of the performance of different artificial intelligence (AI) approaches, from linear regression to complicated advanced techniques in vegetable crop health estimation and the most important indices to be used as input data for AI models must be determined. Therefore, the impact of plant treatments and vegetation indexes needs to be further studied. Furthermore, research should evaluate and demonstrate the AI models' skills in successfully tackling extreme events (Hanifeh et al. 2022). The main purpose of this study is to assess the efficacy of grafting for controlling root nematodes and the possibility of improving crop productivity and evaluate the performance of AI approaches to crop health prediction from grafting treatment and different vegetation indexes such as MLR and MLP artificial networks.

2. MATERIAL AND METHODS

2.1. Study Area and Dataset

This research was carried out in a plastic greenhouse located at the experimental station of Agròpolis (41◦17018.100 N 2◦02038.500 E + 18 m above the sea level, approx.) of the Barcelona School of Agri-food and Biosystems Engineering of the Universitat Politècnica de Catalunya (Barcelona, Spain). Due to rotations, different crops were used for four years. Melon plants (*Cucumis melo* L.) were grown with half non-grafted plants and the others grafted with (*Cv paloma*). Tomato (*Solanum lycopersicum* L.), used with half non-grafted and half with grafting with (*Durinta spp).* The experiment was also done with eggplant *(Solanum melongena* L.*)* with half non-grafted and half grafted with *(Cucumis metuliferus* L.*)*. Finally, pepper plants *(Capsicum annuum*) again half non-grafted plants and other half were grafted. Two crop treatments (grafted or non-grafted) and (control, low, high infection) for 6 total treatments. Every treatment has been repeated with an increase to 10 plots for grafted and non-grafted control. Individual plots consisted of a row 2.5 m long and 1.5 m wide containing 4 plants spaced 0.55 m between them. Parcels were spaced 0.9 m within a row and 1.5 m between rows. The soil has a loamy sand texture, with 1.8% organic matter (w/w) and 0.5 dS m^{-1} electric conductivity. Plants were fertilized and irrigated by a drip irrigation system with NPK solution (15–5-30) at 31 kg ha^{-1}, iron chelate, and micronutrients at 0.9 kg ha^{-1}. The relative crop yield was calculated as the crop yield in infested plot in relation to the mean crop yield in non-infested plots. All sensors were used between September 28th and October 8th on four successive years in the same plots. Each plot was tilled separately to avoid soil contamination.

2.2. Sensors and Measurements

All sensors were used during the fruit development phase at the same time of day for each year (Table 1). SPAD (Soil Plant Analysis Development) values are calculated by division of light transmission intensities at 650 nm (red)

Table 1. The measurements performed from various sensors during the study

Measurement	Sensor
Chlorophyll content and nitrogen in the plant: SPAD	SPAD-502 Plus
Plant health and vigor (NDVI)	Trimble GreenSeeker
Vegetation cover (GA, GGA)	Panasonic Lumix DMC-GX7
Canopy temperature	Infrared thermometer and digital hygrometer
Crop Yield (kg/plant)	-

by 942 nm (infrared) in order to estimate chlorophyll content (Kaufmann et al. 2010; Konica, 2012). The NDVI sensor emits brief bursts of red and infrared light (656 nm and 774 nm), and then measures the amount of each type of light that is reflected from the plant. NDVI index ranges from 0.00 to 0.99 (Gracia-Romero et al. 2019). The RGB images were subsequently analyzed using the Maize Scanner plugin(https://github.com/sckefauver/CIMMY).
This software includes a JAVA8 version of Breedpix 2.0 (https://bio-protocol.org/e1488, IRTA, Lleida, Spain), which calculates RGB vegetation indices through the use of RGB and different color properties (Kefauver et al. 2017) such as GA (Green Area) and GGA (Greener Green Area) which gives an idea on the foliar surface area of the plant canopy (Zaman-Allah. 2015). Temperature measurements in (°C) were taken per plant, for plot and leaf temperature. The canopy temperature was furthermore adjusted by the ambient temperature to offer crop water stress estimate such the plant deeply cools through transpiration; it is the canopy temperature deficit, which may increase as a sign of nematode damage to the crop root system (Silva-Sánchez et al. 2019; Duncan et al. 2005).

2.3. Statistical Processing

The statistical processing was based on two programs: MS Office Excel 2007 for making simple average calculations as well as standard deviation. While the ANOVA statistical processing was obtained using Statgraphics Centurion XVI.I. The calculation of correlation values was completed in MS Office Excel 2007 and the graphics were obtained with Sigma Plot 12.5 (Systat software, Chicago, IL, USA).

2.4. Descriptions of artificial intelligence algorithms

In order to minimize the residual sum of squares, MLR still the most basic form of a linear model. Thus, the objective function is (Citakoglu, 2017; Li and Ren, 2020; Tabari et al. 2011):

$$\sum (y - X_w)^2 \tag{1}$$

where y is the actual or the desired value, X is the input variable value and w is weight.
MLP, multi-layer perceptron of artificial neural networks (ANNs), is a non-linear function approximator in layers utilizing back propagation with no activation function in the output layer. It used the rectified linear unit (Relu) function as the activation function in the hidden layers (Feng et al. 2019; Mehdizadeh et al. 2020; Bayatvarkeshi et al. 2021):

$$g(z) = \max(0, z) \tag{2}$$

Depending on the type of the problem, MLP uses various loss functions. In prediction models, MLP uses the square error loss function as:

$$1/2 \sum(y - Xw)^2 + \alpha/2 \sum w^2 \tag{3}$$

Initial random weights allow MLP to minimize the loss function through repeatedly updating these weights. When the algorithm reaches a pre-set maximum number of iterations, or when the loss improvement is below a specific small number, it stops. Maximum number of iterations was 10,000, which determines the number of epochs, meaning how many times each data point is used.
In the present study, NDVI, GA, GGA, the canopy temperature, and the crop treatments CT (grafted or non-grafted) are the plant and physiological variables used as the inputs of the

benchmark algorithm, and the chlorophyll content and nitrogen in the plant (SPAD) is the output of the model. Artificial Neural Networks (ANN) are interconnected by structures called perceptrons and consist of input, output and hidden layers which transform the input into something that the output layer can utilize using the *NeuroSolutions* software. To facilitate the model performance assessment, the applied AI models outputs recquire to be compared. Several error indicators are employed to measure the quality of modeling, including maximum residual error (MaxE), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), normalized root mean square error (NRMSE) and coefficient of determination (R-squared). The evaluation metrics are defined as:

$$\mathrm{MaxE} = \mathrm{Max}\,(y_{obs} - y_{calc}) \tag{4}$$

$$MAE = \frac{\sum|\mathrm{y\ obs} - \mathrm{y\ calc}|}{\mathrm{n}} \tag{5}$$

$$MSE = \frac{\sum(\mathrm{y\ obs} - \mathrm{y}\ calc)^2}{\mathrm{n}} \tag{6}$$

$$RMSE = \sqrt{\frac{\sum(y\ obs - y\ calc)^2}{n}} \tag{7}$$

$$NRMSE = \frac{RMSE}{[Max\,(y\ obs) - Min\,(y\ obs)]} \tag{8}$$

$$R^2 = 1 - \frac{\sum\,(y\ obs - y\ calc)^2}{\sum(y\ obs - \overline{y\ calc})^2} \tag{9}$$

where y obs is the observed value, y calc is the predicted value by the AI mode, $\overline{\mathrm{y\ calc}}$ is the mean of calculated values and n is the number of data points.

3. RESULTS AND DISCUSSION

3.1. Sensor's physiological parameters

Table 2 presents the values of the various physiological parameters of vegetable crops with grafted and others not grafted grown in semi-controlled greenhouses and with application of the three different levels of infection by the meloidogynous nematode. The values of the different parameters decreased going from the controlled plants to the one heavily infected. We also noted that for the control the role of grafting is not seen. Conversely, the grafted plants shows more affected values for the different parameters than that of the non-grafted plants, which are strongly affected by infection which reduces the various parameters.

The comparison of grafted and non-grafted plants shows that the canopy temperature is higher in non-grafted plants. Non-grafted and grafted plants were slightly different for the temperature recorded. The chlorophyll concentration given by the SPAD for the grafted plants showed greater values than of the non-grafted plants. Concerning the NDVI parameter, the grafted plants showed values that also exceed that non-grafted therefore indicating a higher concentration of nitrogen or uptake (Hamdane, 2020). The plant area presented by GA showed that the non-grafted plants have more plant area (0.57) than that of the grafted plants, up to 0.46. The great amount of photosynthetically efficient plant surface presented by GGA showed that non-grafted plants are more similar in the Control but the grafted plants are healthier in both the Low and High groups. For plants lowly infected by nematode, we show that the difference between grafted and non-grafted plants is very low. Concerning Tomato crop with high infection, the grafted plants showed highest values of GA with 0.55.

According to the Table 3, the Pearson correlation calculated at $p \leq 0.05$ showed that temperature affects negatively on the different parameters. NDVI is positively correlated with other parameters, but most strongly related to GA and GGA with value 0.79. The SPAD chlorophyll content has a positive relationship with most parameters. GA has a strongly positive relationship with GGA but for GGA, their relationship with most parameters is weak. ANOVA (Table 4) mentions that the crop is strongly affecting the GA which is logical since the crops put in place have leaves of different sizes which subsequently affects the GA. But also, we note the treatment (grafted or non-grafted) affects the GA parameter. This may be since grafting protects the root surface from attack by nematode which ensures greater GA values than non-grafted (Hamdane, 2020).

Fig. 1(A) shows that there is a significant difference between eggplant and the two crops tomato and melon. Then we can classify crops according to their GA means, which finds in first place eggplant and after melon, thirdly tomato and finally pepper.

Table 2. Average values of the different physiological parameters for the different vegetable crops with three different infection levels for four years experiments

Crop	Treatment	Nematode	Temp	SD	SPAD	SD	NDVI	SD	GA	SD	GGA	SD
Melon	Non-grafted	Control	26.81	1.25	42.10	1.44	0.46	0.01	0.57	0.22	0.30	0.07
Melon	Grafted	Control	26.76	0.32	49.89	0.46	0.47	0.04	0.46	0.01	0.29	0.01
Melon	Non-grafted	Low	26.55	0.87	49.40	1.20	0.50	0.02	0.50	0.18	0.35	0.01
Melon	Grafted	Low	26.02	0.59	50.26	1.59	0.55	0.07	0.53	0.12	0.36	0.03
Melon	Non-grafted	High	26.51	2.48	46.61	1.45	0.49	0.01	0.49	0.14	0.33	0.04
Melon	Grafted	High	26.17	1.09	49.41	6.16	0.48	0.07	0.54	0.11	0.38	0.04
Melon	Non-grafted	Control	23.95	0.80	34.68	3.61	0.51	0.01	0.43	0.04	0.19	0.04
Melon	Grafted	Control	23.53	0.90	41.41	0.48	0.53	0.04	0.51	0.05	0.28	0.01
Melon	Non-grafted	Low	23.46	0.43	44.12	1.98	0.54	0.07	0.45	0.07	0.27	0.05
Melon	Grafted	Low	24.16	2.43	36.41	1.09	0.47	0.01	0.41	0.12	0.24	0.01
Melon	Non-grafted	High	23.55	1.73	42.19	0.78	0.53	0.04	0.45	0.09	0.33	0.02
Melon	Grafted	High	23.51	2.02	46.53	4.35	0.49	0.02	0.43	0.06	0.36	0.08
Tomato	Non-grafted	Control	24.16	0.44	39.41	3.78	0.40	0.06	0.37	0.09	0.33	0.01
Tomato	Grafted	Control	24.37	0.31	39.82	2.63	0.40	0.05	0.33	0.01	0.26	0.01
Tomato	Non-grafted	Low	22.19	0.44	43.67	5.52	0.45	0.01	0.33	0.13	0.26	0.01
Tomato	Grafted	Low	20.80	1.42	50.78	1.07	0.62	0.01	0.49	0.02	0.41	0.02
Tomato	Non-grafted	High	20.59	1.60	50.06	5.56	0.57	0.06	0.46	0.06	0.39	0.05
Tomato	Grafted	High	21.01	1.59	51.37	4.35	0.52	0.01	0.55	0.01	0.36	0.03
Eggplant	Non-grafted		26.42	1.51	100.30	0.32	0.58	0.12	0.55	0.15	0.36	0.016
Eggplant	Grafted		26.64	0.98	111.65	0.40	0.70	0.08	0.80	0.15	0.60	0.022
Pepper	Susceptible and Grafted		26.96	0.77	55.15	2.88	0.47	0.15	0.09	0.05	0.08	0.05
Pepper	Resistant and Grafted plant		27.15	0.58	57.31	3.40	0.41	0.05	0.07	0.02	0.05	0.02
Pepper	Susceptible and non-grafted		26.36	0.78	51.35	7.56	0.38	0.12	0.08	0.05	0.07	0.04
Pepper	Resistant and Non-grafted		26.20	0.52	56.32	3.25	0.31	0.05	0.04	0.02	0.03	0.02

SPAD, soil plant analysis development, leaf chlorophyll content; NDVI, normalized difference vegetation index; GA, green area; GGA, greener green area; SD, standard deviation.

Table 3. Correlation between the measured parameters for the different vegetable crops (melon, tomato, eggplant, and pepper)

	Temp	NDVI	SPAD	GA	GGA
Temp	1.00				
NDVI	-0.26	1.00			
SPAD	0.33	0.50	1.00		
GA	-0.1	0.79	0.29	1.00	
GGA	-0.27	0.79	0.38	0.93	1.00

Table 4. Analysis of Variance (ANOVA) for Green Area (GA) parameter for the different vegetable crops (melon, tomato, eggplant and pepper) and for both treatments (grafted, non-grafted).

Source	Sum of squares	Gl	Medium Square	Reason-F	P-value
Model	0.71	7	0.10	25.38	0.00
Residue	0.06	16	0.004		
Crop	0.67	3	0.22	55.98	0.00
Treatments	0.03	1	0.03	6.74	0.02
Treatments*Crop	0.03	3	0.01	2.58	0.09
Residue	0.06	16	0.004		
Total (corrected)	0.80	23			

Fig. 1(B) shows the superiority of grafted treatment compared to that not grafted for all combinations; this means that grafting protects the plant roots from nematode attacks, which causes wilting or reduction of the foliar surface (Hamdane, 2020). Therefore, the grafted plants are less affected by the attack and maintain a larger foliar surface allowing obtaining a greater GA value than the non-grafted plants. We also note that the interaction grafted*eggplant was the best possible combination inversely to that grafted*pepper, where the differences between grafted and non-grafted is not as clear.

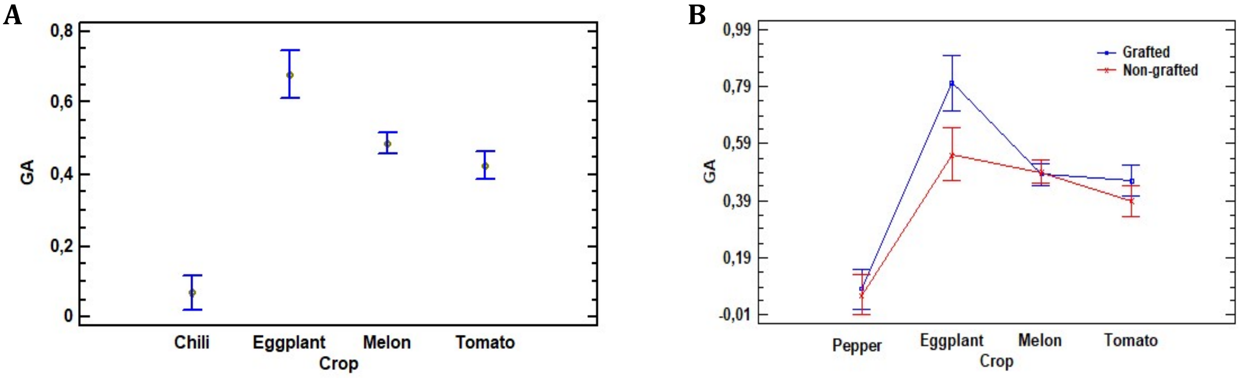


Fig. 1. Dispersion of the green area (GA) means for plant treatments and different vegetable crops

Grafting had also a significant effect on the conservation of the foliar surface against the attack of nematodes causing yellowing of the leaf and reducing the photosynthetic activity in the plant. Plant resistance has been noted as an effective and profitable control method to reduce the RKN reproduction rate and the equilibrium density (Sorribas et al. 2005). This prevents subsequent yield losses on the following crop that are directly related to nematode population densities in the soil at planting stage. Also, some authors have mentioned that a higher fruit yield was obtained when plants of melon were grafted onto different Cucurbita rootstocks (Miguel et al. 2004). This may have resulted from different factors such as increase in uptake of water and nutrients, resulting from the larger root systems and increased diseases tolerance. Other previous studies (Bletsos, 2005) show that the grafting of melon (*Cucumis melo L.*), and watermelon (*Citrullus lanatus*) has been reported to increase crop vigor and yield of melon and may be useful for low-input sustainable horticulture. Fruit yields were also higher in the grafted plants utilizing resistant rootstocks compared to non-grafted plants (Owusu et al. 2016). Some studies mentioned that grafted eggplants had lower disease incidence, higher yield, and larger fruit, which is similar to the present results (Iouannou, 2001). Therefore, root system size and vigor may be associated with resistance to soil borne diseases. Moreover, vigorous roots help improve nutritional status and thus the overall health of plants, which may augment resistance against foliar diseases, though this study focused on the assessment of aboveground biomass and plant physiological properties as proxies for root damage due to nematodes or protection by grafting.

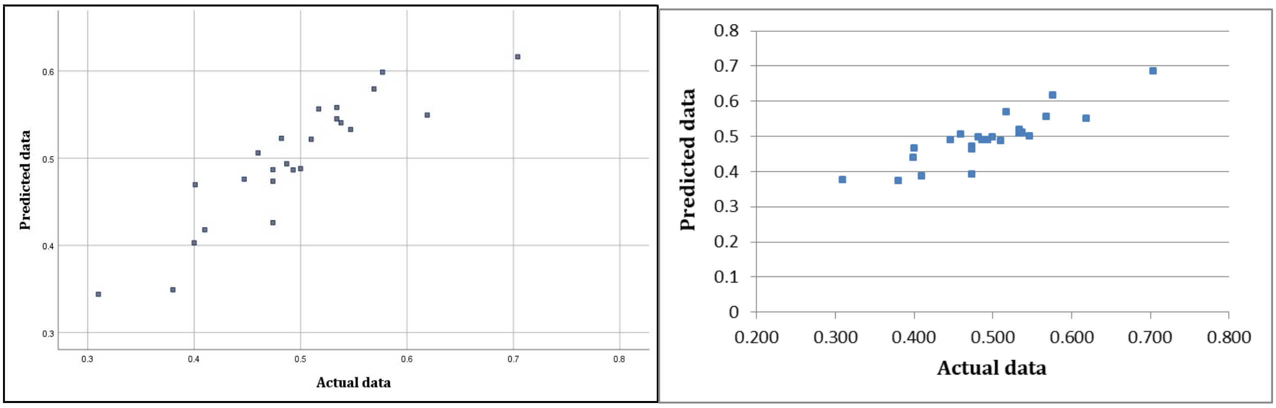
3.2. Performance of developed AI models

The primary step of modeling was splitting the data into two groups. Although the data were randomly split for training and testing purposes, the training and testing data were maintained for all models. Thus, artificial intelligence models were trained and tested with the same data set. After the training procedure, the model was fed with testing data such inputs, and prediction results were acquired. The predicted outcomes and real values were simultaneously reshaped into a 1-dimensional series, and the performances of the models were evaluated using the error metrics (Khemis et al. 2022). In the present study, linear regression and multi-layer perceptron were employed to predict NDVI. The mentioned models were applied to

Table 5. Error analysis of predicted NDVI values using AI models

AI Models	Processing elements (PEs) in each Hl									
MLP	Hidden layer (Hl) number	Upper PEs	Lower PEs	Transfer	MaxE	MAE	MSE	RMSE	NRMSE	R^2
	1	2	2	TANH	0.08	0.026	0.0012	0.034	12.4%	**0.820**
	1	3	3	TANH	0.081	0.026	0.0013	0.034	12.4	0.81
	1	4	4	TANH	0.081	0.026	0.0013	0.034	12.39	0.81
	1	5	5	TANH	0.081	0.027	0.0014	0.035	12.36	0.80
	1	6	6	TANH	0.081	0.028	0.0014	0.035	12.35	0.79
	1	7	7	TANH	0.081	0.028	0.0014	0.036	12.35	0.79
	1	8	8	TANH	0.081	0.028	0.0014	0.036	12.33	0.78
	1	9	9	TANH	0.082	0.029	0.0014	0.037	12.31	0.779
	1	10	10	TANH	0.082	0.029	0.0014	0.037	12.31	0.778
MLR	-	-	-	-	0.082	0.030	0.0014	0.038	12.3%	**0.772**

two sets of data with different quantities of information to assess the performance of the various AI models. To measure the quality of different AI models, the statistical indicators of Equations (4)–(9) were applied, and the results of the error analysis are presented in Table 5.
As seen in Table 5, R-squared values ($R^2>0.7$) which shows a good correlation between the results predicted by AI models and NDVI data. This outcome is confirmed by the scatter plots illustrated in Fig. 2 and offers an overall acceptable performance for MLR and MLP methods. Relatively poor MAE, MSE and NRMSE obtained by the linear regression results demonstrated that this method cannot precisely predict NDVI index. However, MLP with one hidden layer and two nodes in the upper and lower hidden layer had a better performance than other ANN configurations and linear regression model. The MAE for the best configuration of MLP models is 0.026, while MLR model had MAE of 0.030. The RMSE for the best configuration of MLP models is 0.034, while MLR model had MAE of 0.038. The scatter plots of predicted results and actual data are demonstrated in Fig. 3. The fit lines in Fig. 3 scatter plots represent the effect of each individual input parameter in NDVI index



Multi–Layer Perceptron Multi–Linear Regression

Fig. 2. Scatter plots of predicted and observed Normalized Difference Vegetative Index (NDVI) using different AI models

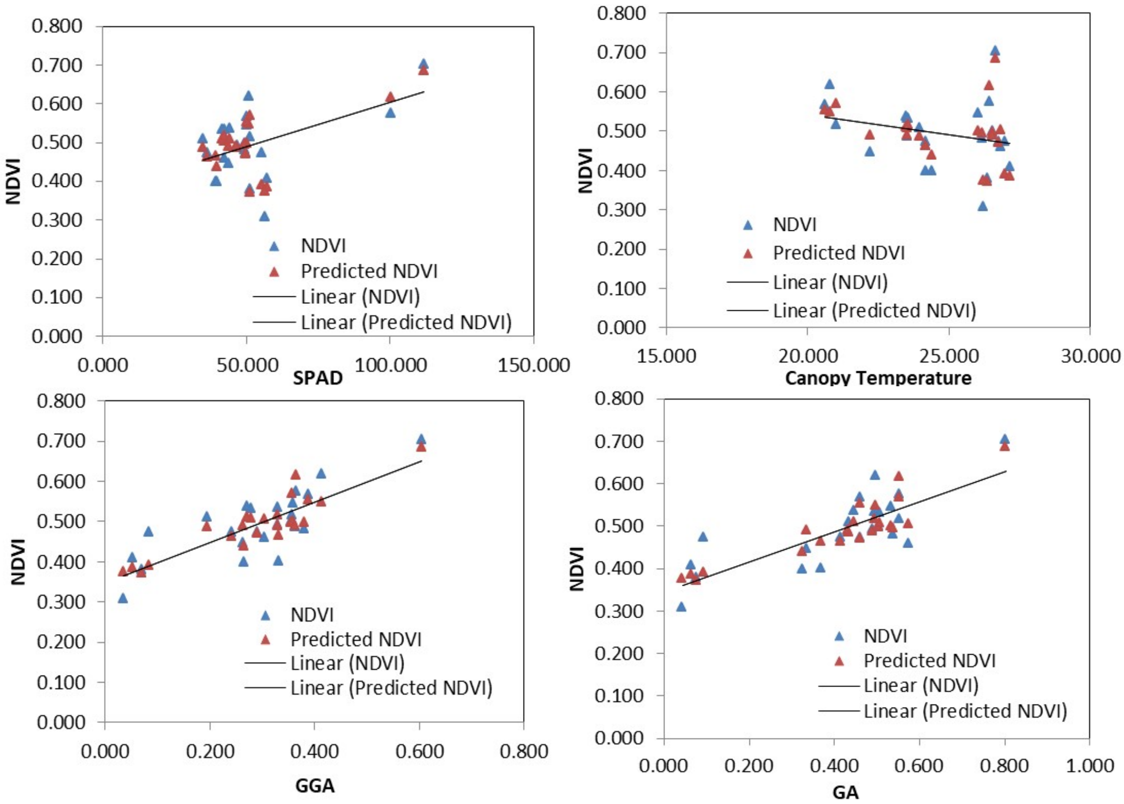


Fig. 3. Scatter plots of predicted NDVI index and individual input parameters

prediction. The relative importance of the variables in the improvement of prediction accuracy can be determined by performing a sensitivity analysis (Abdipour et al. 2019; Kowalski and Kusy, 2017). According to Mehmet et al. (2022) and Sung-Sik et al. (2020), the algorithm employed in the current study divides the connection weights of the network to set the relative importance of each input variable. It can be proven that the most significant predictor variable (Table 6) is the GA index (100% of importance), followed by the canopy temperature (39.6%), SPAD (38.7%), and GGA (32.9%). The least significant parameter is the plant treatment (Grafted or no grafted) (15.2%). Understanding the relationship among GA, T, SPAD, and NDVI is thereby of great interest and importance.

Table 6. Importance of the input variables for the MLP artificial neural network with better performance

Input variable	Importance
Treatments	15.2%
Temperature	39.6%
GA	100%
GGA	32.9%
SPAD	38.7%

4. CONCLUSION

A precise and cost-effective model for soil vegetable crop health prediction, which has the advantages of artificial intelligence techniques, is developed in the present research. Therefore, AI models linear regression, and artificial network MLP were employed to generate a comprehensive assessment of the performance of two AI approaches in NDVI index estimation. In this regard, five variables of plant treatment (grafted or no grafted), canopy temperature, GA, GGA indexes, and SPAD were employed. The results show that AI is a promising approach in crop health estimation, and developed AI models show a reliable ability in NDVI prediction. The key findings of this study are summarized as follows:

- Grafting techniques constitute a means of protection against attack by root nematodes.
- Grafted eggplant the most efficient combination ensuring good resistance and adaptation to soil containing nematodes pests.
- Proximal remote sensing machines and integrated pest management complete strategy may help to ensure both the sustainability of food production and minimize the number of nematodes in the soil.
- MLP method, showed the best performance in predicting NDVI index with the highest correlation coefficient and lowest error metrics.
- A sensitivity analysis shows that green area index (GA), the canopy temperature and SPAD play the most important roles in NDVI prediction, while plant treatment can be neglected in AI models.

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