Identifying Water Stress in Potatoes Using Leaf Reflectance as an Indicator of Soil Water Content

Suraj Amatya, Manoj Karkee, *and* Ashok K. Alva

Abstract*—Soil water content must be monitored and maintained at adequate level for optimal productivity. Accuracy of traditional sensors used to monitor soil water content depends on the installation technique and proper contact between soil and sensor, which is difficult to achieve in light textured sandy soils. Non-contact sensing technique does not have the limitation of contact with soil and can monitor plant status continuously. In this study, hyperspectral imaging was used as a non-contact technique for detecting changes in spectral reflectance of Umatilla Russet potato plants grown under varying soil water content. An experiment was carried out in a greenhouse to subject potato plants at different levels of soil water content from extreme stress to surplus. Yield data was also collected, which showed that maximum yield for Umatilla Russet potato can be achieved at 18% to 21% soil moisture content. Various spectral indices were calculated using spectral reflectance data at different water stress levels. Principal component analysis was used to identify indices that represented maximum variability in the data. Simple Ratio Index and Modified Red Edge Simple Ratio Index were identified as the two most relevant indices for differentiating soil water content. K-Means clustering with these two indices resulted in an accuracy of 75% in identifying highly stressed plants and 92% accuracy in identifying stressed plants (that included both high and low stress levels). These results showed a promise for development of a non-contact sensor for detecting plant water stress in potatoes, which may lead to an automated irrigation system for maintaining *optimal soil water content during potato growing season.

***Index Terms*—Hyperspectral Imaging, Potato, Soil Water Content, Spectral Analysis, Water Stress**

I. Introduction

Water stress causes significant reduction in crop productivity. Timely detection of such plant stress provides an opportunity to make effective management decisions to improve crop quality and yield [1]. Soil moisture sensors are commercially available to measure soil water content so that water deficiency can be predicted and the appropriate amount of water can be applied. Primarily, these sensors work on the basis of variations in dielectric constant [2] and electric resistance [3] with the variation in soil water content.

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Installation of and data acquisition with these sensors in field conditions is difficult as well as labor intensive. The accuracy of measurement of soil water content by these sensors is influenced by the precision in installation of the sensors to maintain good contact between the sensors and the soil without any air or water pockets between them [4]. This is particularly problematic in sandy soil. Remote sensing combined with plant physiological studies allow growers to make better decisions regarding application of water and other nutrients [5]. Remote sensing techniques avoid the issues of installation errors and direct contact with the soil. It will also provide the opportunity for continuous monitoring of soil water content, which will provide timely information for optimal irrigation scheduling. The technique helps to reduce the labor and associated costs, thus leading to increased net returns to growers.

Physical and/or biological changes in plant canopies due to water stress will cause changes in light reflectance from plant canopy surface [1], [6], [7], which can be used for detecting water status using remote sensing techniques. Plants have certain reflectance characteristics at different wavelengths of the spectrum [1]. Typically for a healthy plant, leaf reflectance at visible spectrum (about 400-700 nm) is low due to absorption of light by various plant pigments such as chlorophyll, xanthophylls and carotenoids [8], [9] followed by a rising peak in near infrared region [1]. The general reflectance pattern may vary when plants are diseased or are under nutrient or water stresses. By analyzing the spectral reflectance of plants over a range of wavelengths, the degree of water stress can be estimated, which is an indicator of soil water availability.

The change in plant reflectance can be analyzed by monitoring particular wavelengths but results can be more noticeable when information from different wavelengths are combined by calculating their ratios, differences and/or ratios of differences [9]. These differences or ratios are called spectral indices. Various studies have been conducted to detect plant stress for different species including gerbera plants [10], peanut, wheat [11], apples [1], corn, spinach, snap beans [5], potato [12], [13] and tomato [14].

Most of these studies used spectroradiometer for measuring spectral reflectance [1], [5], [13], [15]of plants in laboratory environment. Spectroradiometer takes measurement from a single point in plant canopy, which makes it difficult to account for the spatial variability of reflectance within a plant canopy. Reference [14] used hyperspectral imaging technology to detect moisture content of tomato leaves, in which band

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representing moisture content was selected using adaptive band selection (ABS) method and was used to segment images for further processing. A partial least squares regression model was developed, which achieved a correlation of 0.9 between predicted and real leaf moisture content.

These studies correlated spectral indices with plant water content [5], [16]. However, there is a need for continuous monitoring of soil moisture content [17] because optimal production of high quality tubers depends on adequate soil moisture content [18]. Therefore, an approach to correlate spectral reflectance to soil moisture content level, which is a better indicator of the general water status in potato fields, is essential. In this work, Hyperspectral imaging was used to take the images of individual leaves, which were then used to evaluate and correlate spectral indices with soil moisture content level. Specific objective of this study were to:

- Assess the capability of hyperspectral imaging to identify differences in reflectance of potato plants grown at different levels of soil water content; and
- Develop a non-destructive in-situ method to identify water-stressed potato plants using their leaf reflectance

II. MATERIALS AND METHODS

In this study, hyperspectral imaging was used as a non-destructive method of estimating soil water content in potato fields. Hyperspectral images of potato plants were captured in a greenhouse environment and then analyzed using MATLAB (R2011a, Mathworks Inc., Natick, MA) software to evaluate spectral reflectance of these plants grown at different levels of soil water content. Various spectral indices were estimated and correlated with soil water content. Potato yield data was also collected and correlated with soil water content and spectral indices.

A. *Experimental Setup*

This study was conducted in a greenhouse at the Irrigated Agricultural Research and Extension Center (IAREC), Washington State University, Prosser, WA. Umatilla Russet potato variety was planted (two per pot) in 38 cm diameter and 30 cm deep pots (40 kg air dry soil) in the greenhouse (Fig. 1a). Silt loam soil with bulk density of 1.3 g/cc and field capacity of 25% (by weight) was used. Required quantities of N (urea), P (KH_2PO_4), and K (KCl) were mixed with top 15 cm depth of soil in each pot and the fertilizer mixed soil was placed back in the pot to attain 1.3 g/cc bulk density. The pre-plant N, P, and K applications were equivalent to 112, 56, 224 kg/ha respectively on soil weight basis. To mimic the field fertilizer practice, in-season N was applied, using ammonium nitrate solution to apply equivalent to 224 kg/ha N in five weekly applications starting 4 weeks after seedling emergence. There were four water treatment levels: 5% – 8%, 12% –15%, 18% – 21%, and 24% – 27% water content by weight with five replications. Water treatment levels were assigned randomly for each pot to minimize the effect of any spatial variability in the greenhouse (Fig. 1b). Potatoes were harvested 12 weeks after emergence. Tuber counts, tuber size as well as, wet and dry weights were recorded. Potato yield with different soil water content was compared to identify soil water content that favored maximum potato yield.

(a)

(b)

Fig. 1. Experimental setup in a greenhouse: a) potato plants seven

Soil water content was monitored using moisture sensors (See the following section). Soil moisture sensors recorded water content every hour using a data logger. Average of 24 hourly readings collected between noon to noon was used as an estimation of current soil water content. If soil water content dropped below desired treatment level in any pot, they were watered to bring the water content level back to the upper limit of the respective treatment range of water content (Fig. 1b). The amount of water needed for each application was calculated based on the percentage depletion of water content in the soil. It took some time for soil water content to return to desired level after watering. Due to this depletion and replenishing cycles, there was some temporal variability in actual soil water content in each pot around the desired water content level. Therefore each treatment was described based on a range of soil water content rather than fixed water content. Hyperspectral image of leaves from 20 pots were taken three times during the experiment (See the following section) thus, making 60 samples of hyperspectral data for analysis. Nine samples fell in the buffer zone between two treatment groups and were neglected from the study. The study then included 12 samples in the first group with soil water content in the range from 5% to 8%. Similarly, second group included 12 samples from 12% to 15% water content, third group included 12 samples from 18% to 21% water content and fourth group included 15 samples from 24% to 27% water content.

B. *Soil Water Content Measurement*

Soil moisture sensors (HS10, Decagon Devices, Pullman, WA) connected to data loggers (Em5b, Decagon Devices, Pullman, WA) were used to continuously monitor soil water content. These moisture sensors were originally calibrated by the manufacturer to measure volumetric water content (VWC). The sensor raw reading was calibrated to gravimetric soil water content (Fig. 2) using pots without plants and soil water content adjusted approximately to 10, 15, 20 or 25%. Two sensors were installed in each pot with different soil water content.

A calibration model was developed to estimate soil water content by weight using the average of the raw sensor data collected over 24 hours. There was some variation in the readings due to temperature fluctuation over a day. However, the effect of this variation was minimized by averaging the raw data over a 24 hours period. The regression model (1) developed between raw data and actual soil water content showed a good relationship with R-squared value of 0.99 (Fig. 2).

$$W_c = 0.442 * R_s - 33.377 \quad (1)$$

where, W_c = predicted soil water content (%); and R_s = raw output from sensor (mV).

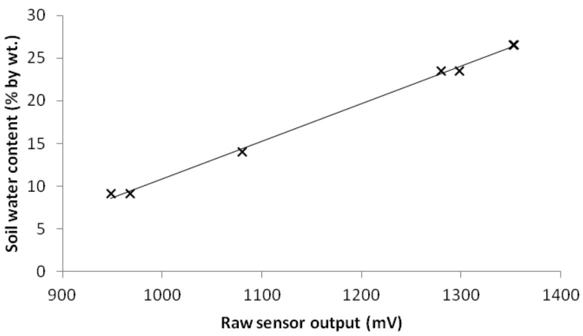
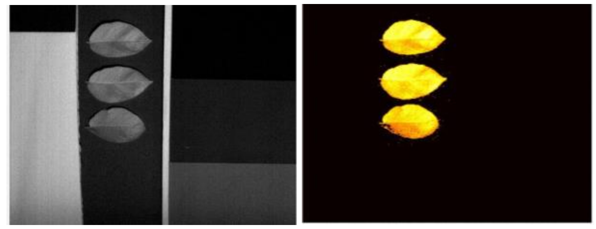


Fig. 2. Regression line for HS10 (Decagon Devices, Pullman, WA) soil

C. Hyperspectral Imaging and Image Processing

Hyperspectral images were acquired using a hyperspectral camera (Hyperspec® VNIR 1003A-10143, Headwall Photonics, Fitchburg, MA) with a spectral range of 400 nm – 1000 nm. Hyperspectral images were taken three times between third and fourth weeks after emergence. Three leaves at about the same growth stages were randomly collected between 11:00 AM and 1:00 PM from fifth or sixth petiole from the top of canopy. Hyperspectral images of those leaves were acquired in the greenhouse environment under natural lighting condition immediately after removal from the canopy (Fig. 3a). From hyperspectral images, it was observed that peak intensity for leaves was at wavelength 732nm. Image segmentation was performed to segment leaves out from the background using threshold intensity (a minimum intensity value above which pixels represented leaf area) of leaf at 732 nm (Fig. 3b). After segmentation, a mask was created on the area covered by the three leaves. The mask was applied to all other bands of the hyperspectral image to extract intensity values within leaf area. Intensities of three leaves from each plant were averaged before calculating plant spectral reflectance.



a)

b)

Hyperspectral images were calibrated using white and dark reference images. The white reference image was acquired in the greenhouse using a white foam board whereas the dark reference image was acquired in the lab by covering the lens with a cap and a dark cloth and turning off all light sources. White foam board used in this study had the same reflectance characteristics as a commercial diffuse reflectance standard board from Gooch and Housego (OL 55RS, Gooch & Housego, Orlando, FL). Reflectance images were calculated by dividing the difference of actual image and dark reference by the difference of white and dark references (2).

$$r = (R - D) / (W - D) * 100\% \quad (2)$$

where, r = Percentage reflectance; R = Real image; D = Dark reference image; W = White reference image

D. Spectral Indices

The differential responses of vegetation for different spectral bands have been used to develop various arithmetic formulas, called spectral indices that reduce additive and multiplicative errors associated with ambient environmental conditions [12]. There are several spectral indices that have been developed to represent various changes in vegetation due to stress caused by water and nutrient deficiency. Such indices help to isolate few bands from the array of hyperspectral bands, which are more sensitive to the stress level and help to magnify the effect making it easier to observe.

Reference [10] used the ratio between the reflectance at wavelengths 900 nm and 970 nm as Water Index (WI) to correlate with water content of gerbera plant. Several other indices were developed for plant stress identification (Table I). These indices were calculated for each hyperspectral image collected in this study. The average reflectance value of three leaves from each plant (See previous section) was used for evaluating spectral indices.

Table I: Spectral Indices evaluated in this study

Index [Reference]	Equation
Water Index (WI) [10]	$WI = \frac{R(900)}{R(970)}$
Normalized Difference Vegetation Index (NDVI) [19]	$NDVI = \frac{R(800) - R(640)}{R(800) + R(640)}$
Red Edge NDVI (rNDVI) [20]	$rNDVI = \frac{R(750) - R(705)}{R(750) + R(705)}$
Modified Red Edge NDVI (mod_rNDVI) [20]	$mod\ rNDVI = \frac{R(750) - R(705)}{R(750) + R(705) - 2 * R(445)}$
Structure-Independent Pigment Index (SIPI) [21]	$SIPI = \frac{R(800) - R(445)}{R(800) - R(680)}$
Floating-Position Water Band Index (fWBI) [22]	$fWBI = \frac{R(900)}{\min(R(930) - R(980))}$
Water Index / NDVI [23]	$\frac{WI}{NDVI} = \frac{R(900)}{R(970)} * \frac{R(800) + R(640)}{R(800) - R(640)}$
Simple Ratio Index (SRI) [1]	$SRI = \frac{R(900)}{R(680)}$
Modified Red Edge SRI (mrSRI) [20]	$mrSRI = \frac{R(750) - R(445)}{R(705) - R(445)}$
Photochemical Reflectance Index (PRI) [24]	$PRI = \frac{R(531) - R(570)}{R(531) + R(570)}$
Enhanced Vegetation Index (EVI) [25]	$EVI = 2.5 * \frac{R(800) - R(680)}{R(800) + 6 * R(680) - 7.5 * R(450) + 1}$
Vogelmann Red Edge Index (VOG REI) 1 [26]	$VOG\ REI\ 1 = \frac{R(740)}{R(720)}$
VOG REI 2 [26]	$VOG\ REI\ 2 = \frac{R(734) - R(747)}{R(715) + R(726)}$
VOG REI 3 [26]	$VOG\ REI\ 3 = \frac{R(734) - R(747)}{R(715) + R(720)}$

E. Water Stress Detection

As mentioned in the introduction section, majority of reported work in non-contact water stress sensing have focused on relating canopy reflectance to leaf water content. However, it is a regular practice for growers to make irrigation management decisions based on soil water content [27]. Therefore in this study, the spectral indices were correlated to soil water content. There were several spectral indices that showed some correlation with soil water content. However, many of those indices were correlated with each other and represented redundant information when it comes to water stress detection.

Principal component analysis (PCA) was employed to identify major spectral indices with minimal cross-correlation. PCA reduces the dimensionality of data which consists of large number of correlated variables to a few uncorrelated variables retaining as much variation as possible in the data set [28]. PCA results in a set of new orthogonal variables such that the first principal component has the highest possible variance. The next succeeding variable has highest possible variance after the first as well as is orthogonal to the first principal component and so on and so forth. PCA was performed to identify spectral indices leading to two major principal components that represented desired level of spectral variations in the data.

Using the spectral indices corresponding to two major principal components, K-means clustering was performed on the spectral data. K-means clustering divides the data set into k mutually exclusive clusters. The number of clusters (k) in which given data set has to be divided is predefined, which was three in this study. A set of k centroids is randomly chosen and each data point is associated to the nearest centroid to form a cluster. On each iteration, the cluster centroid is moved to the mean location of all data points assigned to the cluster. The iteration continues until the centroid of a cluster and mean location of all data points categorized to that cluster are the same.

III. RESULTS AND DISCUSSIONS

A. Potato Yield

Maximum potato yield was 116.0 g per plant of dry tuber weight on average for group 3 with soil water content of 18% to 21% (Table II). Group 2 with water content from 12% to 15% had an average yield of 62.6 g per plant. Group 1 (5% to 8% water content) and group 4 (24% to 27% water content) had average yields of 2.1 g and 12.3 g per plant, respectively. Group 1 was the driest treatment in which very few tubers were formed. Because of excessive water in group 4, most of the tubers were rotten and yield was substantially below that of group 2 or 3.

Table II: Average potato yield for different treatment groups

Group	Soil moisture level (%)	Average dry tuber weight (g/plant)
Group 1	5% - 8%	2.1
Group 2	12% - 15%	62.6
Group 3	18% - 21%	116.0
Group 4	24% - 27%	12.3

The results showed that potato yield increased with increasing soil water content up to a certain limit, then decreased rapidly with further increase in water content of the soil. The optimal soil water content to maximize potato yield was found to be within group 3 where soil water content was between 18% and 21% (Fig. 4). This optimal water content level provides a bench-mark that can be detected by the non-contact sensor developed in this work. Soil water content in Group 1 resulted in practically no potato yield, and therefore represented a high water stress group. Group 2 resulted in an average yield level, indicating a mild or low water stress and Group 3 represented the healthy plant group.

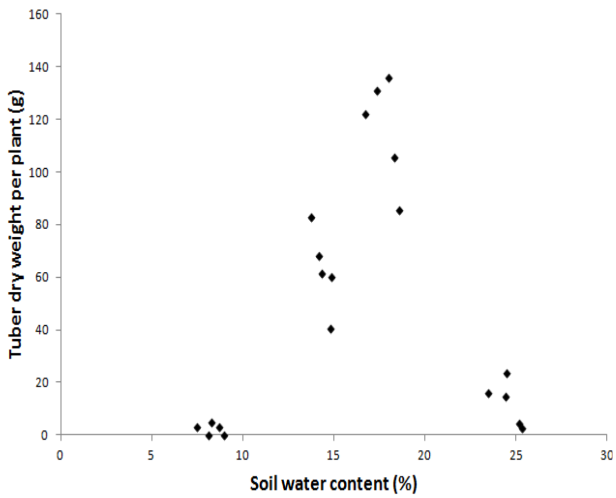


Fig. 4. Potato tuber yield (dry weight) against average soil water content (wt. basis)

It was apparent from the yield data that over watering (>24% in this experiment) is highly unfavorable. With continuous monitoring of soil water content with the non-contact sensing as proposed in this study and with frequent but low-volume watering with an automated irrigation scheduling system, over watering above field capacity can be practically avoided. Therefore, data in group 4 (24% - 27% soil water content) is not considered for further analysis in this study.

B. *Spectral Reflectance*

The reflectance of plant leaves at different water treatment levels were obtained from the hyperspectral images and compared using spectral signature plots (Fig. 5). The spectral signature plots were obtained by average reflectance of all samples within soil water content groups defined in the methods section. The first group (5% - 8% soil water content) represented the high water stress group, which showed comparatively lower reflectance at Near Infra-Red (NIR) region. Group 2 (12% - 15% soil water content) had higher reflectance than group 1 and group3 (18%-21% soil water content) had highest reflectance of all groups. This result was expected because healthy plants generally will have higher reflectance in NIR band than stressed plants.

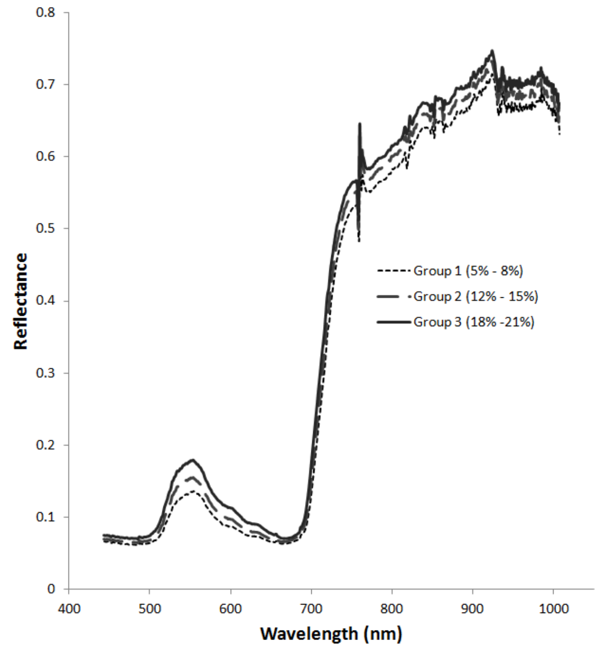


Fig. 5. Average reflectance plot of three treatment groups

C. *Evaluating Spectral Indices*

The reflectance plots showed the qualitative difference in spectral signature of potato leaves with different soil water treatment levels. These differences in reflectance property were quantified using various spectral indices (Table I). Highest R-squared value for a linear regression model relating these indices to soil water content was observed to be 0.58 with red-edge NDVI (Fig. 6). Table III shows the correlation between soil water content and those spectral indices. The highest correlation coefficient was -0.76 with red-edge NDVI. Those indices with correlation coefficient ≥ 0.5 were considered to have good correlation with soil water content. With this threshold, a number of spectral indices showed good correlation with the soil water content. However, the information provided by many of the indices could be redundant since reflectances from the same wavelength (or close wavelengths) were used to calculate them.

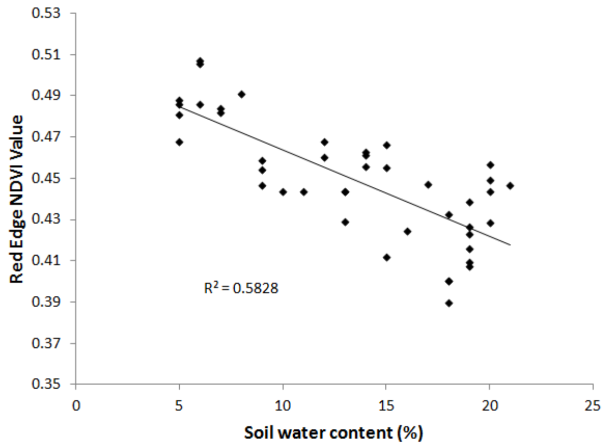


Fig. 6. Relationship between soil water content and Red Edge NDVI

Table IV shows cross-correlation between spectral indices that have been chosen as good indices. High cross correlation coefficient between the indices also shows that there was redundancy in the characteristics represented by them. Therefore, as described in the next section, only two spectral indices were chosen using PCA such that there was minimum correlation between them and also represented good correlation with soil water content.

Table III: Correlation between soil water content and spectral indices. Bold faced font indicates indices with $|R^2|\geq 0.5$.

Index	*Correlation*	*R^2 value*
WI	-0.204	0.042
NDVI	**-0.694**	**0.482**
rNDVI	**-0.763**	**0.583**
mrNDVI	**-0.715**	**0.511**
SIPI	-0.301	0.090
fWBI	-0.105	0.011
WINDVI	**0.522**	**0.272**
SRI	**-0.604**	**0.364**
mrSRI	**-0.731**	**0.534**
PRI	0.331	0.109
EVI	0.068	0.005
VOGREI1	**-0.756**	**0.572**
VOGREI2	**0.618**	**0.382**
VOGREI3	**0.631**	**0.399**

Table IV: Cross-correlation between spectral indices

Indices	*NDVI*	*rNDVI*	*mrNDVI*	*WINDVI*	*SRI*	*mrSRI*	*VOGREI1*	*VOGREI2*	*VOGREI3*
NDVI	1.000								
rNDVI	0.923	1.000							
mrNDVI	0.911	0.991	1.000						
WINDVI	-0.679	-0.699	-0.688	1.000					
SRI	0.645	0.511	0.451	-0.309	1.000				
mrSRI	0.900	0.990	0.995	-0.678	0.478	1.000			
VOGREI1	0.904	0.971	0.954	-0.652	0.510	0.957	1.000		
VOGREI2	-0.898	-0.911	-0.924	0.538	-0.539	-0.935	-0.891	1.000	
VOGREI3	-0.901	-0.921	-0.932	0.550	-0.540	-0.943	-0.902	1.000	1.000

D. Water Stress Detection

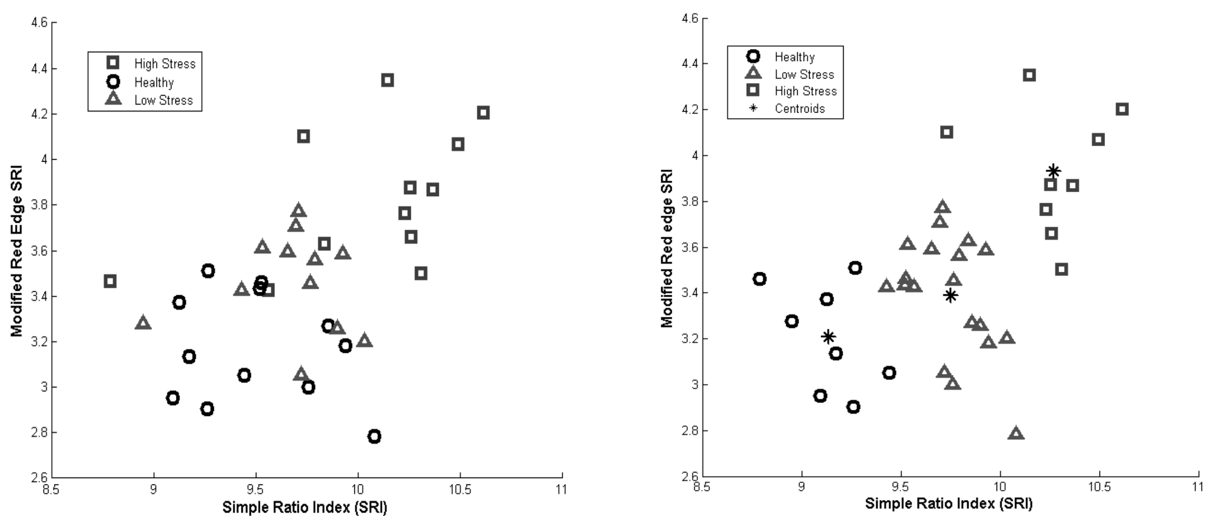
In order to identify spectral indices with least correlation between each other that could represent most variability in reflectance data, principal component analysis was performed on those spectral indices showing good correlation ($|R^2|\geq 0.5$) with soil water content (Table III). The result of principal component analysis is presented in Table V. The first principal component (PC1) explained about 75.3% variability in leaf reflectance. Second principal component (PC2) explained about 24.6% variation in leaf reflectance. Both principal components together represented about 99.8% variability in plant reflectance; therefore these two components were assumed to be enough to represent the differences in leaf reflectance. Most contributing spectral index for each principal component was identified based on the component loadings. Simple Ratio Index (SRI) and Modified Red Edge SRI (mrSRI) were the most contributing indices for PC1 and PC2 respectively.

Table V: Results of principal component analysis on nine spectral indices showing good correlation ($|R^2|\geq0.5$) with soil water content

Principal Component	Percentage Variation (%)	Cumulative Percentage (%)	Contributing Index
PC1	75.3	75.3	Simple Ratio Index (SRI)
PC2	24.6	99.8	Modified Red Edge SRI (mrSRI)

After selecting two spectral indices using principal component analysis, those indices were used for categorizing plants into three groups namely, high stress (Group 1), low stress (Group 2) and healthy (Group 3) groups. Two spectral indices selected from principal component analysis were used as axes to create a scatter plot (Fig. 7a). Square symbol represented high stress plant group whereas triangle and circle represented low stress and healthy plant groups respectively. The scatter plot showed the tendency of plants at certain stress condition to be grouped together, which has a potential to lead to a good clustering accuracy.

K-means clustering was performed using two spectral indices to categorize samples into different soil water content groups. K-means algorithm classified the samples into three clusters and defined a centroid for each cluster (Fig. 7b). Centroid of each cluster is represented by asterisk (*) in Fig. 7b.



a)

b)

Fig. 7 a) Two dimensional scatter plot of plant samples with different soil water content levels plotted in Simple Ratio Index (SRI) and Modified Red Edge SRI axes; b) Clusters of water treatment groups categorized with K-means clustering using SRI and Modified Red Edge SRI

Accuracy of K-means clustering is presented in Table VI. Clustering method was generally effective in classifying the plants into desired groups. Consumer accuracy, which is the percentage of correctly classified data points with regards to all the data points classified as that class, of highly stressed plants (Group 1) was 100%. In other words, all the samples predicted as highly stressed plants actually belonged to that group. Consumer accuracy for Group 2 and 3 were 57.9% and 75.0% respectively. On the other hand, 75% of samples (out of 12 samples) were correctly classified as highly stressed plants. In the remaining 25%, 16.7% (two plants) were classified to low-stress group and one plant was classified to healthy group. Out of 12 samples in low stress group, 11 or 91.7% were correctly classified as low stressed plants whereas only 50% of healthy plants were correctly classified.

Table VI: Results of clustering into treatment groups

		Predicted			
		Group 1	**Group 2**	**Group 3**	**Producers Accuracy (%)**
Actual	**Group 1**	**9**	2	1	75.0%
	Group 2	0	**11**	1	91.7%
	Group 3	0	6	**6**	50.0%
	Consumers Accuracy (%)	100.0%	57.9%	75.0%	

Group 2 and 3 representing low-stress plants and healthy plants were clustered in close proximity, which caused some samples to be incorrectly categorized into another group based on their Euclidean distance from the centroid of each cluster.

However, no plants belonging to low stressed or healthy group were classified as highly stressed group, which shows the obvious distinction of highly stressed plants from the rest. When low-stress and high-stress groups were combined, the clustering method achieved a low false negative (classification of stressed plant to healthy group) of 8.3%, which is highly desirable because failing to apply water to stressed plants would have a substantial adverse effect on yield. At the same time, 21.4% of the plants identified as stressed were actually healthy plants. Even though this is a relatively high error, identifying healthy plants as stressed will have less effect on the final yield because applying some more water to healthy plants (within a specific limit) may not affect yield substantially.

Additional experimental data, and training and testing samples from user will be helpful to refine the model and improve water stress detection accuracy. For practical application, a standalone sensor system can be developed to record the reflectance in only wavelengths necessary to calculate desired spectral indices. Such sensor will have potential to drastically reduce the sensor costs. Manual or automated irrigation controllers can be alerted when a plant water stress threshold is detected so that potato fields can be irrigated to maintain the optimal soil water content.

IV. Conclusion

Reflectance plots of plant leaves at different soil water content showed differences in spectral signature. Spectral indices were calculated from reflectance data and two indices, Simple Ratio Index and Modified Red Edge Simple Ratio Index were selected as the representative spectral indices for detecting water stress. K-means clustering the samples using these spectral indices resulted in 92% accuracy in identifying stressed plants into correct category (8% false negative). The results showed promise for the development of a non-contact sensing system for detecting soil water content and relating that to plant stress levels. Based on the results from this work, field based studies can be carried out to refine and validate the water stress detection model. For practical application, a standalone sensor system can be developed that records the reflectance in only wavelengths necessary to calculate desired spectral indices, which has potential to drastically reduce sensor costs. Manual or automated irrigation controllers can then be alerted when a plant water stress threshold is detected so that potato field can be irrigated to maintain the optimal soil water content.

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