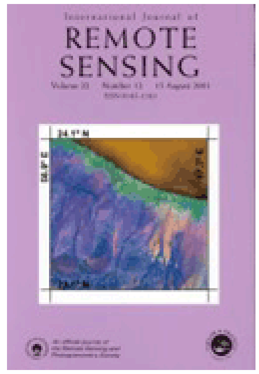

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SWIR-based Spectral Indices for Assessing Nitrogen Content in Potato Fields

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Abstract

Nitrogen (N) is an essential element for plant growth and productivity, and therefore it is a prime fertilizer used in cultivated crops. The amount and timing of N application has economical and environmental implications and consequently it is considered to be an important issue in precision agriculture. Spectral indices, derived from handheld, airborne, and spaceborne spectrometers are used for assessing N content. The majority of these indices are based on indirect indicators, mostly chlorophyll content that is proven to be physiologically linked to nitrogen content. The current research is aimed at exploring the performance of new N spectral indices dependent upon the short wave infrared (SWIR) region (1200 – 2500 nm), and particularly the 1510 nm band since it is directly related to N content. Traditional nitrogen indices and four proposed new SWIR-based indices were implemented on canopy-level spectra data, obtained during two growing seasons in potato experimental plots in the northwest Negev, Israel. Above ground biomass samples were collected at the same location of the spectral sampling, to provide actual N content *in-situ* data. Performance of all indices was evaluated by three methods: correlations between existing and proposed indices and N as well as correlations among the indices themselves; the root mean square error prediction (RMSEP) of N content; and the indices relative sensitivity (Sr) to N content. The results revealed a firm advantage for the proposed SWIR-based indices in the ability to predict N content as well as in showing sensitivity to it. The best index is one that combines information from the 1510 nm and 660 nm but no significant differences were found among the new SWIR-based indices.

Keywords: Spectral indices; SWIR; Nitrogen content; Potato; Nitrogen indices.

1. Introduction

1.1 The role of nitrogen in agricultural crops

Nitrogen (N) is an essential element for plant growth and productivity (Lee et al. 1999, Johnson 2001, Coops et al. 2003, Bonfil et al. 2004, Feng et al. 2008, Lee et al. 2008, Zhu et al. 2008) and is frequently the major limiting factor in agricultural soils (Daughtry et al. 2000). N management of crops has economical and environmental implications (Blackmer et al. 1996, Bonfil et al. 2004). An adequate supply of N to crops is fundamental for optimizing yields (Bonfil et al. 2004, Reyniers et al. 2006, Jain et al. 2007, Feng et al. 2008, Zhu et al. 2008). Fertilizers containing high concentrations of N combined with irrigation or precipitation can result in nitrate (NO_3) waste by leaching or flowing (Daughtry et al. 2000, Kruse et al. 2006) and ultimately low recovery of the applied nitrogen. (Zvomuya et al. 2003). The N loss by leaching and flowing can result in ground and surface water contamination (Levallois et al. 1998, Sripada et al. 2006, Jego et al. 2008, Li et al. 2008) as well as economic losses to the farmer due to the reduction in yields due to N deficiency (Haboudane et al. 2002). On the other hand fertilizers containing low N concentrations can result in inferior yields meaning economic losses (Haboudane et al. 2002). With this dilemma, the optimal solution is N management applied by adequately assessed N status and variability in agricultural landscapes (Bausch and Duke 1996, Haboudane et al. 2002). Implementing N management to a potato field with reduced amounts of N applied at planting resulted in lower leaching, higher N recovery by crops, and improved marketable tuber yield (Errebhi et al. 1998).

1.2 Traditional spectral nitrogen indices

Two specific wavelengths are considered to be related to N content; 850 and 1510 nm. Reflectance at 850 nm was found to be highly correlated with N content at various growing stages of oilseed rape and barley canopies (Behrens et al. 2006). Reflectance at 1510 nm is at a N-H stretch, first overtone, an absorption feature of protein and nitrogen (Curran 1989). The N-H bond is related to the amount of N present in protein (Ferwerda et al. 2005).

Despite using the above single wavelengths, a common method for monitoring N content is by applying spectral *nitrogen indices* (NIs). The term *nitrogen indices* (NIs) is used in this study in order to distinguish it from the general term – *vegetation indices* (VIs) that are widely employed as a measure of green vegetation density, vigor, and productivity. NIs are expected to be robust spectral transformations of two or more spectral bands, at least one of which being directly or indirectly related to N content. The NIs are designed to enhance the nitrogen signal and to allow for reliable spatial and temporal inter-comparisons between the nitrogen content dynamics. The majority of the NIs applied for assessing N content in vegetation are based on indirect indicators, mostly chlorophyll content (Daughtry et al. 2000, Schleicher et al. 2003, Rodriguez et al. 2006). In green vegetation, N and chlorophyll contents are related (Haboudane et al. 2002) since (1) chlorophyll is ~6% N by mass (Asner 2008); (2) the majority of leaf N is contained in chlorophyll molecules (Yoder and Pettigrew-crosby 1995); and (3) ~75% of the total N content of the plant is contained in chloroplasts, mainly in RuBisCO enzyme and chlorophyll binding proteins (Johnson 2001, Rodriguez et al. 2006). Since chlorophyll content is mainly determined by N availability (Bausch and Duke 1996, Martin and Aber 1997, El-Shikha et al. 2008), N shortage will reduce leaf chlorophyll content and consequently the reflectance of the canopy in the visible region (VIS, 400 – 700 nm) will increase (Blackmer et al. 1996, Daughtry et al. 2000).

A common way to construct a spectral index is by differencing reflectance values of two spectral bands that are related to a phenomenon and respond oppositely to changes in its trend. The Normalized Difference Vegetation Index (NDVI) is the most widely used VI for assessing the state and dynamics of vegetation based on a red band at around 660 nm and a reference band from the near infrared (NIR) plateau (700 – 1200 nm) (Rouse et al. 1974). Several NDVI-like indices based on different diagnostic wavelengths were developed for monitoring N. The Normalized Difference Red Edge (NDRE) (Barnes et al. 2000) uses the

NDVI form, but substitutes its bands by a red edge band at 720 nm and a reference band from the NIR plateau at 790 nm:

$$NDRE = \frac{[\rho_{790} - \rho_{720}]}{[\rho_{790} + \rho_{720}]} \tag{1}$$

where ρ is the reflectance value of the corresponding wavelength. The NDRE is indirectly connected to N status since it relies on chlorophyll content that influences the red edge position (Elvidge and Chen 1995). The red edge reflectance line is shifted towards the shorter wavelengths in case of low chlorophyll content, and vice versa for healthy plants. Note that although the red edge is an indirect measure of N content, it was found to be highly correlated to it (Tarpley et al. 2000).

Based on NDRE and NDVI, the Canopy Chlorophyll Content Index (CCCI) is a two dimensional NI developed empirically to infer differences in N status (Barnes et al. 2000):

$$CCCI = \frac{[NDRE - NDRE_{MIN}]}{[NDRE_{MAX} - NDRE_{MIN}]} \tag{2}$$

By scatter plotting NDVI and NDRE the prediction of possible $NDRE_{MIN}$ and $NDRE_{MAX}$ values is performed. The CCCI depends on the indirect relation of NDRE to N while the fractional vegetation cover is obtained by NDVI values. Since the NDVI tends to saturate in dense vegetation (e.g., Buschmann and Nagel 1993), CCCI values might be influenced by false connection to plant variables, e.g., the N content. CCCI was implemented for different crops such as cotton (Barnes et al. 2000, El-Shikha et al. 2008), broccoli (El-Shikha et al. 2007), and wheat (Fitzgerald et al. 2006, Rodriguez et al. 2006, Tilling et al. 2006, Tilling et al. 2007). The CCCI relation to N was affected by water status of cotton and wheat (Barnes et al. 2000, Rodriguez et al. 2006, Tilling et al. 2006, Tilling et al. 2007, El-Shikha et al. 2008). In the case of broccoli the CCCI was sensitive to different N treatments but not to water stress treatment (El-Shikha et al. 2007).

The Normalized Difference Nitrogen Index (NDNI) (Serrano et al. 2002) is a log transformed reflectance NI based on the absorption feature of N at 1510 nm and a reference band at 1680 nm:

$$NDNI = \frac{[\log(1/\rho_{1510}) - \log(1/\rho_{1680})]}{[\log(1/\rho_{1510}) + \log(1/\rho_{1680})]} \quad (3)$$

Both bands are within the shortwave infrared (SWIR) spectral region (1200 – 2500 nm). The NDNI was developed and applied for chaparral vegetation. It was found to be a good estimator of N canopy in low continuous green canopies at the landscape level, and to our knowledge was not applied again.

A more recent study by Fewerda et al. (2005) examined Normalized Ratio Indices (NRIs) of different band combinations for predicting nitrogen content for all wavebands between 350 and 2200 nm in five different species (olive, willow, mopane, grass, and shrubs) and looked for the correlation between these indices and the nitrogen content as well as between species. The study found no specific index with high correlation for all species, however, the authors recommended using the combination of reflectance at 1770 nm and at 693 nm for the best relation to nitrogen content in individual species.

The Modified Chlorophyll Absorption in Reflectance Index (MCARI) was developed by Daughtry et al. (2000):

$$MCARI = [(\rho_{700} - \rho_{670}) - 0.2(\rho_{700} - \rho_{550})](\frac{\rho_{700}}{\rho_{670}}) \quad (4)$$

According to Gitelson and Merzlyak (1998) the range of 530 – 630 nm and the 700 nm are both sensitive to chlorophyll content in higher plant leaves. The 550 nm band matches the minimum chlorophyll absorption in the VIS region (Haboudane et al. 2002). Therefore the MCARI is composed by one chlorophyll absorption band at 670 nm and two bands sensitive to chlorophyll: 550 nm and 700 nm. The MCARI was applied for corn leaf reflectance where the index showed a relatively good sensitivity to leaf chlorophyll (Daughtry et al. 2000) and for cotton canopy where it was correlated quite well with spatial yield variability at late growth stages (Zarco-Tejada et al. 2005b).

The Transformed Chlorophyll Absorption in Reflectance Index (TCARI) was proposed by Haboudane et al. (2002):

$$TCARI = 3[(\rho_{700} - \rho_{670}) - 0.2(\rho_{700} - \rho_{550})(\frac{\rho_{700}}{\rho_{670}})] \quad (5)$$

This index is composed by the same bands as MCARI, with the ratio of 700 nm and 670 nm used to counteract the influence of the background only in the 700 nm and 550 nm difference and not in the 700 nm and 670 nm one. The MCARI was also applied by Haboudane et al. (2002) to show that TCARI is more sensitive to chlorophyll at lower chlorophyll leaf content. They applied TCARI for corn, concluding that while evaluating bare soils and vegetation with low Leaf Area Index (LAI) both MCARI and TCARI could have similar values to these obtained when higher chlorophyll content canopies were examined (Haboudane et al. 2002). By using TCARI, cotton canopy correlated quite well with spatial yield variability at later growth stages (Zarco-Tejada et al. 2005b). Working on barley, Pettersson and Eckersten (2007) successfully predicted grain protein concentration at harvest by a combined model of soil condition, sowing day, fertilization rate and the TCARI at stem elongation growth stage. Measuring potato leaves and canopy, Cohen et al. (2007) found high correlation between TCARI and N-NO_3 petiole in the leaf level for different N treatments, 90 and 100 days after seeding (DAS) but no correlation at all at 50 DAS.

The TCARI and the Optimized Soil-Adjusted Vegetation Index (OSAVI) were combined into one index named TCARI/OSAVI. The OSAVI is similar to the Soil Adjusted Vegetation Index (SAVI; Huete 1988) with a fixed optimized parameter of L=0.16 for improving the reduction of soil effect on the vegetation spectra in the case of aggregated pixels (Rondeaux et al. 1996):

$$TCAVI/OSAVI = \frac{3[(\rho_{700} - \rho_{670}) - 0.2(\rho_{700} - \rho_{550})(\frac{\rho_{700}}{\rho_{670}})]}{[\frac{(1+0.16)(\rho_{800} - \rho_{670})}{(\rho_{800} + \rho_{670} + 0.16)}]} \quad (6)$$

The TCARI/OSAVI was proposed for reducing soil background effect and enhancing the sensitivity to chlorophyll content. Haboudane (2002) applied this index on corn, presenting no sensitivity to LAI varied values while predicting chlorophyll. Hu et al. (2004) successfully predicted chlorophyll content by an airborne sensor, applying TCARI/OSAVI on corn, soybean, and wheat fields. Zarco-Tejada et al (2005a) compared chlorophyll estimation between TCARI/OSAVI and TCARI for vines, concluding that there was an advantage for TCARI in the case of pure vegetation data and an advantage for TCARI/OSAVI in the case of mixed data containing soil and vegetation. Norway spruce needles chlorophyll concentration was found to be highly correlated to TCARI/OSAVI (Lhotakova et al. 2007).

The CCCI as well as the MCARI, TCARI, and TCARI/OSAVI are relatively good chlorophyll indices, each with its limitations and benefits but none of them is directly connected to nitrogen content. The NDNI is a SWIR based vegetation index developed to assess N content by direct connection to an absorption feature. Consequently, there is a need for additional studies on the ability of SWIR-based vegetation indices to represent the N content, specifically indices that apply the N absorption feature at 1510 nm.

1.3 The shortwave infrared spectral region

The number of vegetation indices using the SWIR (1200 – 2500 nm) region is relatively small compared to that of using the visible and near infrared region (VNIR, 400 – 1200 nm). The major reason is the scarce availability of data, due to several traditional and technical reasons. The first is the development of NIR photography and the second is the development of the low cost silicon detectors. The cutoff of the emulsion sensitivity and the quantum efficiency of the silicon detector are around 900 and 1100 nm, respectively (Brew and Neyland 1980, Freden and Grdon 1983, Ciampini et al. 2005). Consequently, the VNIR bands have been available on all satellites, and especially on the earlier spaceborne system such as Landsat-MSS, SPOT-HRV and more (Cyr et al. 1995), while the SWIR bands are available only on more recent spaceborne systems.

Despite the traditional use of the VNIR region for vegetation monitoring, there are several advantages in utilizing the SWIR spectral region (Karnieli et al. 2001, Ben-Ze'ev et al. 2006): (1) the total transmittance in the atmospheric windows within the SWIR region is more than 90%; (2) the soil and vegetation signals at the SWIR atmospheric windows are rather strong; (3) the SWIR region contains many unique absorption features that are not available in the VNIR but are diagnostic for characterizing vegetation and terrestrial rocks and minerals; (4) from the bio-physiological point of view, when the plant is healthy more radiation is absorbed in the red band due to chlorophyll absorption and more radiation is absorbed in the SWIR bands due to water content; (5) soil moisture and self shadow that reduce reflectance in VIS region have similar influences on the SWIR region reflectance; (6) the SWIR wavelengths can penetrate the atmosphere when most common types of aerosols, such as smoke or sulphates (but not dust) are present; and (7) the SWIR region is less affected than the thermal infrared region by Earth's peak emission at about 10 µm.

Employing the SWIR spectral region, sometimes in combination with the VNIR region, has some advantages over using the VNIR region alone since it allows various advanced agricultural and environmental applications (Hardinsky et al. 1983, Ungar and Goward 1983, Rock 1989, Nemani et al. 1993, Dadhwal et al. 1996, Gao 1996, Martin and Aber 1997, Miura et al. 1998, Erasmi and Kappas 2001, Karnieli et al. 2001, Asner and Heidebrecht 2005, Seshadri et al. 2005, Khanna et al. 2007, Pimstein et al. 2007a, Pimstein et al. 2007b). Within the range of 400 to 2500 nm, the SWIR narrow bands, particularly the 1510 nm absorption feature, are considered to be uniquely and directly related to N content in plants (Yoder and Pettigrew-crosby 1995, Ebbers et al. 2002, Ferwerda et al. 2005).

1.4 Objectives and hypotheses

The prime objective of this study is to improve the ability to evaluate N content based on spectral data. For achieving this goal, a number of known NIs, along with new proposed NIs, are compared. The new NIs were created by combining SWIR with VNIR bands that are directly and indirectly related to N. It is important to emphasize that this study involves total N content acquired by the above-ground biomass of potato plants (in contrast to petiole in the leaf, for example).

It is hypothesized that by replacing the 670 nm band, which is indirectly related to N, with the 1510 nm band, which is a direct absorption feature of N, the resulting index will amplify the ability to detect N content in plants.

2. Methodology

2.1 Study area and experimental design

The field work was conducted during two seasons in experiment plots of a potato field in northwest Negev, Israel (31°28'N; 34°41'E, 200 m above mean sea level). N applications were 0, 100, 150, 200, and 300 kg/ha for autumn 2006 and 0, 100, 200, 300, and 400 kg/ha for spring 2007. Each plot was 50 or 100 m long and 18 m wide, each row was a ridge of 1 m width, thus in every plot there were 18 rows. Spectral and biomass samples were acquired as close as possible to the center of each plot. The field was irrigated according to need for healthy development of the crop based on the growers' experience and knowledge.

2.2 Spectral and field data

Field work included reflectance measurements and biomass sampling of the potato plants. The canopy reflectance was obtained by Analytical Spectral Devices (ASD) FieldSpec Pro FR spectrometer with a total spectral range of 350-2500 nm, and 25° field of view. The spectra is sampled at a resolution of 1.4 nm and 2 nm for the VNIR and SWIR regions, respectively and resampled to 5 nm resolution. The spectral measurements were collected +/- 2 hours around solar noon, under clear sky conditions. The ASD was programmed to average automatically 40 spectra per sampling. The sensor was measuring in nadir orientation from 1.5 m above the ground, corresponding to a circular field of view with radius of 0.33 m and area of about 0.35 m^2. As the season progressed and the height of the crop increased, the sensor's distance from the top of the canopy diminished to 0.9-1.3 m corresponding to a field of view with radius of 0.20-0.29 m and area of about 0.13-0.26 m^2. A pressed and smoothed powder of barium sulfate ($BaSO_4$) was used as a white reference (Hatchell 1999).

The above ground biomass samples were collected along a 60 cm line of one ridge at the same place of the spectral measurements. The procedure of determining N content was according to the micro-Kjeldhal method (Jones and Case 1990). In the first season (autumn 2006) the seeding occurred on day of the year (DOY) 275 and there were 4 dates of spectral measurements and biomass sampling on 38, 50, 58, and 78 DAS. In the second season (spring 2007) the seeding occurred on DOY 61 and there were 5 dates of spectral measurements and biomass sampling on 41, 54, 77, 84, and 91 DAS.

2.3 SWIR-based Nitrogen indices

Following the study hypothesis, the 670 nm band in the MCARI, TCARI, and TCARI/OSAVI indices (Eqs. 4, 5, 6) was substituted by the 1510 nm band, proposing the following revised indices:

$$MCARI_{1510} = [(\rho_{700} - \rho_{1510}) - 0.2(\rho_{700} - \rho_{550})](\frac{\rho_{700}}{\rho_{1510}}) \quad (7)$$

$$TCARI_{1510} = 3[(\rho_{700} - \rho_{1510}) - 0.2(\rho_{700} - \rho_{550})(\frac{\rho_{700}}{\rho_{1510}})] \quad (8)$$

$$(TCARI_{1510} / OSAVI_{1510}) = \frac{3[(\rho_{700} - \rho_{1510}) - 0.2(\rho_{700} - \rho_{550})(\frac{\rho_{700}}{\rho_{1510}})]}{[\frac{(1+0.16)(\rho_{800} - \rho_{1510})}{(\rho_{800} + \rho_{1510} + 0.16)}]} \quad (9)$$

In addition, following the NRI concept a new index consisting of the chlorophyll absorption feature (660 nm) and the N absorption feature (1510 nm) bands is proposed:

$$NRI_{1510} = \frac{[\rho_{1510} - \rho_{660}]}{[\rho_{1510} + \rho_{660}]} \tag{10}$$

Although recommended by Ferwerda et al. (2005), since the 1770 nm band reflects the effect of cellulose absorption feature, which is located at 1780 nm and the 693 nm band is related to the red edge, these bands are indirectly connected to N content and therefore the NRI obtained by them is not presented in the current study. However, for the proposed NRI_{1510} the principal is similar with a crucial distinction of applying only wavelengths that are absorption features of chlorophyll and nitrogen at 660 nm and 1510 nm, respectively (Curran 1989). Therefore, the NRI_{1510} is expected to perform better than the first three suggested indices, unless the chlorophyll absorption feature at 660 nm is saturated (Ferwerda et al. 2005).

The research compares the new 1510 nm based NIs to the previously-proposed chlorophyll related NIs. Three out of the four SWIR-based indices are treated as pairs – MCARI vs. $MCARI_{1510}$, TCARI vs. $TCARI_{1510}$, and TCARI/OSAVI vs. $TCARI_{1510}/OSAVI_{1510}$. The prediction and sensitivity abilities of the four SWIR-based indices were also compared to the spectral signal of individual bands at 850 and 1510 nm and other known NIs, as presented in Eqs. 2 and 3.

2.4 Evaluation of the indices performance

Performance of the VNIR-based and SWIR-based NIs was carried out by three measures, namely, correlation between the different indices and N and among the indices themselves, the root mean square error of prediction (RMSEP), and the relative sensitivity (Sr). The RMSEP method provides comparable values among all indices while the Sr enables comparison only between pairs of indices.

2.4.1 Root mean square error of prediction

Randomly chosen 140 samples (out of a total of 220) were used to perform linear regression analysis between the NIs (dependent) and the N content (independent) variables, and determine the calibration parameters of the indices. The remaining 80 samples were used for validation compared to the predicted N contents. The RMSEP was calculated as:

$$RMSEP = \sqrt{\frac{\Sigma(P-O)^2}{N}} \quad (11)$$

Where P is the predicted nitrogen value, O is the observed nitrogen value of the same sample, and N is the number of validation samples (80 in this study).

2.4.2 Relative Sensitivity

The sensitivity of the NIs to N content was obtained by Relative Sensitivity analysis (Sr; Eq. 12) as suggested by Gitelson (2004) in order to compare the performance of two spectral indices (X and Y) with respect to the N content:

$$Sr = \left(\frac{dX}{dY}\right)\left(\frac{\Delta Y}{\Delta X}\right) \quad (12)$$

Where dX and dY are first derivatives of the compared indices under study i.e., the slope of the regression line that holds the N content as the independent variable and the NI as the dependent one. ΔY and ΔX are the ranges of the indices. $Sr > 1$ means that index X is more sensitive (i.e., varies more with variations in N content), $Sr = 1$ means the sensitivities are equal, and $Sr < 1$ means that index Y is more sensitive to N content (Ji and Peters 2007). If higher than one, the larger the value, either positive or negative, the more sensitive is index X to the variable under study. If lower than one the closer the value to zero, either positive or negative, index Y is more sensitive to the variable under study.

3. Results and discussion

3.1 Correlation analysis

Table 1 presents correlation coefficients (R) of all indices versus N and among the indices themselves. Analysis is derived from the entire dataset of 220 samples. Moderate and significant correlations were found between N and the reflectance at individual wavelengths at 850 and 1510 nm and the indices CCCI and NDNI. Very low and insignificant values were observed for the correlations between N and the TCARI, MCARI, and TCARI/OSAVI while CCCI and NDNI produced moderate and significant correlations. The highest correlations (R = 0.72-0.75) were found between N and the SWIR-based NIs $TCARI_{1510}$, $MCARI_{1510}$, $TCARI_{1510}/OSAVI_{1510}$, and NRI_{1510}. Intercorrelation among the indices highlights two groups that are highly correlated. The first is the VNIR-based NIs - TCARI, MCARI, and TCARI/OSAVI, and the second is the SWIR-based NIs - $TCARI_{1510}$, $MCARI_{1510}$, $TCARI_{1510}/OSAVI_{1510}$, and NRI_{1510}. It is worth mentioning that there are low and very low correlation values between the indices of these two NIs groups.

3.2 Root mean square error of prediction

Table 2 presents the relationships between the predicted versus observed N content for the individual wavelengths and NIs, along with their corresponding coefficient of determination (R^2), significance, and the RMSEP values. Figure 1 illustrates the comparison between several pairs of these indices. Note that the four SWIR-based NIs ($TCARI_{1510,}$ $MCARI_{1510}$, $TCARI_{1510}/OSAVI_{1510}$, and NRI_{1510}) are the best predictors of N content. Specifically, the first three of these NIs ($TCARI_{1510,}$ $MCARI_{1510}$, and $TCARI_{1510}/OSAVI_{1510}$,) perform better than their corresponding VNIR-based NIs. ρ_{1510} and NDNI have higher R^2 values and lower RMSEP values than the NIs with no SWIR component, therefore confirming that the 1510 nm absorption band relates well to N content. The SWIR-based NIs can predict N content in a range that is similar to the measured N content and provide significant and higher R^2 values than the VNIR-based NIs.

3.3 Relative sensitivity

A preliminary step in obtaining relative sensitivity values is to correlate each index to N content as presented in Table 1. Figure 2 illustrates the correlation of the three SWIR-based NIs in comparison to their corresponding VNIR-based indices and the NRI_{1510}. The figure demonstrates the advantage of the SWIR-based NIs over the VNIR-based NIs.

The relative sensitivity values among all NIs are presented in Table 3. Negative values should be considered as absolute values, the minus presents the difference in the direction of the relationship between the indices to N. As hypothesized, the four SWIR-based NIs are more sensitive to N content than the VNIR-based NIs. Furthermore, these indices are more sensitive than ρ_{1510} and NDNI. Sr values around zero, showing extreme advantage in sensitivity to the X indices, were obtained when each of the four SWIR-based NIs was compared to MCARI, TCARI, and TCARI/OSAVI. In each of these 12 cases the SWIR-based NIs were more sensitive. For example, the relative sensitivity values to N of TCARI vs. $TCARI_{1510}$, $MCARI_{1510}$, $TCARI_{1510}/OSAVI_{1510}$, and NRI_{1510} are -0.12, -0.11, -0.13, and 0.01, respectively. The ρ_{1510} is more sensitive than the other NIs (except the four new SWIR-based NIs) expressing the advantage of the N absorption feature. The Sr values of the four new SWIR-based NIs among themselves present no absolute advantage for each of them since the values are relatively close to one when compared to the other Sr values presented in this study.

4. Summary and conclusions

Three methods for evaluating and comparing indices' performance demonstrate unequivocal advantages of the four proposed SWIR-based NIs. These indices combine direct and indirect relations to N content, meaning combining actual presence of N in the plant and repercussions of it. The four new SWIR-based

NIs are higher correlated, better predictors of N content, and more sensitive to it than the other NIs examined in this study. These findings support the hypothesis of amplifying the N predicting ability of NIs combining direct and indirect relations to N content as well as reinforcing the sensitivity of the four new SWIR-based indices to N content. In addition, the NRI_{1510} also presents the advantage of combining N and chlorophyll absorption features. Among the four new SWIR-based NIs there is no one with apparent absolute advantage over the others.

The VNIR and SWIR spectral regions have similar properties (e.g., relation to the plant condition). Therefore without previous knowledge concerning the SWIR band that was selected for the new SWIR-based NIs it can be expected that the new SWIR-based NIs will perform similarly to the VNIR-based NIs. It was also acceptable to assume that the new SWIR-based NIs would perform better since the SWIR region is less affected by the atmosphere. Therefore a portion, with unknown weight, of the SWIR-based NIs advantage over the VNIR-based NIs can be related to the SWIR spectral region properties and not to the combination of direct and indirect relation to N content.

Cohen et al. (2007) conducted a parallel study on relationships between spectral data in leaf and canopy levels and N-NO_3 petiole content of potato in the same experimental plot as the current study. Their study results present high correlation between TCARI and N-NO_3 petiole content in the leaf level. Some possible reasons for the differences in performance of TCARI between the studies were that first, the TCARI in the study of Cohen et al. (2007) was calibrated by N-NO_3 petiole content but in the current study it was calibrated by the above ground biomass N content; secondly, Cohen et al. (2007) study presents specific dates and treatments of high correlation between TCARI and N-NO_3 petiole content of one growing season while the current study engages the whole data of two growing seasons as one database; thirdly, the high correlation values between TCARI and N-NO_3 petiole content for the spectrometer data are obtained for 90 and 100 DAS in Cohen et al. (2007) while in the current study only one date of measurements corresponds to these growing stages; fourthly, the spectral resolution was 10 – 25 nm for hyperspectral images and 1.5 nm for a portable spectrometer in Cohen et al. (2007) vs. 5 nm for a different portable spectrometer in the current study. Furthermore, the canopy level can simulate, up to a point, the mix of elements (e.g., leaves, stems, soil), the bidirectional reflectance distribution function (BRDF) influences (e.g., wind, sun and sensor angles), and the atmospheric impact as observed by an air/spaceborne sensor.

Since the best index in this study was NRI_{1510}, the one that combines information from the 1510 nm and 660 nm it is suggested to use these bands and/or index for further research and application. It should be noted that this study was limited to autumn and spring potato crops in the northern Negev, Israel. Therefore, the proposed use of the SWIR-based NIs or the concept of combining direct and indirect relation to N content requires further study under different environmental and geographical conditions and of specific growth stages, as well as other crops.

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Table 1: Correlation matrix (R) of nitrogen content (N), individual wavelengths, and nitrogen indices. Note high correlations within the VNIR-based indices and the SWIR-based indices groups, but no correlations between indices of these two groups. Italic numbers indicate no significant correlation ($P > 0.05$).

	N (%)	ρ_{850}	ρ_{1510}	**CCCI**	**NDNI**	**TCARI**	**MCARI**	**TCARI/ OSAVI**	**TCARI$_{1510}$**	**MCARI$_{1510}$**	**TCAR$_{1510}$/ OSAVI$_{1510}$**	**NRI$_{1510}$**
N (%)	1											
ρ_{850}	0.37	1										
ρ_{1510}	0.52	0.57	1									
CCCI	0.28	0.26	-0.25	1								
NDNI	0.46	0.86	0.53	0.18	1							
TCARI	*0.12*	0.70	0.65	-0.47	0.64	1						
MCARI	*0.03*	0.66	0.42	-0.38	0.58	0.90	1					
TCARI/ OSAVI	*-0.05*	0.41	0.60	-0.74	0.37	0.92	0.78	1				
TCARI$_{1510}$	-0.72	-0.30	-0.66	-0.36	-0.37	*0.01*	0.15	0.16	1			
MCARI$_{1510}$	-0.75	-0.32	-0.61	-0.43	-0.36	*0.04*	0.16	0.22	0.97	1		
TCAR$_{1510}$/ OSAVI$_{1510}$	-0.72	-0.34	-0.66	-0.39	-0.40	*0.00*	*0.12*	0.17	0.99	0.97	1	
NRI$_{1510}$	0.75	0.55	0.56	0.47	0.60	0.16	0.17	-0.12	-0.87	-0.89	-0.89	1

Table 2: Relations between observed (N_O) and predicted (N_P) nitrogen content by spectral nitrogen indices and individual wavelengths. The root mean square error of prediction (RMSEP) values are in units of N content (%). Italic values indicate no significant correlation (P > 0.05).

Individual bands and indices	Regression	R^2	Significance	RMSEP
ρ_{850}	$N_P = 2.78 + 0.12N_O$	0.14	P<0.005	0.607
ρ_{1510}	$N_P = 2.33 + 0.25N_O$	0.19	P<0.005	0.595
CCCI	$N_P = 2.94 + 0.08N_O$	0.16	P<0.005	0.614
NDNI	$N_P = 2.62 + 0.18N_O$	0.23	P<0.005	0.578
TCARI	*$N_P = 3.15 + 0.002N_O$*	*0.0001*	*P>0.05*	*0.662*
MCARI	*$N_P = 3.18 - 0.003N_O$*	*0.002*	*P>0.05*	*0.658*
TCARI/OSAVI	*$N_P = 3.18 - 0.002N_O$*	*0.03*	*P>0.05*	*0.656*
$TCARI_{1510}$	$N_P = 1.42 + 0.55N_O$	0.49	P<0.005	0.474
$MCARI_{1510}$	$N_P = 1.26 + 0.6N_O$	0.54	P<0.005	0.488
$TCARI_{1510}/OSAVI_{1510}$	$N_P = 1.47 + 0.54N_O$	0.49	P<0.005	0.471
NRI_{1510}	$N_P = 1.38 + 0.57N_O$	0.59	P<0.005	0.421

Table 3: Relative sensitivity (Sr) values of individual wavelengths and coupled spectral indices with respect to N content. If Sr < 1, the index or wavelength in the X line is more sensitive to N content; if Sr > 1, the index or wavelength in the Y column is more sensitive to N content; and if Sr = 1 the sensitivity of the compared indices and wavelengths is equal.

		Y										
		ρ_{850}	ρ_{1510}	CCCI	NDNI	TCARI	MCARI	TCARI/ OSAVI	$TCARI_{1510}$	$MCARI_{1510}$	$TCARI_{1510}$/ $OSAVI_{1510}$	NRI_{1510}
X	ρ_{850}	1										
	ρ_{1510}	0.69	1									
	CCCI	1.22	1.76	1								
	NDNI	1.10	1.58	0.90	1							
	TCARI	4.05	5.86	3.32	3.70	1						
	MCARI	12.06	17.43	9.89	11.00	2.98	1					
	TCARI/ OSAVI	-10.32	-14.92	-8.47	-9.41	-2.55	-0.86	1				
	$TCARI_{1510}$	-0.47	-0.68	-0.39	-0.43	-0.12	-0.04	0.05	1			
	$MCARI_{1510}$	-0.43	-0.63	-0.35	-0.39	-0.11	-0.04	0.04	0.91	1		
	$TCARI_{1510}$/ $OSAVI_{1510}$	-0.52	-0.75	-0.42	-0.47	-0.13	-0.04	0.05	1.09	1.19	1	
	NRI_{1510}	0.47	0.68	0.39	0.43	0.01	0.04	-0.05	-1.00	-1.10	-0.92	1

Figure 1: Predicted versus observed N content computed by NIs. (A) MCARI vs. $MCARI_{1510}$; (B) TCARI vs. $TCARI_{1510}$; (C) TCARI/OSAVI vs. $TCARI_{1510}/OSAVI_{1510}$; (D) NRI_{1510}. Note that the SWIR-based spectral nitrogen indices perform better than the corresponding indices. NRI_{1510} produces the best results.

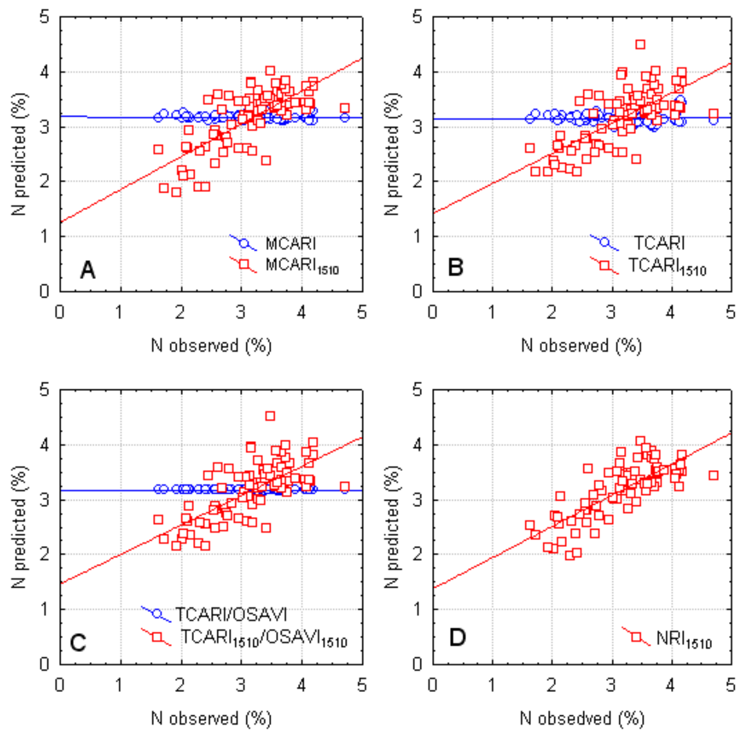

Figure 2: Correlating VNIR-based and SWIR-based NIs to N content. (A) MCARI vs. $MCARI_{1510}$; (B) TCARI vs. $TCARI_{1510}$; (C) TCARI/OSAVI vs. $TCARI_{1510}/OSAVI_{1510}$; (D) NRI_{1510}. Note that the SWIR-based spectral indices perform better than the corresponding indices.