International Journal of Remote Sensing
Vol. 31, No. 19, 10 September 2010, 5127–5143

SWIR-based spectral indices for assessing nitrogen content in potato fields

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(*Received 15 November 2008; in final form 30 January 2009*)

Nitrogen (N) is an essential element in plant growth and productivity, and N fertilizer is therefore of prime importance in cultivated crops. The amount and timing of N application has economic and environmental implications and is consequently 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, which is proven to be physiologically linked to N content. The current research aimed to explore the performance of new N spectral indices dependent upon the shortwave infrared (SWIR) region (1200–2500 nm), and particularly the 1510 nm band because it is related directly to N content. Traditional nitrogen indices (NIs) and four proposed new SWIR-based indices were tested with canopy-level spectral 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 *in-situ* N content data. The performance of all indices was evaluated by three methods: (1) correlations between the existing and proposed indices and N as well as correlations among the indices themselves; (2) the root mean square error prediction (RMSEP) of the N content; and (3) the indices relative sensitivity (S_r) to the N content. The results reveal a firm advantage for the proposed SWIR-based indices in their ability to predict, and in their sensitivity to, N content. The best index is one that combines information from the 1510 and 660 nm bands but no significant differences were found among the new SWIR-based indices.

1. Introduction

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

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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 N (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). However, fertilizers containing low N concentrations can result in inferior yields and 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).

Two specific wavelengths are considered to be related to N content: 850 and 1510 nm. Reflectance at 850 nm (ρ_{850}) 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 (ρ_{1510}) is at a N–hydrogen (H) stretch, first overtone, an absorption feature of protein and N (Curran 1989). The N–H bond is related to the amount of N present in protein (Ferwerda *et al.* 2005). Rather than using these single wavelengths, the common method for monitoring N content is by applying spectral nitrogen indices (NIs). The term NIs is used in this study to distinguish it from the general term vegetation indices (VIs), which are widely used as a measure of green vegetation density, vigour and productivity. NIs are expected to be robust spectral transformations of two or more spectral bands, at least one of which is directly or indirectly related to N content. The NIs are designed to enhance the N signal and to allow for reliable spatial and temporal intercomparisons between the N 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) because (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 the enzyme RuBisCO and in chlorophyll-binding proteins (Johnson 2001, Rodriguez *et al.* 2006). As 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 have been 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:

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

where ρ is the reflectance value of the corresponding wavelength. The NDRE is indirectly connected to N status because it relies on chlorophyll content, which influences the red edge position (Elvidge and Chen 1995). The red edge reflectance line is shifted towards shorter wavelengths in the 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 the 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):

$$\mathrm{CCCI} = \frac{[(\mathrm{NDRE}) - (\mathrm{NDRE})_{\mathrm{MIN}}]}{[(\mathrm{NDRE})_{\mathrm{MAX}} - (\mathrm{NDRE})_{\mathrm{MIN}}]} \tag{2}$$

By scatter plotting NDVI and NDRE, the prediction of possible $\mathrm{NDRE}_{\mathrm{MIN}}$ and $\mathrm{NDRE}_{\mathrm{MAX}}$ values is performed. The CCCI depends on the indirect relationship between NDRE and N while the fractional vegetation cover is obtained by NDVI values. As 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, for example the N content. The CCCI has been implemented for various crops, including 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, 2007). The CCCI relationship to N was affected by the water status of cotton and wheat (Barnes *et al.* 2000, Rodriguez *et al.* 2006, Tilling *et al.* 2006, 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 $\log_{10}$ transformed reflectance NI based on the absorption feature of N at 1510 nm and a reference band at 1680 nm:

$$\mathrm{NDNI} = \frac{[\log_{10}(1/\rho_{1510}) - \log_{10}(1/\rho_{1680})]}{[\log_{10}(1/\rho_{1510}) + \log_{10}(1/\rho_{1680})]} \tag{3}$$

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 has not been applied again.

A more recent study by Ferwerda *et al.* (2005) examined Normalized Ratio Indices (NRIs) of different band combinations for predicting N 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 N 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 and at 693 nm for the best correlation to N content in individual species.

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

$$\mathrm{MCARI} = [(\rho_{700} - \rho_{670}) - 0.2(\rho_{700} - \rho_{550})]\left(\frac{\rho_{700}}{\rho_{670}}\right) \tag{4}$$

According to Gitelson and Merzlyak (1998), the 530–630 nm range and the 700 nm band 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 of one chlorophyll absorption band at 670 nm and two bands sensitive to chlorophyll: 550 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 fairly 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):

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

This index is composed of the same bands as MCARI, with the ratio of 700 and 670 nm used to counteract the influence of the background only in the 700 and 550 nm difference and not in the 700 and 670 nm one. The MCARI was also applied by Haboudane *et al.* (2002) to show that the TCARI is more sensitive to chlorophyll at lower chlorophyll leaf content. They applied the 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 the TCARI, the cotton canopy correlated reasonably 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 a 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 50 DAS.

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

$$\mathrm{TCARI/OSAVI} = \frac{3\left[(\rho_{700} - \rho_{670}) - 0.2(\rho_{700} - \rho_{550})\left(\frac{\rho_{700}}{\rho_{670}}\right)\right]}{\left[\frac{(1+L)\,(\rho_{800} - \rho_{670})}{(\rho_{800} + \rho_{670} + L)}\right]} \quad (6)$$

The TCARI/OSAVI was proposed for reducing the 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. Chlorophyll concentration in Norway spruce needles 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 N content. The NDNI is an SWIR-based VI 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 VIs to represent the N content, specifically indices that apply the N absorption feature at 1510 nm.

The number of VIs using the SWIR (1200–2500 nm) region is relatively small compared to those using the visible and near-infrared region (VNIR, 400–1200 nm). The major reason is the scarce availability of data for several traditional and technical reasons, including the development of NIR photography and low-cost silicon detectors. The cut-off 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 Gordon 1983, Ciampini *et al.* 2005). Consequently, the VNIR bands have been available on all satellites, and especially on the earlier spaceborne systems such as Landsat-Multi-Spectral Scanner (MSS) and Satellite Pour l'Observation de la Terre-High Resolution Visible (SPOT-HRV) (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 using 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 fairly 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 a 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 the water content; (5) soil moisture and self shadow that reduce reflectance in the 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 sulfates (but not dust) are present; and (7) the SWIR region is less affected than the thermal infrared region by the Earth's peak emission at around 10 μm.

Use of the SWIR spectral region, sometimes in combination with the VNIR region, has some advantages over using the VNIR region alone because it allows various advanced agricultural and environmental applications (Hardinsky *et al.* 1983, Ungar and Goward 1983, Hunt and 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,b). Within the range 400–2500 nm, the SWIR narrow bands, and 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).

The main aim of the present study was to improve the ability to evaluate N content based on spectral data, by comparing several known NIs with newly proposed NIs. The new NIs were created by combining the SWIR with the VNIR bands that are directly and indirectly related to N. It is important to emphasize that this study involved total N content acquired by the above-ground biomass of potato plants (in contrast to petiole in the leaf, for example). We 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 would increase the ability to detect N content in plants.

2. Methodology

2.1 *Study area and experimental design*

The fieldwork 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). For maximizing N content variability, the N applications were 0, 100, 150, 200 and 300 kg ha^{-1} for autumn 2006 and 0, 100, 200, 300 and 400 kg ha^{-1} 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 centre of each plot. The field was irrigated according to the need for healthy development of the crop based on the growers' experience and knowledge.

2.2 *Spectral and field data*

Fieldwork included reflectance measurements and biomass sampling of the potato plants. The canopy reflectance was obtained by using an Analytical Spectral Devices (ASD Boulder, CO) FieldSpec Pro FR spectrometer with a total spectral range of 350–2500 nm, and 25° field of view (FOV). The spectra is sampled according to the spectrometer properties at a resolution of 1.4 nm and 2 nm for the VNIR and SWIR regions, respectively, and both regions resampled to 5 nm resolution. The spectral measurements were collected ±2 h 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 FOV with a radius of 0.33 m and an 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 FOV with a radius of 0.20–0.29 m and an 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 four 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 five dates of spectral measurements and biomass sampling on 41, 54, 77, 84 and 91 DAS.

2.3 *SWIR-based NIs*

Following the study hypothesis, the 670 nm band in the MCARI, TCARI and TCARI/OSAVI indices (equations (4)–(6)) was substituted by the 1510 nm band, resulting in the following revised indices:

$$\mathrm{MCARI}_{1510} = [(\rho_{700} - \rho_{1510}) - 0.2\,(\rho_{700} - \rho_{550})]\left(\frac{\rho_{700}}{\rho_{1510}}\right) \tag{7}$$

$$\mathrm{TCARI}_{1510} = 3\left[(\rho_{700} - \rho_{1510}) - 0.2\,(\rho_{700} - \rho_{550})\left(\frac{\rho_{700}}{\rho_{1510}}\right)\right] \tag{8}$$

$$\mathrm{TCARI}_{1510}/\mathrm{OSAVI}_{1510} = \frac{3\left[(\rho_{700} - \rho_{1510}) - 0.2(\rho_{700} - \rho_{550})\left(\frac{\rho_{700}}{\rho_{1510}}\right)\right]}{\left[\frac{(1 + L)\,(\rho_{800} - \rho_{1510})}{(\rho_{800} + \rho_{1510} + L)}\right]} \tag{9}$$

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:

$$\mathrm{NRI}_{1510} = \frac{[\rho_{1510} - \rho_{660}]}{[\rho_{1510} + \rho_{660}]} \tag{10}$$

Although recommended by Ferwerda *et al.* (2005), the 1770 nm band reflects the effect of the 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 principle is similar with the important distinction of applying only wavelengths that are absorption features of chlorophyll and N 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 current study 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. $\mathrm{TCARI}_{1510}/\mathrm{OSAVI}_{1510}$. 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 equations (2) and (3).

2.4 *Evaluation of the performance of the indices*

The performance of the VNIR-based and SWIR-based NIs was carried out by three measures: (1) correlation between the different indices and N and among the indices themselves, (2) the root mean square error of prediction (RMSEP), and (3) the relative sensitivity (S_r). The RMSEP method provides comparable values among all indices while the S_r enables comparison only between pairs of indices.

2.4.1 RMSEP. The data set of 220 samples was randomly sorted by applying the Office-Excel software ‘random number generation’. The first 140 randomly sorted samples, out of 220, were used to perform a 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 content. The RMSEP was calculated as:

$$\mathrm{RMSEP} = \sqrt{\frac{\Sigma\,(\mathrm{N_P} - \mathrm{N_O})^2}{n}} \tag{11}$$

where $\mathrm{N_P}$ is the predicted N content, $\mathrm{N_O}$ is the observed N content 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 S_r (equation (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:

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

where dX and dY are first derivatives of the compared indices under study, that is the slope of the regression line that holds the N content as the independent variable and the NI as the dependent variable. ΔY and ΔX are the ranges of the indices. $S_r > 1$ means that index X is more sensitive (i.e. varies more with variations in N content), $S_r = 1$ means the sensitivities are equal, and $S_r < 1$ means that index Y is more sensitive to N content (Ji and Peters 2007). If $S_r > 1$, the larger the value, either positive or negative, the more sensitive is index X to the variable under study. If $S_r < 1$, 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 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 content and ρ_{850}, ρ_{1510} 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 NI groups.

3.2 *RMSEP*

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 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 S_r 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 S_r 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

Table 1. *R* value matrix of N content, individual wavelengths, VIs and NIs. Note the high correlations within the VNIR-based indices and the SWIR-based indices groups, but no correlations between the indices of these two groups.

	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		
$TCARI_{1510}$/ $OSAVI_{1510}$	–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. Relationships between N_O and N_P by VIs, NIs and individual wavelengths.

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

relationship between the indices to N. As hypothesized, the four SWIR-based NIs are

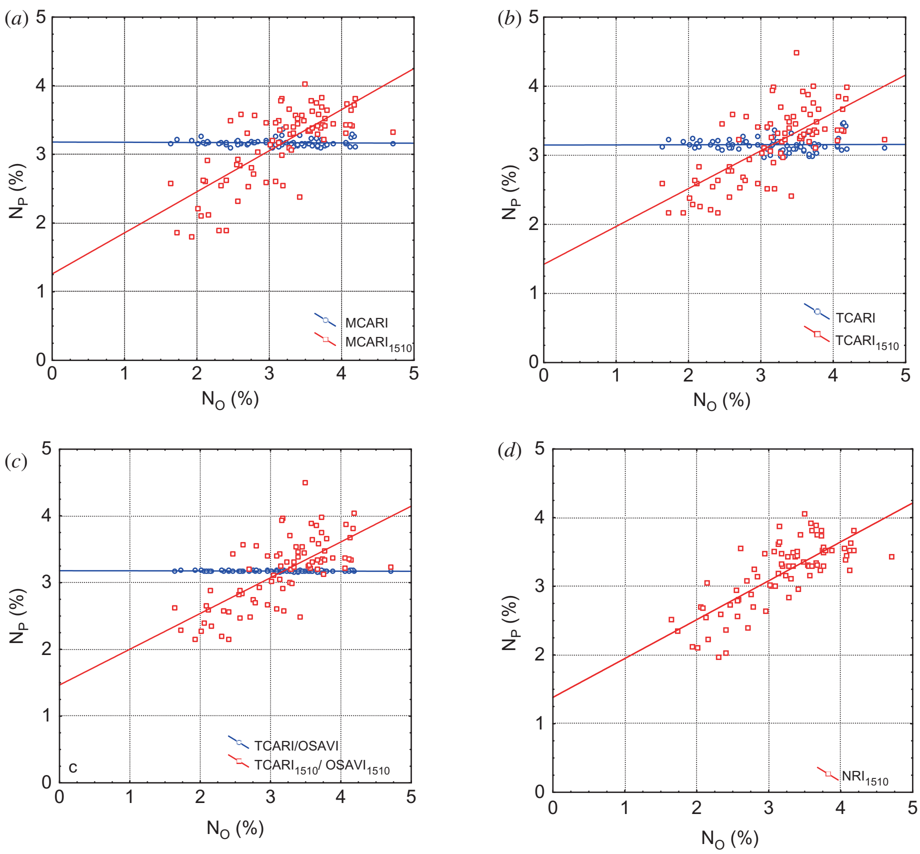

Figure 1. Predicted N content (N_P) vs. observed (N_O) computed by NIs. (*a*) MCARI vs. $MCARI_{1510}$; (*b*) TCARI vs. $TCARI_{1510}$; (*c*) TCARI/OSAVI vs. $TCARI_{1510}/OSAVI_{1510}$; (*d*) NRI_{1510}. Note that the SWIR-based spectral NIs perform better than the corresponding indices. NRI_{1510} produces the best results.

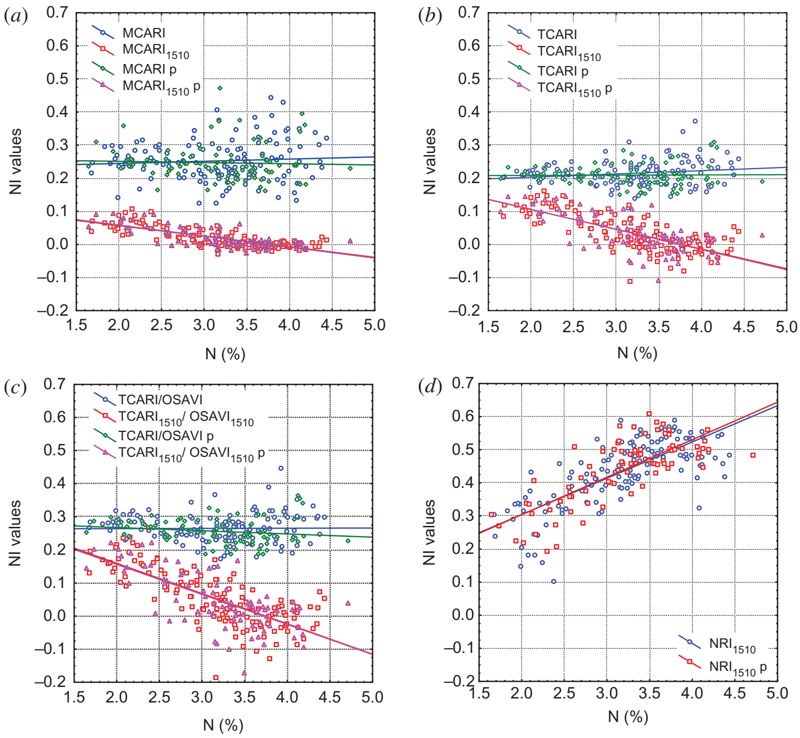

Figure 2. Correlating VNIR-based and SWIR-based NIs to N content. (*a*) MCARI vs. MCARI_{1510}; (*b*) TCARI vs. TCARI_{1510}; (*c*) TCARI/OSAVI vs. $\mathrm{TCARI}_{1510}/\mathrm{OSAVI}_{1510}$; (*d*) NRI_{1510}. Each NI dataset is divided to two parts, the points randomly chosen for the calibration set (140) and the validation set (80). The suffix p, in the legend, stands for the validation points. Note that the SWIR-based spectral indices perform better than the corresponding indices and there is a strong similarity in the linear correlation between the calibration and validation sets of each NI.

more sensitive to N content than the VNIR-based NIs. Furthermore, these indices are more sensitive than ρ_{1510} and NDNI. S_r 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 S_r values to N of TCARI vs. TCARI_{1510}, MCARI_{1510}, $\mathrm{TCARI}_{1510}/\mathrm{OSAVI}_{1510}$ 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), demonstrating the advantage of the N absorption feature. The S_r values of the four new SWIR-based NIs among themselves present no absolute advantage for each of them because the values are relatively close to one when compared to the other S_r values presented in this study.

4. Summary and conclusions

Three methods for evaluating and comparing the performance of the indices demonstrate the unequivocal advantages of the four proposed SWIR-based NIs. These indices combine direct and indirect associations with N content, combining the presence of N in the plant and its repercussions. The four new SWIR-based NIs are

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

	Y										
X	ρ_{850}	ρ_{1510}	CCCI	NDNI	TCARI	MCARI	TCARI/ OSAVI	$TCARI_{1510}$	$MCARI_{1510}$	$TCARI_{1510}$/ $OSAVI_{1510}$	NRI_{1510}
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

correlated higher, and are better predictors of and more sensitive to N content, than the other NIs examined in this study. These findings support the hypothesis of amplifying the N predicting ability of NIs by combining direct and indirect relationships to N content as well as reinforcing the sensitivity of the four new SWIR-based indices to N content. In addition, the NRI_{1510} presents the advantage of combining N and chlorophyll absorption features. Among the four new SWIR-based NIs, none show an apparent absolute advantage over the others.

The VNIR and SWIR spectral regions have similar properties (e.g. relationship 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 because the SWIR region is less affected by the atmosphere. Therefore, a portion, with unknown weight, of the advantage of the SWIR-based NIs over the VNIR-based NIs can be related to the SWIR spectral region properties and not to the combination of direct and indirect associations with the N content.

Cohen *et al.* (2007) conducted a parallel study on the 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 are that: first, the TCARI in Cohen *et al.*'s study was calibrated by the N–NO_3 petiole content whereas in the current study it was calibrated by the above-ground biomass N content; second, Cohen *et al.* (2007) present specific dates and treatments of the high correlation between TCARI and N–NO_3 petiole content of one growing season while the current study engages the whole data from two growing seasons as one database; third, the high correlation values between the 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; and fourth, the spectral resolution was 10–25 nm for the hyperspectral images and 1.5 nm for a portable spectrometer in Cohen *et al.* (2007) versus 5 nm for a different portable spectrometer in the current study. Other differences between the studies include the fact that the canopy level can simulate, up to a point, the mix of elements (e.g. leaves, stems, soil), the influences of the bidirectional reflectance distribution function (BRDF) (e.g. wind, sun and sensor angles), and the atmospheric impact as observed by an air/spaceborne sensor.

As the best index in this study was NRI_{1510}, the one that combines information from the 1510 and 660 nm bands, we suggest that these bands and/or the index should be used for further research and applications. 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 indices that are directly and indirectly related to N content requires further study under different environmental and geographical conditions and of specific growth stages, as well as other crops.

Acknowledgements

This project was supported by the Israeli Space Agency, the Israeli Ministry of Science and also by Research Grant Award No. CA-9102-06 from BARD-AAFC, The United States–Israel Binational Agricultural Research and Development Fund. The field experiments could not have been made without the collaboration of Gadi Hadar and Ran Ferdman, the potato farmers of Kibbutz Ruhama, and Yossi Sofer from Haifa Chemicals.

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