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Lettuce (*Lactuca sativa* L.) yield prediction under water stress using artificial neural network (ANN) model and vegetation indices

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Abstract

Water stress is one of the most important growth limiting factors in crop production around the world. Water in plants is required to permit vital processes such as nutrient uptake, photosynthesis, and respiration. There are several methods to evaluate the effect of water stress on plants. A promising and commonly practiced method over the years for stress detection is to use information provided by remote sensing. The adaptation of remote sensing and other non-destructive techniques could allow for early and spatial stress detection in vegetables. Early stress detection is essential to apply management practices and to maximize optimal yield for precision farming. Therefore, this study was conducted to 1) determine the effect of water stress on lettuce (*Lactuca sativa* L.) grown under different watering regime and 2) explore the performance of the artificial neural network (ANN) technique to estimate the lettuce yield using spectral vegetation indices. Normalized difference vegetation index (NDVI), green NDVI, red NDVI, simple ratio (SR), chlorophyll green (CL_g), and chlorophyll red edge (CL_r) indices were used. The study was carried out *in vitro* conditions at three irrigation levels with four replicates and repeated tree times. The different irrigation levels applied to the pots were 33, 66 and 100 % (control) of pot water capacity. Spectral measurements were made by a hand-held spectroradiometer after the irrigation. Decrease in irrigation water resulted in reduction in plant height, plant diameter, number of leaves per plant, and yield. Using all indices in a feed-forward, back-propagated ANNs model provided the best prediction with R^2 values of 0.86, 0.75, and 0.92 for 100, 66, and 33 % water treatments, respectively. The overall results indicated that spectral data and ANNs have high potential to predict the lettuce yield exposed to water deficiency.

Key words: remote sensing, stress detection, water deficiency, precision agriculture, irrigation, management practices.

Introduction

Water stress is one of the factors that severely limits the crop growth including but not limited to semi-arid and arid regions (Imanishi et al., 2007). To minimize the negative effects of drought on plant growth, irrigation is required but it should be applied with care not only to avoid environmental problem such as runoff and groundwater contamination but also maintain the water availability and minimize irrigation cost (DeTar et al., 2006).

Lettuce is one of the leaf-edible vegetables that should be free from water stress (Tsabedze, Wahome, 2010) because it is extremely sensitive to drought due to shallow root system. A reliable, accurate, repeatable, quick, and inexpensive method is greatly desirable to assess water stress in lettuce both temporally and spatially.

Various remote sensing sensors from ground-based to satellite system have successfully been used to study plant health (Mirik et al., 2006 c). There are numerous studies that used remote sensing to detect a large number of stresses in crops over the years (Liu et al., 2010). Because the remote sensing techniques are non-destructive, quick, and accurate (Mirik et al., 2006 b), and the same portion of the plant can be sampled for many times, it has become one of the most important tools for researchers (Feilhauer, Schmidtlein, 2011). The use of spectral reflectance characteristics, collected by ground-based sensors has enabled detection of stress before the symptoms appear. Outcomes of increasing water stress are reductions in the photochemical activity of pigments and in the absorption of nutrients from soil, and in nutrient transport from root to shoots (Elmetwalli et al., 2012). Plant water deficiency may cause differences in reflectance from vegetative canopy if not all, in some portions of the electromagnetic spectrum. Chlorophyll pigments are one of the main determinants of responses in visible wavelengths (Gaussman, 1977) of green vegetables. These pigments are related with photosynthetic potential (Barton, 2011). Therefore, chlorophyll content is one of the most important indicators of plant health (Gitelson, Merzlyak, 1994). Chlorophyll content can be predicted via a variety of indices derived from specific wavelength combinations (Gitelson, Merzlyak, 1996; Bürling et al., 2011) Stress conditions cause not only reflectance increase in the visible part (Yu et al., 2000); but also alter reflectance from vegetative canopy in the near infrared (NIR) and middle infrared (MIR) region of the spectrum (Sims, Gamon, 2003). Vegetation indices calculated using specific bands of spectrum such as normalized difference vegetation index NDVI, green NDVI, SR, are used for detecting various plant stress factors (DeTar et al., 2006; Mirik et al., 2007 b; Liu et al., 2010).

With the advance in signal processing and spectral analysis, the ANNs have received great attention for its sensitivity, accuracy, non-destruction, and rapidity in a wide variety of applications (Wu et al., 2012). The spectral analysis in remote sensing studies is a central domain, in particular in the field of precision farming such as estimating crop yield and crop growing and extraction of stress information (Irmak et al., 2006). The ANNs are an approach that can be effectively used to estimate yield losses due to yield preventive factors in precision farming (Irmak et al., 2006). The ANNs have also been widely used in other disciplines including food safety, open channel flows, erosion, runoff modelling, and manure management (Kizil, Sacan, 2010).

The ANNs can be considered as electronic networks of "neurons" that do not require mathematical formulations (Irmak et al., 2006). They mimic the neural structure of human brain by processing the inputs one at a time and learning by comparing their prediction of the inputs with the known actual record called training phase of ANNs. During the training phase, the errors from the first prediction are fed back into the network and used to modify the networks algorithm for the second time, and so on for many iterations (epochs).

Several researchers argued that remote sensing is a better method to detect and quantify the impact of plant stress compared to visual techniques because a vegetative unit can be repeatedly, objectively, and non-destructively examined in a fast, robust, accurate, and inexpensive way (Elsayed et al., 2011). In addition, it removes human bias in visual interpretation that can be highly variable among individuals. Despite the fact that spectral detection and quantification of foliar stress have been successful in plant science, little research has been carried out to quantify the relationship between spectral vegetation indices and lettuce yield grown under different levels of water stress using the ANNs model. Our objective was two-fold: 1) to examine the use of spectral vegetation indices, to discern water-stressed and unstressed lettuce and 2) to quantify the relationship between spectral vegetation indices and lettuce yield using combinations of normalized difference vegetation index, green NDVI (GNDVI), red NDVI (RNDVI), SR, CL_g, CL_r indices in ANNs.

Materials and methods

Experimental design. The study was carried out in *in vitro* conditions at Agricultural Sensor and Remote Sensing Laboratory, Faculty of Agriculture, Çanakkale Onsekiz Mart University, Turkey in 2010. Three week-old seedlings of lettuce were transplanted individually into 4,000 cm^3 plastic pots filled with fine structured peat used for young vegetables with pH value of 6.0, and fertilization value of 1.5 g l^{-1}. Plants were grown under artificial illumination provided by cool white fluorescent tubes and a light/dark photoperiod of 16/8 hours. The temperature and humidity of the growing room were 20 ± 2ºC and 40%, respectively.

Experimental design was based on randomized plots with four replications. Experiment consisted of three irrigation levels 33, 66 and 100 % (control). Irrigation treatments were determined based on the water-holding capacity of pots. The experiment was repeated three times.

The plants were watered every two days during the experiment and the pots were weighed prior to each irrigation schedule. The reduced amount of water was added to the pots to maintain 33, 66 and 100 % water contents. Hoagland solution (HS) was used in irrigation water. The contents of HS applied with irrigation are given in Table 1. The averages of water added to the pots are 1855 ml, 2423 ml and 2907 ml for 33, 66 and 100 %, respectively.

Table 1. The contents of hoagland solution (HS) used in this study

Content	mg l^{-1}
KNO_3	505.50
$Ca(NO_3)_2.4H_2O$	1181.00
$MgSO_4.7H_2O$	493.00
KH_2PO_4	136.10
EDTA(Na_2 EDTA)	29.22
Na_2SO_4	14.20
$FeSO_4.7H_2O$	27.80
H_3BO_3	0.71
$MnCl_2.4H_2O$	0.91
$ZnSO_4.7H_2O$	0.06
$Na_2MO_4.2H_2O$	0.03
$CuSO_4.5H_2O$	0.02

Hyperspectral data collection. The first spectral data was recorded 10 days after transplanting (DAT). Spectral reflectance from plants was collected at 48 hours time span under halogen light source after watering. Reflectance measurements were made using the portable spectroradiometer "ASD HH FieldSpec" ("Analytical Spectral Device Inc.", USA) sensitive to 325–1075 nm of the spectrum. Spectral measurements were taken from a middle leaf of plants using an optical lens with a 10º field of view (FOV) (Fig. 1). A sensor was placed 30 cm above the canopy and it was calibrated using barium sulphate panel prior to the measurements. Each spectral measurement represents an average of 5 scans.

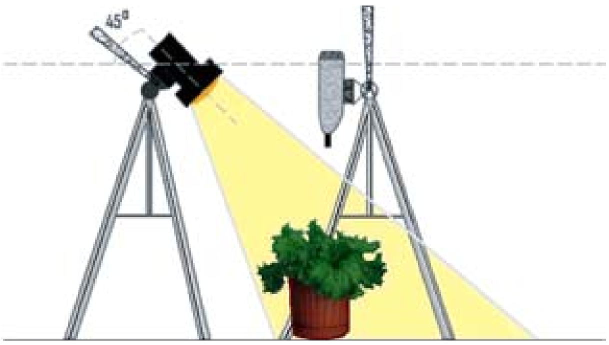

Figure 1. Representation of spectral data collection over the lettuce plants

Initially, several indices were calculated using different combinations of visible and near-infrared wavelengths. Among these indices, six vegetation indices were selected and evaluated for estimation of lettuce yield in this study. The equations of those indices used in this study are as follows:

$$SR = \frac{R_{800}}{R_{675}} \quad \text{(Rouse et al., 1973)} \qquad (1),$$

$$NDVI = \frac{R_{800} - R_{675}}{R_{800} + R_{675}} \quad \text{(Rouse et al., 1973)} \qquad (2),$$

$$GNDVI = \frac{R_{800} - R_{550}}{R_{800} + R_{550}} \quad \text{(Gitelson, Merzlyak, 1996)} \qquad (3),$$

$$RNDVI = \frac{R_{800} - R_{700}}{R_{800} + R_{700}} \quad \text{(Gitelson, Merzlyak, 1994)} \qquad (4),$$

$$CL_g = \left(\frac{R_{800}}{R_{550}}\right) - 1 \quad \text{(Gitelson et al., 2003)} \qquad (5),$$

$$CL_r = \left(\frac{R_{800}}{R_{700}}\right) - 1 \quad \text{(Gitelson et al., 2003)} \qquad (6),$$

where: SR – simple ratio, NDVI – normalized difference vegetation index, GNDVI – green normalized difference vegetation index, RNDVI – red normalized difference vegetation index, CL_g – chlorophyll green, CL_r – chlorophyll red edge, R_x – x^{th} wavelength (nm).

Plant sampling. Plants were harvested 24 DAT. The head fresh and dry mass, head height, head diameter, number of leaves were determined for each plant.

Artificial neural networks (ANNs) architecture and training parameters. The ANNs model was developed in three steps including partitioning of data, training ANNs model and validation of trained ANNs model. The *XLMiner* ("Cytel Software Corporation", USA) add-in of *MS Excel* was used to conduct ANNs analysis.

The *XLMiner* randomly partitions the data into two groups including training and validation before building the model. Sixty percent of the data was used to obtain network weights and build ANNs model while the remaining was used for model validation.

Input variables (x_i), associated weights (w_i), and a function (g) that sums the weights and yields the output (y) are the sections of a neuron (Balasubramanian et al., 2005) (Fig. 2).

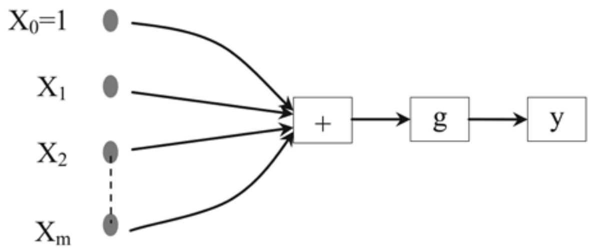

Figure 2. Schematic representation of a typical neuron

Methods of connecting nodes, computing weights, the number of nodes in hidden layers, and the type of transfer function between layers are used to differentiate the ANN models. The ANNs architecture determines how weights are interconnected and which learning rules may be used. The feed-forward, back-propagation neural network (BPNN) architecture is the most effective learning rule for ANNs (Irmak et al., 2006). In a BPNN, forward sweep is made through the network in learning process followed by computing output of each element for each layer. The difference between the computed and desired output is back-propagated to the previous layer. This process proceeds to the input layer. There are three layers in a typical BPNN architecture including input, hidden and output layers. The input layer is the data provided to model to train the ANNs. There may be more than one hidden layers followed by an output layer where there is one node for each class.

In this study, a standard fully connected BPNN model with a standard sigmoid input transfer function was used. There are many theoretical approaches in the determination of number of hidden nodes (Chen et al., 2008). However, in this study trial and error method was used to determine the number of hidden nodes and other model parameters. A series of ANNs with different model parameters was trained. The most accurate results that yield the highest R^2 values were selected.

Data processing and model evaluation. The *XLMiner* provides an option to normalize input data before building the BPNN models. The mean/standard deviation transformation was used for normalization:

$$X'_{imn} = \frac{X_{imn} - \overline{X}_i}{SD_i} \qquad (7),$$

where X'_{imn} is normalized input for treatment i, replication m, and day n; X_{imn} – input for treatment i, replication m, and day n without normalization, $\overline{X}_i$ – the mean value of all inputs for treatment i, and SD_i –

the standard deviation. The output variable was yield of lettuce. Normalized data was used to train ANNs model. The model performance was tested using validation datasets. The observed and predicted yields were plotted to see if there is a meaningful R^2 value between the two for all treatment conditions including 33, 66, and 100 %.

Results and discussion

Morphological measurements at harvest. The results of morphological measurements are given in Figure 3.

Water deficiency caused an obvious change in head weight, plant diameter, plant length, and a slight difference in number of leaves. Decreased irrigation levels resulted in lower plant head weight, plant diameter, plant height, and number of leaves per plant. In Figure 3, 100% irrigation level is considered to be the control plants.

Vegetation indices. The index values over the DAT for three irrigation levels are shown in Figure 4. Values of indices usually decreased due to reduction in irrigation levels when compared to control plants but usually increased for all irrigation levels over time except for GNDVI and CL_g indices. NDVI and SR indices exhibited similar patterns that these index values were increased for all dates when spectral measurements were made. The GNDVI and CL_g values of plants with 66% and 33% irrigation levels decreased during the early stages of water stress between 10 and 12 DAT in which increases in index values were observed thereafter. Similar decreases in these index values were obtained between 19 and 21 DAT. The GNDVI and CL_g values of plants with 100% irrigation level were nearly identical. RNDVI and CL_r had very close values for irrigation levels. GNDVI, RNDVI, CL_g, and CL_r values for control plants were lower in the early stage compared to 66% and 33% plants. For all the indices, plants in the control treatment produced higher values in comparison with 66% and 33% treatments from 12 to 20 DAT. For the last spectral measurement on 24 DAT, values of these indices for 100% irrigation level were lower than those for irrigation levels 66% and 33%.

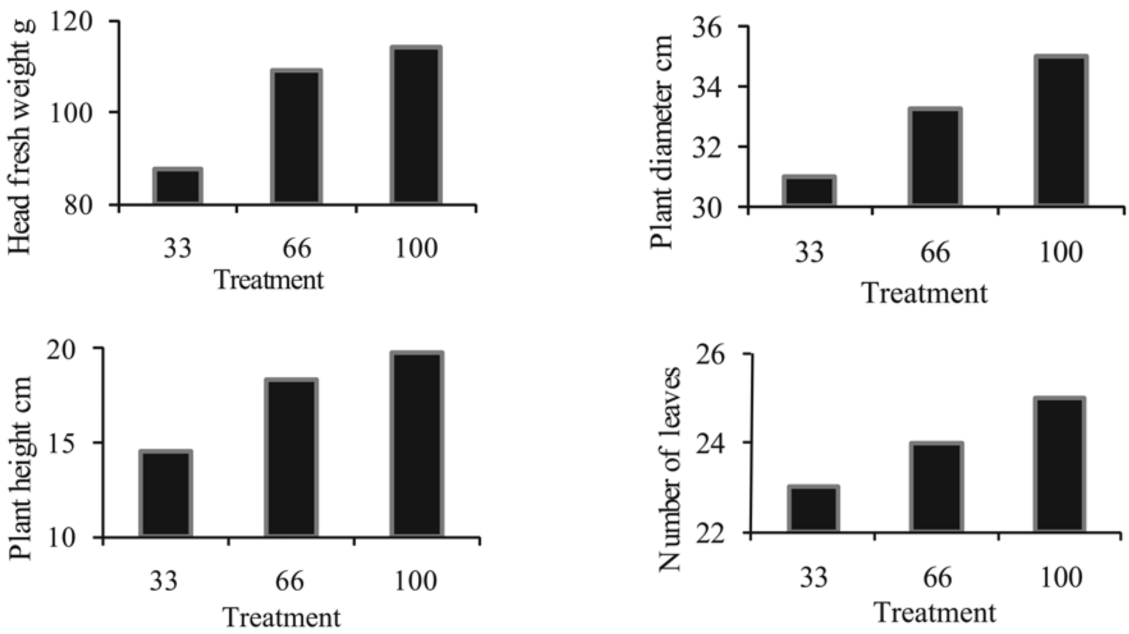

Figure 3. Results of harvest measurements of water stressed lettuce

Artificial neural networks (ANNs). The model parameters for the ANNs models used in this study are listed in Table 2. The ANNs topology with processing function determines the accuracy of model developed for correct representation of the ANNs behaviour. Therefore, it is important to determine the optimal number of hidden layers.

In order to identify the best indices that can be used to estimate lettuce yield, different combinations of indices were selected as input variables. The data processing and evaluation procedures were applied to all scenarios. Figure 5 summarizes the combinations of input variables for estimating lettuce yield under different treatment conditions and resulting R^2 values.

Table 2. Artificial neural networks (ANNs) model parameters/options

Number of hidden layers	2
Number of nodes in hidden layer-1	3
Number of nodes in hidden layer-2	3
Number of epochs	600
Step size for gradient descent	0.1
Weight change momentum	0.6
Error tolerance	0.01
Weight decay	0
Inputs normalized	Yes

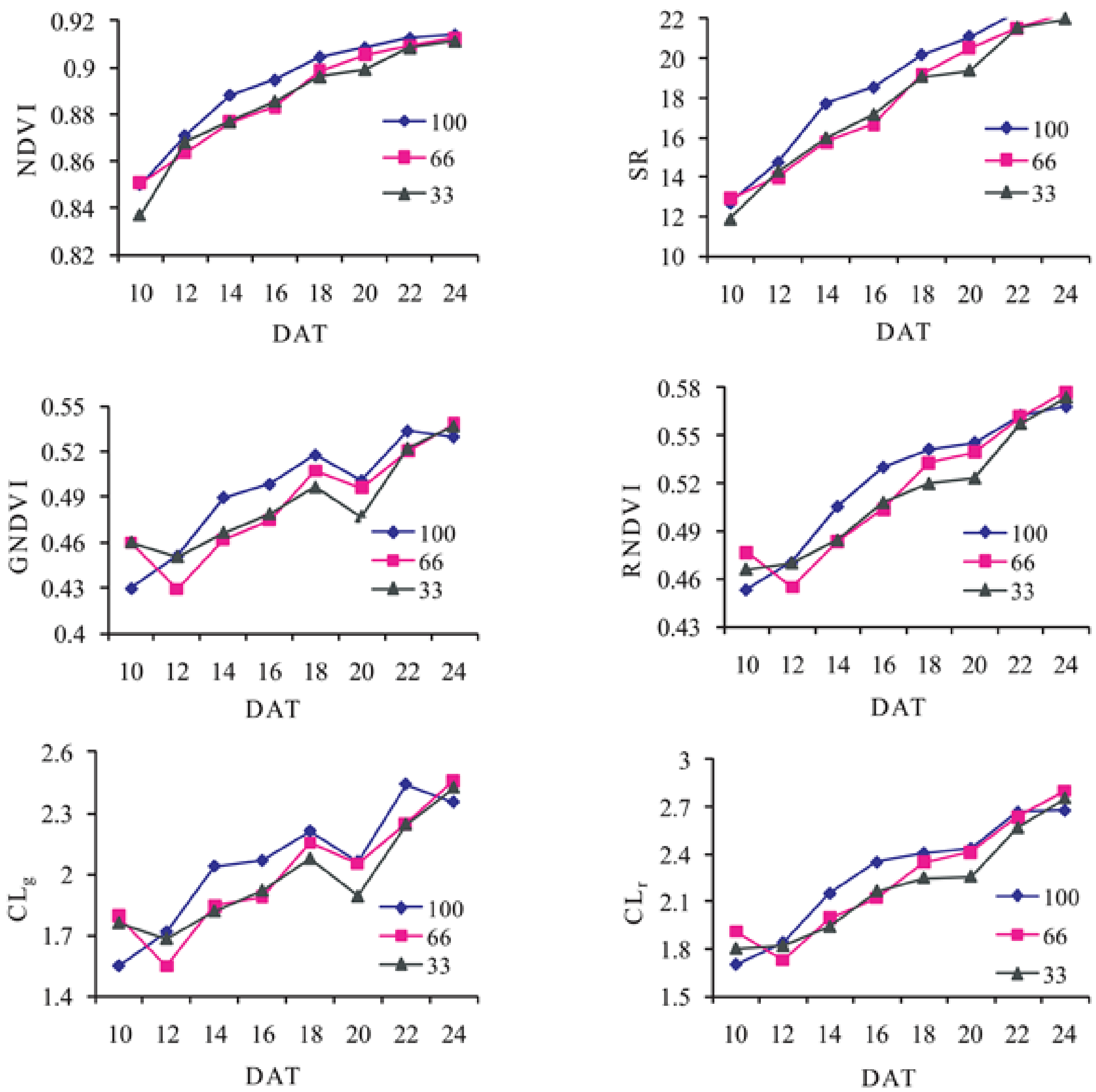

Figure 4. Daily changes in average values for spectral indices during the study (DAT 100, 66, 33 denote day after transplanting, and irrigation levels of 100, 66 and 33 %, respectively)

The ANNs model confirmed that there were good to strong relationships between observed and predicted lettuce yields for all data sets examined with the R^2 values ranging from 0.49 to 0.92. The ANNs model with all indices produced the strongest relationships between observed and predicted lettuce yields, whereas CL_r had the weakest relationship. The results also showed that trend lines for 33% and 100% treatment conditions have a slope of 45° and predicted values are equally scattered around the 1:1 line (dashed lines). This indicates that predicted values represent true values of lettuce yield. However, for the treatment with irrigation level 66%, most of the points lie to the left of 1:1 line that may indicate some unknown bias. The relationships across all data sets were positive, indicating that the value of an index increased with increasing lettuce yield.

The presence of biotic and abiotic stress agents such as water and nutrient deficiencies, insect infestation in vegetative canopy leads to change in chemical-pigment concentrations and cell structure that impedes photosynthesis and transpiration in affected tissue or plant (Genc et al., 2008; Kim et al., 2011; Mirik et al., 2011; Prabhakar et al., 2011; Mirik et al., 2012). Furthermore, water stress in plants is known to reduce leaf area that causes leaf curling, wilting (Kim et al., 2011), and rapid senescence in plants. These negative impacts of water stress on lettuce resulted in lower head fresh weight, plant diameter, height, and number of leaves compared to full irrigation level. All these parameters decreased further with the decreasing water application and 33% irrigation level yielded the lowest lettuce weight, diameter, height, and number of leaves.

Previously reported results on the effects of water stress on lettuce yield and growth characteristics varied probably depending on the water stress severity and duration (Soundy et al., 2005). A full irrigation treatment caused the significantly highest yields, whereas the lowest amount of water applied to lettuce resulted in

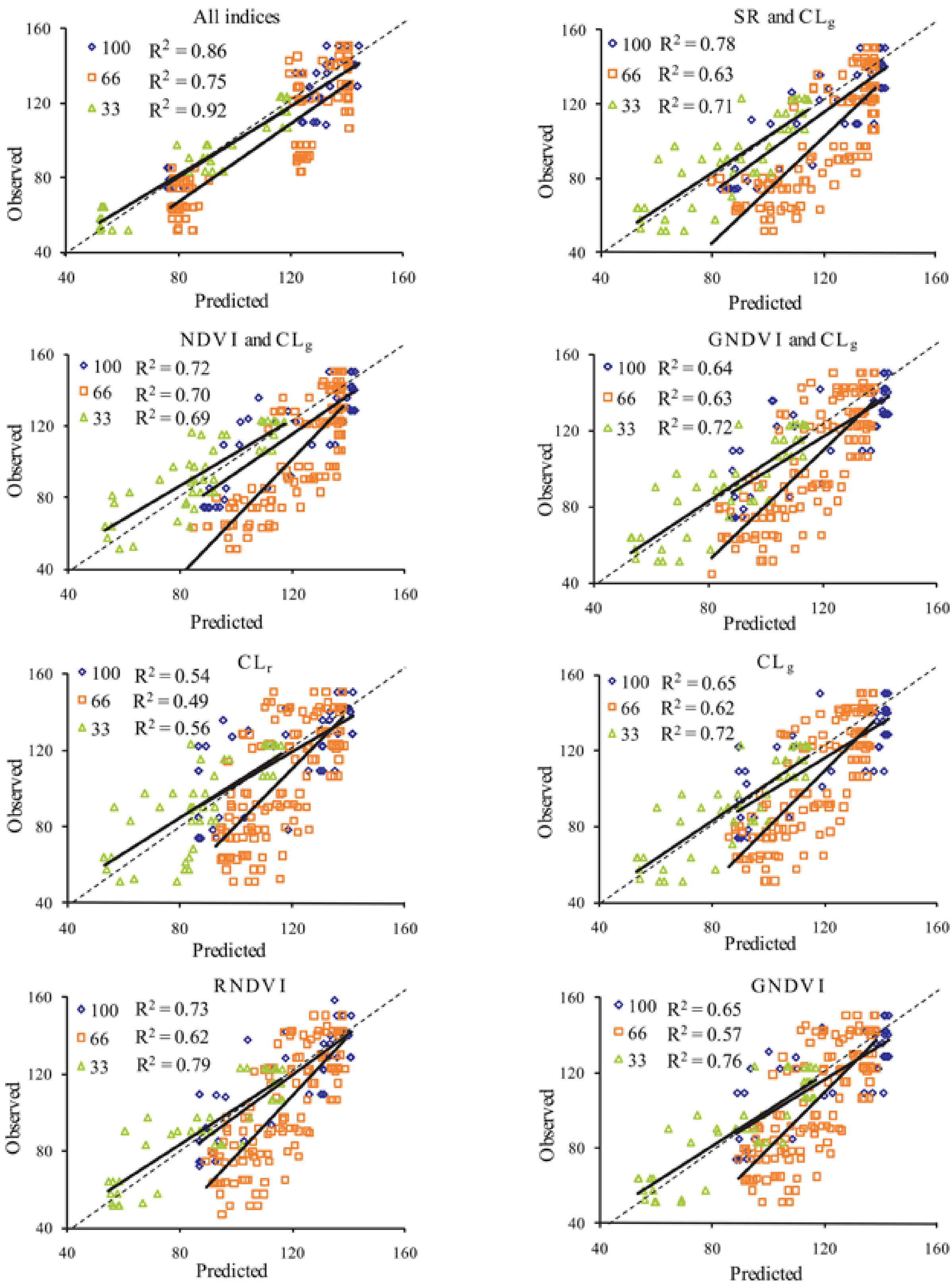

Figure 5. The relationship between observed and predicted lettuce yield using vegetation indices in the artificial neural networks (ANNs)

minimal yields (Mansuroglu et al., 2010). Parallel to our results, lettuce yields decreased with the decreasing water application (Mansuroglu et al., 2010). There was no significant treatment effect of irrigation levels on lettuce head weight even though head weight became lower with decreased water application (Acar et al., 2008). Three levels of irrigation treatment had insignificant effect on lettuce head weight (Yazgan, Buyukcangaz, 2006). A significant difference in lettuce diameter due to water stress was observed (Mansuroglu et al., 2010), while others obtained no treatment effect on plant diameter because of limited water supply (Acar et al., 2008;

Mansuroglu et al., 2010). Lettuce plant height responded significantly to the irrigation level (Bozkurt et al., 2009) but was significantly affected by water deficiency (Acar et al., 2008). The amount of applied water significantly changed the number of lettuce leaves (Acar et al., 2008; Bozkurt, Mansuroglu, 2011).

A significant increase in percent reflectance values from vegetative canopies suffering from water or nutrient stress, insect feeding, and disease incidence in the visible region has been observed by various researchers (Mirik et al., 2006 a; Mirik et al., 2007 a). Water deficiency at 66% and 33% irrigation levels apparently degraded the photosynthetic pigments and changed the leaf morphology in lettuce plants. Since the leaf morphology has a strong influence on the leaf spectral properties (Lee et al., 2011), the change in leaf morphology because of water stress resulted in optical differences between water-stressed and unstressed lettuce. In addition, water stress may cause a reduction in chlorophyll a and b and carotenoids in stressed lettuce plants (Netto et al., 2005; Zhang et al., 2008). Apparently, the changes in pigment concentrations and leaf morphology induced by water deficiency created difference in visible light reflectance between stressed and unstressed lettuce plants. In addition to modified spectral reflectance from stressed lettuce in the visible region, water stress is often related to the decrease in NIR reflectance (Huang et al., 2007) due to reduced leaf or canopy area and increased process of plant senescence. In the present study, reflectance in the NIR region from stressed lettuce was apparently modified due to reduced green leaf area and increased lesion formation when compared to control plants.

Modified spectral properties of lettuce in the visible and NIR regions are related to index values computed for three irrigation levels. The spectral vegetation indices we used are known for their ability to discriminate levels of biomass, cover, plant health, and other vegetative attributes. Some researchers recommended the use of these indices not only as an indicator of early stages of leaf senescence, aging, and stress responses to environmental extremes or herbicides, but also for quantifying different phases of disease severity, pest damage, and density (Gitelson, Merzlyak, 1996; 1997; Sims, Gamon, 2003; Gitelson et al., 2003; Rodriguez et al., 2006; Genc et al., 2008). The index values we examined were significantly reduced in response to irrigation treatments compared to unstressed lettuce. Reduced index values for vegetative cover under stress compared to healthy vegetation have been observed by other researchers. For example, NDVI, GNDVI, modified NDVI, and SR significantly lowered due to Russian wheat aphid (*Diuraphis noxia*) feeding in wheat (*Triticum aestivum* L.) (Mirik et al., 2012).

The combination of all indices as well as individual index performed well and exhibited good relationships with yield of greenhouse-grown lettuce. Using all indices as inputs in ANNs model produced the strongest relationships with lettuce yield from three irrigation levels. The relationships between CL_r and lettuce yield were the weakest but good when compared to other regression models. The rest of the models developed in this study yielded R^2 values that are between these maximum and minimum values. The significant relationships between spectral vegetation indices and lettuce yield and reduced index values demonstrate that water stress in lettuce can be rapidly identified and estimated using remote sensing techniques. Regression models resulted in strong and significant positive relationships for all data sets analyzed. In addition, the wavebands used to calculate spectral vegetation indices covered a large range of available wavelengths in the hand-held spectroradiometer "FieldSpec". This indicated that the spectral vegetation indices we used can be applied to detect water stress and estimate lettuce yield under water stress. Significant relationships between vegetation indices and leaf water content of wheat and maize (*Zea mays* L.) were observed (Elsayed et al., 2011). The ANNs model was a competent and feasible tool for predicting coliforms and *Escherichia coli* levels on tomato (*Solanum lycopersicum* L.) and lettuce with the relationships >73% and was recommended to be used over a high dimensional polynomial regression because of its simplicity and easily trainable nature (Keeratipibul et al., 2011). This method showed that the BPNN technique could predict spatial yield variability of soybean (*Glycine max* L.) with high accuracy (Irmak et al., 2006).

Hand-held remote sensing instruments are useful for small-scale operational field monitoring of biotic and abiotic stress agents and novel research purposes (Jackson, 1986). A limiting factor is their applicability to small areas when compared with aerial and space-borne sensors. Using hand-held spectrometers to quantify the spectral characteristics of water-stressed and unstressed lettuce plants at smaller scales is needed because hand-held remote sensing devices have better temporal, spectral, and spatial resolutions. Reflectance data obtained by hand-held instruments over small areas provides information to understand spectral interactions between deficiency in water and affected plants, as well as fundamental ground-truth for interpretation of remote sensing data measured from satellite and aircraft. Studies using image data acquired by satellite and aircraft platforms for their ability to detect water stress in lettuce at broader spatial scales are needed.

Conclusion

We observed that as the water stress decreases, lettuce yield increases accordingly. The highest water stress was recorded when the irrigation level was the lowest (33%), which caused the lowest lettuce yield. Reflectance responses of the lettuce plants growing under water deficiency indicated that remote sensing can detect water stress severity. In general, water stress significantly reduced values of vegetation indices for the 66% and 33% irrigation levels compared to the control treatment. This indicates that the spectral properties of lettuce plants are markedly degraded by water deficiency. A back-propagation neural network (BPNN) model was used to predict lettuce yield using simple ratio (SR), normalized difference vegetation index (NDVI), green NDVI (GNDVI), red NDVI (RNDVI), chlorophyll green (CL_g) and chlorophyll red edge (CL_r) indices. The relationships between lettuce yield and spectral vegetation indices showed that remotely sensed data transformed into spectral vegetation indices provides a method for detecting water stress. The results of the present study demonstrate that there exists high potential to distinguish water stress in lettuce and estimate lettuce yield using remote sensing. This can provide managers and producers a quick and repeatable method for detecting stress and quantifying yield in time and place. The weather and soil conditions were kept constant for all experimental pots in this study, which can differ from open field conditions. Therefore, the next logical step is to apply the method used in this study in open field conditions and/or commercial lettuce fields.

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Sėjamosios salotos (*Lactuca sativa* L.) derliaus prognozavimas vandens streso sąlygomis, taikant dirbtinio neurotinklo (ANN modeliavimo) metodą ir vegetacinius rodiklius

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Santrauka

Vandens stresas yra vienas svarbiausių veiksnių, pasauliniu mastu ribojančių augalų augimą. Vanduo augalams reikalingas įvairiems gyvybiškai svarbiems procesams – maisto medžiagų įsisavinimui, fotosintezei ir kvėpavimui. Yra keletas metodų, skirtų įvertinti vandens streso įtaką augalams. Perspektyvus ir daug metų plačiai taikomas metodas vandens stresui nustatyti yra netiesiogiai nustatytos informacijos naudojimas. Netiesioginio nustatymo ir kitų nežalingų metodų derinimas tiriant daržoves padėtų nustatyti ankstyvą ir vėlesnį stresą. Ankstyvas streso nustatymas yra labai svarbus ūkininkaujant ir siekiant optimalaus derliaus tiksliojoje žemdirbystėje. Tyrimas atliktas siekiant: 1) nustatyti vandens streso įtaką sėjamajai salotai (*Lactuca sativa* L.), auginamai taikant skirtingus vandens režimus, ir 2) ištirti dirbtinio neurotinklo (ANN) metodo efektyvumą, naudojant spektrinius vegetacinius rodiklius salotų derliui nustatyti. Naudoti vegetacijos normalizuoto skirtumo indeksas (NDVI), žaliasis NDVI, raudonasis NDVI, paprastasis santykis (SR), žaliojo (CL_g) ir ilgabangio raudonojo (CL_r) chlorofilo rodikliai. Tyrimas atliktas *in vitro* sąlygomis, naudojant tris drėkinimo lygius; keturi pakartojimai, eksperimentai kartoti tris kartus. Taikyti trys drėkinimo lygiai sudarė 33, 66 ir 100 % (kontrolinis variantas) vegetacinio indo vandentalpos. Spektrų matavimas atliktas rankiniu spektroradiometru po drėkinimo. Sumažinus vandens kiekį, sumažėjo augalų aukštis, jų skersmuo, augalo lapų skaičius ir derlius. Naudojant mitybos modelį ir bandymams padaugintų augalų rodiklius, dirbtinio neurotinklo modelis pateikė geriausią prognozę su R^2 vertėmis – 0,86, 0,75, ir 0,92 – atitinkamai 100, 66, ir 33 % laistymo variantams. Tyrimo rezultatai parodė, kad esant vandens trūkumui, spektrų duomenys ir dirbtinio neurotinklo modelis suteikia dideles galimybes prognozuoti salotų derlių.

Reikšminiai žodžiai: numatomas jautrumas, streso nustatymas, vandens trūkumas, tikslioji žemdirbystė, drėkinimas, auginimo technologija.