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Hyperspectral aerial imagery for detecting nitrogen stress in two potato cultivars

Tyler J. Nigon [a,*], David J. Mulla [a], Carl J. Rosen [a], Yafit Cohen [b], Victor Alchanatis [b], Joseph Knight [c], Ronit Rud [b]

[a] Department of Soil, Water, and Climate, University of Minnesota, St. Paul, MN, USA
[b] Institute of Agricultural Engineering, Agricultural Research Organization (ARO), Volcani Center, Bet-Dagan, Israel
[c] Department of Forest Resources, University of Minnesota, St. Paul, MN, USA

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ABSTRACT

To use remotely sensed spectral data for determining rates and timing of variable rate nitrogen (N) applications at a commercial scale, the most reliable indicators of crop N status must be determined. This study evaluated the ability of hyperspectral remote sensing to predict N stress in potatoes (*Solanum tuberosum*) during two growing seasons (2010 and 2011). Spectral data were evaluated using ground based measurements of leaf N concentration. Two canopy-scale hyperspectral images were acquired with an AISA-Eagle hyperspectral camera in both years. The experiment included five N treatments with varying rates and timing of N fertilizer and two potato cultivars, Russet Burbank (RB) and Alpine Russet (AR). Partial Least Squares regression (PLS) models resulted in the best prediction of leaf N concentration ($r^2 = 0.79$, Root Mean Square Error of Cross Validation (RMSECV) = 14% across dates for RB; $r^2 = 0.77$, RMSECV = 13% across dates for AR). Applying the Nitrogen Sufficiency Index (NSI) formula to spectral indices/models made them mostly insensitive to the effects of cultivar. The most promising technique for determining N stress in potato based on spectral indices was found to be the MERIS Terrestrial Chlorophyll Index (MTCI) due to a combination of relatively high r^2 values, lower RMSECVs, and high accuracy assessment. Pairwise comparison tests from the means separation showed that spectral indices/models from the imagery resulted in more statistically significant groupings of crop stress levels for the spectra than leaf N concentration because canopy-scale spectral data are affected by both tissue N concentration and biomass. The results of this study suggest that upon proper sensor calibration, canopy-scale spectral data may be the most sensitive tool available to detect N status of a potato crop.

1. Introduction

Potato (*Solanum tuberosum* L.) is an important crop worldwide, ranking first in 2010 among all other non-cereal food crops with over 324 million Mg produced (FAOSTAT, 2010). The coarse-textured soils typically used for irrigated potato production are relatively low in organic matter and cation exchange capacity, and therefore, are generally low in soil nutrient reserves. Potato plants are relatively shallow rooted compared to other field crops and are sensitive to nitrogen (N) and water stress (Bailey, 2000; Lesczynski and Tanner, 1976). Previous studies have shown that only about one-third to one-half of applied N is recovered in years of moderate to heavy leaching (Errebhi et al., 1998; Waddell et al., 2000). Therefore, precise N management is important for irrigated potatoes to optimize production and to minimize environmental N losses.

Abbreviations: MTCI, MERIS Terrestrial Chlorophyll Index; NUE, Nitrogen Use Efficiency; NO_3-N, Nitrate-Nitrogen; NH_4-N, Ammonium-Nitrogen; LAI, Leaf Area Index; NSI, Nitrogen Sufficiency Index; S, Surfactant; AISA, Airborne Imaging Spectrometer for Applications; CALMIT, Center for Advanced land Management Information Technologies; DAE, Days After Emergence; NIR, Near Infrared; PLS, Partial Least Squares Regression; LV, Latent Variables; PRESS, Predicted Residual Sum of Squares; ROI, Region of Interest; ANOVA, Analysis of Variance; RMSECV, Root Mean Square Error of Cross Validation; NG, Normalized Green; CV, Coefficient of Variation; RF, Relative Fluctuation; NDVI, Normalized Difference Vegetation Index; DCNI, Double-peak Canopy Nitrogen Index; NDI2, Normalized Difference Index 2; NNI, Nitrogen Nutrition Index; SR8, Simple Ratio 8.

* Corresponding author at: 111 Marquette Avenue, Apartment 1709, Minneapolis, MN 55401, USA. Tel.: +1 715 937 2942.

E-mail addresses: nigo0024@umn.edu (T.J. Nigon), mulla003@umn.edu (D.J. Mulla), rosen006@umn.edu (C.J. Rosen), yafitush@volcani.agri.gov.il (Y. Cohen), victor@volcani.agri.gov.il (V. Alchanatis), jknight@umn.edu (J. Knight), ronit@volcani.agri.gov.il (R. Rud).

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Matching the timing and rate of N fertilizer with the N needs of the crop during different growth stages is a strategy used to increase N Use Efficiency (NUE) and minimize N losses (Canter, 1997; Errebhi et al., 1998). The use of fertigation (i.e., the application of a water-soluble fertilizer through an irrigation system) provides a convenient method to split post-emergence N applications. The challenge lies in the ability to estimate the appropriate rate and timing of split N applications so that fertilizer N best matches crop demands. This is because crop uptake rates and soil N transformations/losses depend on the interaction of many complicated and sometimes unpredictable factors throughout the growing season, including: fertilizer source, soil fertility, physical soil properties, and weather conditions (Gupta et al., 1997; Mamo et al., 2003).

A current best management practice for potato production on coarse-textured soils is to base the rate and timing of post-emergence N fertilizer applications on petiole Nitrate-Nitrogen (NO_3-N) concentrations (Zebarth and Rosen, 2007). The limitation of petiole analysis is that it uses point sampling, and it does not account for within-field spatial variability at a fine spatial scale. Remote sensing of the crop canopy is better suited for precision agriculture applications because of its ability to cover large areas at fine spatial resolutions, usually in a fraction of the time. This provides a major advantage over using point measurements such as petiole samples for N stress determination.

A major limitation to the widespread use of remote sensing for making N fertilizer recommendations is the difficulty in identifying spectral algorithms and calibration procedures that are reliable over many growing conditions such as soil types, growth stages, cultivars, and weather (Samborski et al., 2009). In an operational setting, remote sensing alone cannot differentiate whether N status at a particular time and place is related to soil, growth stage, cultivar, weather, or management. Therefore, it is essential that differences among these factors are understood, so objective protocols can be developed for accurate and reliable variable rate N fertilization over many growing conditions.

Remote sensing has been effectively used in many crops to predict biophysical parameters that depend on crop N uptake, such as Leaf Area Index (LAI), tissue N or NO_3-N concentration, and leaf chlorophyll content (Reyniers et al., 2006; Lamb et al., 2002; Chen et al., 2010; Cohen et al., 2010; Haboudane et al., 2004, 2008). Spectral data acquired during the growing season can be used to monitor crop N status because spectral characteristics of green vegetation change as leaf chlorophyll content changes, and N is closely related to chlorophyll in plant cell metabolism (Stroppiana et al., 2012). Hundreds of spectral indices have been developed with the aim of predicting particular plant biophysical parameters while minimizing the effects of solar irradiance and soil background (Jackson and Huete, 1991; Rees, 2001).

Hyperspectral imagery is a powerful research tool that can be used to monitor crop N status at a high spatial scale over a variety of conditions and growth stages, therefore making it suitable for precision agriculture applications (Mulla, 2012). Chemometric models that use all hyperspectral wavebands (e.g., partial least squares regression or principal components analysis) have been found to predict crop biophysical parameters well, especially for leaf N concentration (Cohen et al., 2010; Hansen and Schjoerring, 2003; Nguyen et al., 2006).

Research on aerial-based hyperspectral imagery for N sufficiency in potatoes, specifically using chemometric models to make variable rate management decisions under various cultural conditions, has not been previously published. The main purpose of this study was to determine the approaches necessary to make spectral data more versatile across environments (i.e., cultivars and growth stages) so it can be easily calibrated and used for detecting N stress in a potato crop. Three objectives were defined to complete this task: (i) determine the relationship between spectral data and leaf N concentration and determine the ability of these measurements to detect differences among N treatments, (ii) evaluate the differences in variability across experimental treatments for various spectral indices/models, and (iii) evaluate the ability of spectral indices/models to classify N Sufficiency Index (NSI) stress levels into pre-determined N stress classes using an accuracy assessment procedure.

2. Materials and methods

2.1. Study site

Field experiments were conducted over 2 years (2010–2011) at the University of Minnesota Sand Plain Research Farm (45°23′N, 95°53′W) near Becker, MN. The soil at this location is classified as an excessively drained Hubbard loamy sand (sandy, mixed, frigid Typic Hapludoll) comprised of 82% sand, 10% silt, and 8% clay. The available water holding capacity in the upper 120 cm of soil is 85.1 mm. Irrigation was applied to the treatment plots with an overhead sprinkler system; rates and timing of application were scheduled using a water balance method (Wright, 2002). In 2010 and 2011, 32 cm and 26 cm of irrigation were applied, respectively. Timing of irrigation was variable between years and depended on weather conditions. Rainfall and irrigation data throughout each growing season are presented in Nigon (2012). After rainfall (80 cm in 2010 and 64 cm in 2011), total cumulative water at the end of the growing season was 112 and 90 cm in 2010 and 2011, respectively. During the growing season (April–September), the 30-year average (1971–2000) temperature and rainfall are 16.5 °C and 550 mm, respectively (Midwest Regional Climate Center). Soil drainage was calculated as part of the general water budget equation (Errebhi et al., 1998), in which the Penman–Monteith equation was used to calculate daily evapotranspiration (as described by Venterea et al., 2011). Cumulative soil drainage from planting through the second image date was 401 mm in 2010 and 402 mm in 2011. During this time frame, there were 40 and 21 drainage events greater than 5.0 mm in 2010 and 2011, respectively. The previous crop in both years was non-irrigated cereal rye (*Secale cereal* L.). Pre-plant KCl extractable soil N (NH_4-N + NO_3-N) in the upper 60 cm was 15 kg ha^{-1} in 2010 and 20 kg ha^{-1} in 2011 (Nigon, 2012).

2.2. Experimental design

This experiment was set up using a randomized complete block design with a split plot restriction on randomization replicated four times. The whole plot treatment included a low, medium, and high N rate (i.e., 34, 180, and 270 kg N ha^{-1}) with variable timing of post-emergence N applications for the high rate, for a total of five N treatments (i.e., 34 early, 180 split, 270 split, 270 split + surfactant (s), and 270 early; Table 1). Treatments 270 split and 270 split + s had the same rate and timing of N application, but a soil surfactant (IrrigAid Gold) was applied to 270 split + s at a rate of 10 L ha^{-1} to investigate the effects of the surfactant on improving NUE. Because treatments 180 split, 270 split, and 270 split + s had split applications of post-emergence N fertilizer, actual N applied at the time of remote sensing data acquisition varied (Table 2). All N applications were completed by the later image date in 2010, but one post-emergence N application remained at the later image date in 2011. In each year, the planting and emergence N source was mono-ammonium phosphate and urea, respectively. The subplot treatment consisted of two potato cultivars: Russet Burbank (RB) and Alpine Russet (AR; Whitworth et al., 2011).

Table 1
Rate and timing of nitrogen (N) fertilizer treatments for 2010 and 2011.

Nitrogen fertilizer treatment	Timing of application					Total N
	Planting	Emergence		Post-emergence		
		2010	2011	2010	2011	
	kg N ha^{-1}					
34 N early	34	0	0	0	0	34
180 N split	34	78	90	17×4[b]	11.2×5[b]	180
270 N split	34	124	124	28×4[b]	22.4×5[b]	270
270 N split + s[a]	34	124	124	28×4[b]	22.4×5[b]	270
270 N early	34	124	124	112	112	270

[a] A soil surfactant (IrrigAid Gold) was used in this treatment, and was applied at a rate of 10 L ha^{-1}.
[b] On average, about 2 weeks passed between split applications of post-emergence N.

Table 2
Actual nitrogen (N) fertilizer applied at the time of data acquisition for N treatments with split applications of post-emergence fertilizer.

N fertilizer treatment	2010		2011	
	47 DAE[a]	83 DAE	43 DAE	66 DAE
	kg N ha^{-1}			
180 N split	146	180	139	166
270 N split	214	270	203	248

[a] DAE = Days After Emergence.

Seed was hand planted in furrows with 90 cm row spacing and approximately 30 cm spacing between seed pieces within rows. Each plot consisted of seven 13.7 m rows. There was normal row spacing (90 cm) between subplot treatments within a block, but there were 3.0 m alleyways between the whole plot treatments and blocks. Planting dates were 16 April 2010 and 29 April 2011, and plant emergence occurred on 15 May 2010 and 24 May 2011. Two days after plant emergence in each year, emergence fertilizer was applied and rows were mechanically hilled. Chemicals were applied as needed during the season for the control of pests, disease, and weeds according to standard practices in the region (Engel et al., 2012).

2.3. Aerial image acquisition

Aerial hyperspectral imagery was acquired with an Airborne Imaging Spectrometer for Applications (AISA Eagle) visible/near-infrared hyperspectral imaging sensor (SPECIM, Spectral Imaging, Ltd., Oulu, Finland) by the Center for Advanced Land Management Information Technologies (CALMIT) from the University of Nebraska-Lincoln, USA. The AISA Eagle is a complete pushbroom system, consisting of a hyperspectral sensor head, a miniature GPS/INS sensor, and a data acquisition unit in a ruggedized PC with a display unit and power supply. It has a 1000-pixel swath width and was configured to capture imagery in 63 narrowbands covering the visible and near-infrared portions of the solar spectrum from 401 to 982 nm. The original spectral resolution of the sensor was 2.9 nm with 2.3 nm full width at half maximum (FWHM) prior to binning; after binning, FWHM ranged from 8.8 to 9.6 nm.

Images were captured from approximately 1900 m above the ground on 1 July 2010 (1240 h local time), 6 August 2010 (1144 h), 6 July 2011 (1443 h), and 29 July 2011 (1013 h); in the experimental year, these dates corresponded to 47, 83, 43, and 66 days after plant emergence (DAE), respectively. Solar zenith angle at the times of image acquisition were 22.5° (1 July 2010), 30.3° (6 August 2010), 34.0° (6 July 2011), and 38.9° (29 July 2011). On each image date, five white georeferenced plastic sheets (3.0×1.8 m) were placed on the ground to serve as white references for conversion to relative reflectance. A georeferenced sheet was placed in the alleyway of the center and in each of the four corners of the experiment.

2.4. Image pre-processing

A post-processing software package, CaliGeo, was used for radiometric correction (using NIST traceable calibrations), rectification (using a C-Migits III GPS/INS unit manufactured by Systron Donner Inertial Division, Walnut Creek, CA, USA), and geo-referencing. The system recorded GPS and aircraft altitudinal positions (roll, pitch, yaw, speed, and heading). The rectification process used the GPS and INS inputs to generate a global lookup table which was applied to the unrectified image without the use of ground control points. Geographic coordinates of plot corners were acquired with a GPS unit (0.3 m accuracy), which allowed in-house geo-referencing to minimize image distortion. The spatial resolution of the rectified images was 1.0 m. Image processing software (ENVI; version 4.8, Exelis, Inc., McLean, VA, USA) was used for all subsequent image analysis. Image units were converted from radiance to relative reflectance using the flat field calibration tool in ENVI. Pixels from the white references were used to normalize the images.

2.5. Leaf sampling and tuber yield

Leaf samples were collected on 1 July and 5 August in 2010 and 7 July and 28 July in 2011; these dates were on the same day or within one day of image acquisition. The fourth leaf from the apex of the shoot was sampled on twenty plants in the fifth row from the alley in each treatment plot. Leaf samples were oven-dried at 60 °C, and then ground with a Wiley mill to pass a 2-mm sieve. Total N concentration was determined with a combustion analyzer (Elementar Vario EL III, Elementar Americas Inc., Mt. Laurel, NJ) following the methods of Horneck and Miller (1997).

Tubers were mechanically harvested from the third and fourth rows from the alley on 28 September 2010 and 22 September 2011 (i.e., 165 and 146 days after planting in 2010 and 2011, respectively). Tubers were weighed on a fresh weight basis to determine total tuber yield.

2.6. Spectral data

Because in-season remote sensing of the crop canopy can be performed during crop growth and development, it is suited to account for seasonal weather conditions and other growth factors that make N status determination unpredictable going into the growing season (Meisinger et al., 2008). To fully understand the behavior of spectral data when there are many confounding conditions present, it is important to first understand the behavior of spectral data when some of these confounding factors can be controlled. Therefore, spectral data in this study were evaluated based on their ability to detect N stress both with and without knowing differences in growth stage and cultivar.

In this study, selected published broadband and narrowband indices, as well as predicted values from partial least squares regression based on narrowband reflectance and first derivative reflectance were used as indicators of N stress. Broadband data were obtained by aggregating hyperspectral data into four broad spectral regions: blue (427–518 nm), green (508–572 nm), red (657–695 nm), and NIR (770–828 nm). The first derivative reflectance was calculated for a given wavelength as the slope of the reflectance between neighboring bands.

2.6.1. Pixel extraction

To extract pixel data from treatment plots for subsequent analysis, Regions of Interest (ROI) were created for each treatment plot. Pixels that were most influenced by the effects of bare soil were excluded from data analysis by including pixels in the ROIs only if they were above a minimum threshold when tested against a narrowband Greenness index (Smith et al., 1995). This technique effectively filtered out pixels that were most influenced by bare soil during growth stages with full canopy cover (e.g., pixels representing border plants). By filtering out mixed pixels, the analysis of this study became less dependent on biomass, which enabled the analysis to focus more on plant N concentration. The number of pixels included in each ROI ranged from 15 to 78 among each of the four image dates; each pixel represented an area of 1.0 m^2, and each treatment plot had an area of ~88 m^2.

2.6.2. Spectral indices

Reflectances for all broadband and narrowband wavelengths, first derivative reflectances for all narrowband wavelengths, and a comprehensive list of 17 broadband and 82 narrowband previously published spectral indices were used in a preliminary analysis to determine the wavelengths and/or indices that had the most potential to be useful for detecting N stress. The correlation coefficient (r) was calculated for each of these wavelengths/indices using the CORR procedure of SAS (SAS Institute, 2008) to determine the wavelengths/indices that had the closest relationships with leaf N concentration on each image date. To determine which wavelengths and indices had the most potential to be useful for predicting leaf N concentration, the coefficient of determination (r^2) was averaged for each wavelength/index among the four image dates. Some of the indices that had the highest average r^2 from this preliminary analysis are listed in Table 3, and were used for comparison in all subsequent analysis techniques in this study. Neither broadband reflectance, narrowband reflectance, nor first derivative reflectance had the highest r^2 values in the preliminary analysis, so these individual bands are not discussed further. The r^2 values for the relationship between narrowband reflectance and leaf N concentration within image dates are presented in Nigon et al. (2012).

2.6.3. Partial least squares regression

Partial Least Squares regression (PLS) is an extension of the standard multiple linear regression procedure; it is a method for constructing predictive models that is especially useful when there are many independent variables which are highly collinear (Phatak and de Jong, 1997), as is the case with hyperspectral data. PLS uses data compression by transforming the high dimensional dataset along the axes to maximize covariance in the data. This transformation produces a given number of latent variables (LV; also known as *factors* or *components*) that are used to predict the response variables. Refer to Tobias (1995), Thorp et al. (2011), and Abdel-Rahman et al. (2014) for more detailed discussions of PLS concepts.

Three PLS models were constructed across image dates, and three PLS models were constructed for each cultivar by image date combination in a preliminary analysis, each using different sets of independent spectra. Independent spectra for the three models included: (i) hyperspectral reflectance only; (ii) first derivative reflectance only; and (iii) both hyperspectral and first derivative reflectance, and only the bands that were statistically significant ($r > 0.3$) for their linear relationship with leaf N concentration were used (determined in the preliminary analyses). The independent spectra were used to predict leaf N concentration in the models. There were 20 samples used as input for each of the models constructed within image dates, and 80 samples used as input for each of the models constructed across image dates. Of the PLS models, those using the first derivative reflectance only as independent spectra were used in this study.

The PLS models were calibrated and cross-validated by a full leave-one-out cross-validation using the PLS procedure of SAS (SAS Institute, 2008). This option calibrated the PLS models iteratively using leaf N concentration and spectral data from all treatment plots except for one; in each iteration, a different sample was left out from the dataset until every sample had been left out once. Using the *CVTEST* (*STAT* = *PRESS*) option of the PLS procedure of SAS (SAS Institute, 2008), model predictions were made for the least number of LVs in which the Predicted Residual Sum of Squares (PRESS) were not significantly greater than those of the model with the minimum PRESS. The PRESS is used as an indication of the predictive power of a model, and is calculated according to Eq. (1):

$$\mathrm{PRESS} = \sum_{i=1}^{n} (y_i - \hat{y}_{(i)})^2 \quad (1)$$

where PRESS is the predicted residual sum of squares; y_i is the observed value of sample i; $\hat{y}_{(i)}$ is the predicted value of sample i

Table 3
Summary of the best performing indices evaluated in this study. A total of 17 broadband and 82 narrowband previously published indices were used for the initial analysis.

Index	Name		Formula[a]	Developed for	Developed by
Broadband indices					
NG	Normalized Green	=	$R_G/(R_{NIR} + R_R + R_G)$	Nitrogen	Sripada et al. (2006)
Narrowband indices					
DCNI	Double-Peak Canopy Nitrogen Index	=	$\frac{(R_{723}-R_{704})/(R_{704}-R_{666})}{(R_{723}-R_{666}+0.03)}$	Nitrogen	Chen et al. (2010)
MTCI	MERIS Terrestrial Chlorophyll Index	=	$(R_{751} - R_{713})/(R_{713} - R_{676})$	Chlorophyll	Dash and Curran (2004)
NDI2[b]	Normalized difference index2	=	$(R_{847} - R_{713})/(R_{847} - R_{676})$	Chlorophyll	Datt (1999)
NDVI	Normalized Difference Vegetation Index	=	$(R_{799} - R_{676})/(R_{799} + R_{676})$	Structure	Lichtenthaler et al. (1996)
NDVI1[b]	Normalized Difference Vegetation Index1	=	$(R_{751} - R_{732})/(R_{713} + R_{723})$[c]	Chlorophyll	Vogelmann et al. (1993)
SR8[b]	Simple ratio8	=	$R_{857}/(R_{554} \times R_{704})$	Chlorophyll	Datt (1998)

[a] R_i = reflectance at wavelength i (nanometers).
[b] Named in this study.
[c] The bands in the numerator of NDVI1 were switched to the formula shown so the index yielded positive values.

not included in the model formulation; and n is the total sample number (Méndez Mediavilla et al., 2008).

2.7. Evaluation of N stress prediction

Several techniques were used to evaluate the spectral indices/wavelengths that were best able to determine N stress. These techniques included: (i) linear regression analysis; (ii) normalization using the nitrogen sufficiency index; (iii) Analysis of Variance (ANOVA) and means separation; (iv) coefficient of variation across N treatments; and (v) accuracy assessment.

2.7.1. Linear regression analysis

A linear regression analysis with leaf N concentration was performed for spectral indices/models using the REG procedure of SAS (SAS Institute, 2008). The root mean squared error of cross-validation (RMSECV) was calculated from the PRESS according to Eqs. (1) and (2) as a measure of the model's ability to predict new samples.

$$\mathrm{RMSECV} = \sqrt{\frac{\mathrm{PRESS}}{n}} \tag{2}$$

where RMSECV is the root mean squared error of cross-validation; PRESS is the predicted residual sum of squares (Eq. (1)); and n is the total sample number.

The RMSECV values were normalized by calculating the ratio between RMSECV values and the range of predicted values, and are denoted as % RMSECV. Due to the statistical significance of leaf N concentration between cultivars on each image date (Nigon, 2012), linear regression analysis was performed separately for each cultivar. The prediction analyses between leaf N concentration and each of the spectral indices/models were evaluated both within and across image dates.

2.7.2. Normalization using the nitrogen sufficiency index

A Nitrogen Sufficiency Index (NSI) was applied to leaf N concentration and spectral indices/models to normalize them for comparative purposes. By applying an NSI to the data, values were normalized to a non-limiting N reference area (Peterson et al., 1996). The NSI was calculated using Eq. (3):

$$\mathrm{NSI} = \frac{N_i}{N_{ref(270\ split)}} \times 100 \tag{3}$$

where NSI is nitrogen sufficiency index; N_i is the measured value of leaf N concentration, spectral index value, or PLS predictions of leaf N concentration from the non-reference treatment plot; and $N_{ref(270\ split)}$ is the reference value – the higher average replicate value between 270 split and 270 split + s was used.

For Normalized Green (NG), the index values representing the treatments with the most N stress were higher than those representing the treatments with the least N stress; therefore, the reciprocal of the NSI was used for these indices.

2.7.3. ANOVA and means separation

An analysis of variance was conducted for leaf N concentration and the indices/models that were normalized by the NSI (Eq. (3)). A means separation was performed within cultivar and image date to determine the ability of each plant measurement and spectral index/model to distinguish between N treatments. The treatment groupings for the spectral indices/models can be directly compared to those for leaf N concentration; this technique is used to determine if a spectral index/model has similar separation capabilities among N treatments as leaf N concentration.

Data were analyzed using PROC MIXED (SAS Institute, 2008) with N treatments and cultivars considered as fixed variables and replications considered as random variables. For the main effects and interactions of the fixed variables, pairwise comparisons of the least square means were made using the *lsmeans/pdiff* option of the MODEL statement ($\alpha = 0.05$). The PDMIX800 macro (Saxton, 1998) was used to place treatment means into letter groupings based on the pairwise comparisons. Each image date was analyzed separately.

2.7.4. Coefficient of variation across N treatments

The Coefficient of Variation (CV) was calculated to estimate the relative amount of variability present in leaf N concentration and spectral indices/models. The Relative Fluctuation (RF) in CVs among image dates was calculated to determine the plant measurements and spectral indices/models that had the most consistent variability among image dates (Eq. (4)).

$$\mathrm{RF} = \frac{CV_{max} - CV_{min}}{CV_{avg}} \times 100 \tag{4}$$

where RF is relative fluctuation; CV_{max} and CV_{min} are the maximum and minimum coefficient of variation values among image dates, respectively; and CV_{avg} is the average coefficient of variation among image dates.

2.7.5. Accuracy assessment

An accuracy assessment was performed to evaluate the ability of spectral indices/models to classify N stress levels into predefined ranges according to leaf N concentration (Congalton and Green, 2008). Prior to conducting the accuracy assessment, treatment data for each spectral index/model were normalized using the Nitrogen Sufficiency Index (NSI; Eq. (3)) and were placed into three predetermined N stress classes: "High" < 80% NSI; 80% NSI ⩽ "Moderate" ⩽ 95% NSI; and "Low" > 95% NSI. The 95% division was chosen because it is a common NSI threshold used in the literature, most commonly used for chlorophyll meter readings (Blackmer and Schepers, 1995; Peterson et al., 1996; Waskom et al., 1996; Varvel et al., 1997; Samborski et al., 2009). The 80% division was chosen because it was an NSI value that usually fell between the 34 kg N ha^{-1} and 180 kg N ha^{-1} treatments for the ground truth (i.e., leaf N concentration). A confusion matrix was constructed to calculate the overall accuracy, overestimated stress, underestimated stress, and high cost errors. To account for the effects of chance agreement, a Kappa analysis was completed to obtain a KHAT statistic, $\widehat{K}$, an estimate of Kappa (Cohen, 1960; Congalton, 1991). The spectral indices/models with the highest overall accuracies and $\widehat{K}$, as well as those with the most balanced misclassified treatment plots (between overestimated and underestimated stress levels) were considered to be the most useful for N stress prediction.

3. Results and discussion

3.1. Nitrogen stress prediction

Spectral indices were selected based on the preliminary analysis as described above, and represent the highest correlations with leaf N concentration (Table 3). Because these indices were selected from a list of over 100 spectral indices, the r^2 and corresponding Root Mean Square Error of Cross Validation (RMSECV) values among indices in Table 3 were similar overall (with the exception of NDVI, which was included for comparison purposes). Variability in spectral indices' r^2 values can be the result of the particular dataset rather than differences in their true ability to detect N stress. Therefore, the r^2 values and the ability to detect N stress will not be discussed in great detail for each spectral index. Instead, this discussion will focus on interpretation of data for the purpose of accurately and consistently detecting N stress in a potato crop using spectral indices or models that may perform mechanistically different (in terms of the structure of the index and the wavebands it uses). An explanation of the sensor and index components that should be considered are provided so that accurate in-season N recommendations can be made.

The indices that resulted in the highest r^2 values and corresponding RMSECV varied by image date and cultivar. Normalized Green (NG; Table 3) had r^2 values that ranged from 0.59 to 0.81 and an RMSECV that ranged from 17% to 28% among image dates (r^2 = 0.69, RMSECV = 17% across all dates) for RB, and r^2 values that ranged from 0.54 to 0.82 and an RMSECV that ranged from 16% to 30% among image dates (r^2 = 0.49, RMSECV = 25% across all dates) for AR. The narrowband indices (Table 3) generally had higher r^2 values and lower corresponding RMSECV than NG. This improvement with narrowband spectral data is consistent with previous literature (Blackburn, 1998). The information obtained from a narrowband sensor is much more descriptive than information obtained from a broadband sensor, especially near the red-edge region of the spectrum. As a band becomes broader, information generally becomes saturated across the spectral region it represents.

The Double-peak Canopy Nitrogen Index (DCNI), the MERIS Terrestrial Chlorophyll Index (MTCI), and Normalized Difference Index 2 (NDI2) are all derivative-based indices (i.e., they measure the ratio between the amplitudes of two or more regions of the reflectance spectra using narrowbands). These indices were very well correlated with leaf N concentration in this study. The Double-peak Canopy Nitrogen Index (DCNI) had r^2 values that ranged from 0.73 to 0.81 and an RMSECV that ranged from 16% to 21% among image dates (r^2 = 0.70, RMSECV = 16% across all dates) for RB, and r^2 values that ranged from 0.61 to 0.86 and RMSECV that ranged from 15% to 25% among image dates (r^2 = 0.57, RMSECV = 20% across all dates) for AR. Spectral derivatives and derivative-based indices near the red-edge region are well suited to predict concentrations per unit mass of pigments from both leaf- and canopy-scale spectral data (Blackburn, 1998), and they have been found to be closely related to N concentration in corn and wheat (Chen et al., 2010). Their ability to predict crop N concentration can be partly attributed to their ability to reduce variability due to changes in illumination to background reflectance properties (Curran et al., 1991; Elvidge and Chen, 1995), however, this typically only holds true if there is sufficient biomass present (data not shown). In the case that derivative-based indices use red-edge bands, there is a phenomenon that may exist in which there is potential for the index value to be higher for bare soil than for healthy crop. This is notable because the typical behavior of these derivative-based indices is to have a positive correlation between the index values and leaf N concentration. If sufficient biomass is not present in a field, a correction factor should be introduced to these indices to account for this phenomenon, much like the *L* factor in the Soil Adjusted Vegetation Index (Huete, 1988) or the Modified Soil Adjusted Vegetation Index (Qi et al., 1994). The Transformed Chlorophyll Absorption in Reflectance Index (TCARI; Haboudane et al., 2002) suffers from this same phenomenon, so it was normalized with the Optimized Soil Adjusted Vegetation Index (OSAVI; Rondeaux et al., 1996) to produce [TCARI/OSAVI] (Haboudane et al., 2002). Taking steps to account for this phenomenon was not a focus of this study because there was sufficient biomass for all experimental plots at the growth stages in which measurements were collected, and it was not a problem. Areas for further research include establishing definitive thresholds that constitute "sufficient biomass", as well as modifying these derivative indices to use a correction factor and/or a biomass normalization technique so they can be used with confidence in a commercial setting for N management.

With the exception of NDVI, the other narrowband indices listed in Table 3 resulted in r^2 and RMSECV values that represented overall similar relationships with leaf N concentration as DCNI and NG. The Normalized Difference Vegetation Index (NDVI) had r^2 values that ranged from 0.47 to 0.75 and an RMSECV that ranged from 21% to 34% among image dates (r^2 = 0.31, RMSECV = 28% across all dates) for RB, and r^2 values that ranged from 0.47 to 0.76 and an RMSECV that ranged from 17% to 33% among image dates (r^2 0.27, RMSECV = 37% across all dates) for AR. The weaker relationship between NDVI and leaf N concentration compared to the other indices is expected because only the pixels representing "pure canopy" were used in the analysis of this study. Because NDVI is a structural index that is only sensitive to pigment changes in crop canopy cover up to 90% (Barnes et al., 2000), it was a poor indicator of leaf N concentration for a potato crop in this study. As crop canopy cover increases over 90%, reflectance response in the red region begins to saturate out and differences due to leaf N concentration are not detectable (Barnes et al., 2000).

From the preliminary analysis, the PLS models constructed using first derivative reflectance spectra only always had the same or higher r^2 values than the models constructed using reflectance spectra only. The PLS models that used first derivative reflectance as input for independent variables showed an improvement over the narrowband indices with the highest r^2 on three of the four image dates for both cultivars; improvement was also observed across image dates for both cultivars. The PLS models had r^2 values that ranged from 0.68 to 0.92 and an RMSECV that ranged from 14% to 20% among image dates (r^2 = 0.78, RMSECV = 15% across all dates) for RB, and r^2 values that ranged from 0.71 to 0.94 and an RMSECV that ranged from 9% to 22% among image dates (r^2 = 0.71, RMSECV = 15% across all dates) for AR. These results show that PLS models are an improvement over simple indices and have promise for predicting leaf N concentration in a potato crop. They are consistent with other studies that estimated biophysical and biochemical properties of agricultural crops including leaf and canopy N concentration (Alchanatis and Cohen, 2011). The advantage of PLS analysis over narrowband indices can be attributed to the sensitivity of the gradual change in reflectance in the spectral ranges that are significant for predicting leaf N concentration (i.e., red edge region). Partial least squares regression can capture this sensitivity, while most narrowband indices cannot. The major challenge with PLS, however, is that in order to be confident in its implementation, the biophysical basis to the loading weights of each of the latent variables must be understood. Furthermore, the number of latent variables used to construct the PLS models should be known for a particular environmental scenario (e.g., growth stage or cultivar). This is notable because different environmental scenarios might result in more or less latent variables, which can change the predicted value(s). In this study, all PLS models within a particular growth stage used only one latent variable, except 29 July for RB and 6 July for AR, in which two were used. The PLS models across growth stages used four latent variables for RB and two latent variables for AR. Implementation of PLS models for commercial agriculture requires hyperspectral data, as opposed to multispectral data that are used for simple indices. Hyperspectral data is generally more expensive because of sensor cost, platform/payload requirements, and data storage and processing requirements. However, more compact hyperspectral imaging systems are being built in an attempt to reduce these costs and requirements. Making hyperspectral systems lightweight and compact allows them to be fit to small unmanned aerial vehicles. The combination of low cost imaging systems with low cost platforms will increase the opportunity for this technology to be adopted by commercial users.

3.2. Practical use of the nitrogen sufficiency index

In an operational setting, it is difficult for remote sensing alone to determine whether N status at a particular time and place is related to soil, growth stage, cultivar, weather, or management. Use of remote sensing to guide N management decisions requires an understanding of all other possible variables, and more importantly, how to properly account for them if they affect spectral data (e.g., normalization is one such technique). Optimal fertility besides N, as well as adequate water are essential. Normalizing imagery using a Nitrogen Sufficiency Index (NSI; Eq. (3)) can reduce variability that may occur across fields or management zones. The NSI can be applied to plant measurements or spectral data over a large spatial scale at a low cost, making it a practical approach for determining relative N stress for precision agriculture applications (Tremblay et al., 2011).

3.2.1. Agronomic justification

The N treatments that had post-emergence N split applied had the highest tuber yields numerically among N treatments, although this was only statistically significant in 2011 (data not shown; Nigon, 2012). Errebhi et al. (1998) and Westermann et al. (1988) reported similar yield responses with split applications of N fertilizer, especially during leaching years. Within N treatments, tuber yields were always higher in 2010 than 2011; average yields across N treatments were 54.2 Mg ha^{-1} in 2010 and 49.5 Mg ha^{-1} in 2011 (Nigon, 2012).

The main effect of nitrogen rate/timing was highly significant for leaf N concentration and all spectral indices/models (Table 4). Before the NSI was applied, the main effect of cultivar for leaf N concentration and the spectral indices/models was significant in many cases (data before the NSI transformation are not presented). However, after the NSI was applied, the main effect of cultivar and the N $\times$ cultivar interaction (where applicable) were not significant for leaf N concentration or for most spectral indices. This general transition of statistical significance following the NSI transformation occurred because the references used for the NSI transformations were cultivar dependent (i.e., they were selected within cultivar); the transition was especially apparent on the second image date in each year. Spectral indices/models that are insensitive to external factors such as cultivar can be useful over a broader range of environmental conditions, and therefore, the normalization of data using an NSI is recommended. Different cultivars may have various N stress thresholds and N fertilizer requirements, so the user should be aware that these differences exist when making fertilizer recommendations.

The reference value used to calculate the NSIs are reported so that there is insight into the absolute values of leaf N concentration and each of the spectral indices/models before the NSI was applied (Tables 5 and 6). As the rate of applied N fertilizer increased (refer to Tables 1 and 2), leaf N concentration also increased. Leaf N concentration was more sensitive to N treatments in 2011 than in 2010, and was higher in RB than in AR across all N treatments and image dates. In both cultivars, leaf N concentration was above the threshold sufficiency level (i.e., 3.5%; Westermann, 1993) on all image dates for 270 split and 270 split + s. Leaf N concentration for 180 split was statistically similar to 270 split and 270 split + s for both cultivars and both image dates in 2010, but was lower than 270 split and 270 split + s for both cultivars and both image dates in 2011. Leaf N concentration was consistent from the first to the second image date in each year for all N treatments that had post-emergence N split applied. Alternatively, for 270 early, leaf N concentration substantially decreased on the second image date for both cultivars and both years, which was likely caused by NO_3-N leaching out of the root zone. Due to high drainage in each year through the second image date (i.e., 401 mm in 2010 and 402 mm in 2011), increased leaching was expected for the 270 N early treatment. For a different experiment, but using the same plots as this experiment, leaching was estimated at 108 kg N ha^{-1} across all N treatments (Vashisht et al., submitted for publication).

3.2.2. Means separation of NSI

On the first image dates in each year, the NSI values for the 270 kg N ha^{-1} early treatment were typically above 100% (Tables 5 and 6). This occurred because the 270 early treatment received more N fertilizer than the NSI reference treatments (i.e., 270 split and 270 split + s) on these dates (Table 2).

In many cases, the means separation analysis for the spectral indices/models could detect more groups than leaf N concentration. In other words, many of the spectral indices/models were able to distinguish between N treatments better than leaf N concentration measurements. This is likely because canopy-scale spectral data capture the impacts of N deficiency on biophysical parameters, which determine factors such as leaf N concentration and leaf chlorophyll content, as well as plant growth processes, which determine factors such as leaf architecture, leaf area index, and background soil (Daughtry et al., 2000). Leaf N concentration is a leaf-scale sample, so it is largely unaffected by external factors such as leaf architecture, leaf area index, and background soil effects. Data from this study suggest that the combined effects between these external factors and biophysical parameters on canopy-scale spectral data is likely responsible for the more accurate determination of the overall N status of a potato crop. This provides evidence that tissue samples may not fully detect crop N stress, while measurements that depend on plant nutrient

Table 4
Analysis of variance for leaf nitrogen concentration and spectral indices/models after normalization using the nitrogen sufficiency index at different Days After Emergence (DAE) in 2010 and 2011.

Year	DAE	Source of variation	Leaf N	NG	DCNI	MTCI	NDVI	SR8	NDI2	NDVI1	PLS RD[b]
2010	47	Nitrogen [N]	**[a]	**	**	**	**	**	**	**	**
		Cultivar [C]	–	*	**	–	*	**	**	–	**
		N × C	**	–	**	**	–	–	**	–	**
	83	Nitrogen	**	**	**	**	**	**	**	**	**
		Cultivar	–	–	–	–	**	–	–	–	**
		N × C	–	–	–	–	**	–	–	–	*
2011	43	Nitrogen	**	**	**	**	**	**	**	**	**
		Cultivar	–	*	**	–	**	*	**	–	–
		N × C	–	–	**	–	**	**	**	–	**
	66	Nitrogen	**	**	**	**	**	**	**	**	**
		Cultivar	–	–	**	–	–	–	–	–	–
		N × C	–	–	*	–	–	–	–	–	–

[a] ** and * are significant at 0.01 and 0.05, respectively; – is nonsignificant.
[b] Partial least squares regression using the reflectance derivative as input for its independent variables.

Table 5
Mean Nitrogen Sufficiency Index (NSI) values for leaf N concentration and spectral indices/models for the Russet Burbank cultivar at different years and Days After Emergence (DAE).

Year	DAE	N treatment	Leaf N	NG	DCNI	MTCI	NDI2	NDVI	NDVI1	SR8	PLS RD[b]
2010	47	34 early	74 c[a]	68 d	69 d	58 d	79 d	95 b	48 d	51 d	72 d
		180 split	98 b	94 c	95 c	93 c	97 c	99 a	91 c	90 c	96 c
		270 split	100 b	100 ab	100 b	100 b	100 b	100 a	100 b	100 ab	100 b
		270 split + s	99 b	97 bc	100 b	100 b	100 b	99 a	99 b	95 bc	99 b
		270 early	109 a	104 a	105 a	106 a	102 a	100 a	108 a	107 a	104 a
		Reference[c]	4.43	0.104	2.37	1.62	0.640	0.898	−0.183	34.6	4.50
	83	34 early	75 c	67 c	66 c	48 c	77 c	76 c	39 c	55 c	76 c
		180 split	93 ab	87 b	88 b	79 b	92 b	95 b	75 b	80 b	92 b
		270 split	99 a	101 a	100 a	100 a	100 a	100 a	100 a	100 a	100 a
		270 split + s	100 a	100 a	99 a	99 a	100 a	100 a	100 a	97 a	100 a
		270 early	84 bc	87 b	81 b	76 b	90 b	97 ab	74 b	74 b	90 b
		Reference	4.41	0.122	2.38	1.37	0.614	0.836	−0.147	27.5	4.34
2011	43	34 early	71 d	69 d	73 d	56 d	80 d	93 c	47 d	57 d	70 d
		180 split	89 c	92 c	91 c	88 c	96 c	99 b	85 c	86 c	91 c
		270 split	98 b	99 b	99 b	99 b	100 b	100 a	98 b	98 b	100 b
		270 split + s	100 b	100 b	100 b	100 b	100 b	100 a	100 a	100 b	100 b
		270 early	107 a	103 a	102 a	105 a	102 a	100 a	106 a	104 a	104 a
		Reference	4.85	0.101	2.85	1.77	0.674	0.874	−0.205	41.8	4.87
	66	34 early	70 c	70 d	66 d	55 d	77 d	94 c	47 d	55 c	71 c
		180 split	86 b	89 c	87 c	82 c	92 c	99 b	79 c	82 b	88 b
		270 split	99 a	100 a	100 a	100 a	100 a	100 a	100 a	100 a	100 a
		270 split + s	100 a	99 ab	99 a	97 ab	99 ab	100 ab	97 ab	99 a	100 a
		270 early	90 b	95 b	93 b	91 b	96 b	99 ab	90 b	91 ab	93 b
		Reference	4.73	0.108	2.36	1.46	0.619	0.883	−0.160	32.5	4.65

[a] Means followed by the same letter within an image date are not significantly different ($\alpha = 0.05$).
[b] Partial least squares regression using the reflectance derivative as input for its independent variables.
[c] Reference values, $N_{ref(270\ split)}$, for leaf N concentration and spectral indices/models according to Eq. (3).

Table 6
Mean Nitrogen Sufficiency Index (NSI) values for leaf N concentration and spectral indices/models for the Alpine Russet cultivar at different years and Days After Emergence (DAE).

Year	DAE	N treatment	Leaf N	NG	DCNI	MTCI	NDI2	NDVI	NDVI1	SR8	PLS RD[b]
2010	47	34 early	77 b[a]	71 c	75 c	61 c	82 c	96 b	50 c	59 c	79 c
		180 split	96 a	97 b	97 b	96 b	98 b	100 a	95 b	95 b	97 b
		270 split	97 a	100 ab	100 ab	100 b	100 ab	100 a	100 b	100 ab	100 ab
		270 split + s	100 a	99 b	98 b	99 b	99 b	100 a	98 b	97 b	99 b
		270 early	100 a	105 a	103 a	105 a	102 a	100 a	107 a	107 a	103 a
		Reference[c]	3.86	0.0921	2.70	1.82	0.669	0.900	−0.211	44.5	3.79
	83	34 early	70 c	68 c	62 d	48 c	74 c	86 b	40 c	51 c	66 d
		180 split	96 a	88 b	87 b	82 b	93 b	97 a	77 b	80 b	90 b
		270 split	99 a	98 a	98 a	96 a	99 a	99 a	95 a	98 a	99 a
		270 split + s	100 a	100 a	100 a	100 a	100 a	100 a	100 a	100 a	100 a
		270 early	82 b	87 b	80 c	76 b	90 b	97 a	73 b	74 b	83 c
		Reference	3.98	0.114	2.45	1.48	0.632	0.850	−0.164	29.9	4.06
2011	43	34 early	77 d	67 d	83 d	59 d	84 d	87 c	46 d	64 d	76 d
		180 split	88 c	92 c	93 c	88 c	96 c	99 b	84 c	88 c	88 c
		270 split	99 b	99 b	99 b	98 b	99 b	100 a	96 b	98 b	100 b
		270 split + s	100 b	100 ab	100 ab	100 ab	100 a	100 a	100 a	100 a	100 b
		270 early	107 a	102 a	101 a	102 a	101 a	100 a	103 a	102 a	104 a
		Reference	4.57	0.0935	3.14	1.91	0.691	0.878	−0.223	50.2	4.60
	66	34 early	72 d	73 c	75 c	60 c	80 c	94 c	51 c	63 c	73 c
		180 split	85 c	91 b	89 b	86 b	94 b	99 ab	85 b	84 b	89 b
		270 split	100 a	98 a	99 a	99 a	100 a	100 a	99 a	97 a	99 a
		270 split + s	97 ab	100 a	100 a	100 a	100 a	100 a	100 a	100 a	100 a
		270 early	89 bc	93 b	94 ab	89 b	96 b	99 b	87 b	92 ab	95 ab
		Reference	4.36	0.102	2.40	1.48	0.624	0.885	−0.166	35.7	4.25

[a] Means followed by the same letter within an image date are not significantly different ($\alpha = 0.05$).
[b] Partial least squares regression using the reflectance derivative as input for its independent variables.
[c] Reference values, $N_{ref(270\ split)}$, for leaf N concentration and spectral indices/models according to Eq. (3).

concentration as well as biomass or leaf area index have a greater potential to predict crop N stress. The indices that detected differences among N treatments best in this study used narrowbands in the red, red-edge, and near-infrared regions of the spectrum. Reflectance in the red or beginning of the red-edge regions (620–720 nm) is inversely related to leaf chlorophyll as a consequence of energy absorption by chlorophyll (Pinter et al., 2003). In contrast, reflectance in the near-infrared or end of the red-edge regions (750–1000 nm) is related to canopy structure effects and increased leaf area index or biomass.

The Nitrogen Nutrition Index (NNI) is a rather cumbersome point measurement that considers both plant nitrogen concentration and biomass to determine crop N stress. Duchenne et al. (1997) and Bélanger et al. (2001) report the use of the NNI for a potato crop. However, because it is a point measurement, it is not feasible to account for within-field spatial variability using the NNI. It is reasonable to suggest, however, that canopy-scale spectral data would have a good relationship with the NNI since both are influenced by the effects of plant N concentration and biomass/leaf area index (Daughtry et al., 2000). In fact, Mistele and Schmidhalter (2008) reported an average r^2 of 0.95 for the relationship between the NNI and the red edge inflection point (REIP; Guyot et al., 1988) in wheat. If this is also the case for a potato crop, canopy-scale spectra would be a good alternative to the NNI to serve as an indicator of crop N stress for variable rate fertilizer recommendations since canopy-scale imagery can accurately account for spatial variability. Further research is needed to evaluate the relationship between NNI and canopy-scale spectra in a potato crop.

3.2.3. Variability in NSI values

NSI values of leaf N concentration and spectral indices/models differed over N treatments and image dates (Tables 5 and 6). The variation among N treatments corresponded to different levels of N stress as determined by leaf N concentration and tuber yield (Nigon, 2012). The variation over N treatments was different for each plant measurement and spectral index/model. The Coefficient of Variation (CV) was calculated on each image date to objectively measure the spread of NSI values among N treatments for leaf N concentration and each spectral index/model (Table 7). To make observations about the variability among image dates, the relative fluctuation (RF; Eq. (4)) of the CVs was calculated. High RF values indicate inconsistent variability among image dates. This inconsistency is the result of a high sensitivity to absolute N stress among image dates according to the respective measurement used; in other words, the inconsistency is a result of differing NSI values for similar N treatments across image dates.

For most spectral indices/models, the RF values were smaller for RB than for AR (Table 7). DCNI and NG had the smallest RF values for RB and AR, respectively. If an NSI is used, spectral indices/models with smaller RF values are better for N stress determination over a broader range of growth stages and years (i.e., they will have more consistent NSI values among growth stages and years).

Overall, CVs between leaf N concentration and spectral data were similar, which is consistent with results reported by Cohen et al. (2010). Normalized Difference Vegetation Index 1 (NDVI1), Simple Ratio 8 (SR8), and MTCI had the highest CVs among spectral indices and PLS models (each had a CV greater than 20% for RB and greater than 19% for AR).

Although high CVs are desirable for observing differences between N treatments for a spectral index/model, the CV does not have any dependence on its ability to predict leaf N concentration. Instead, the CV can be used as a general indicator of the theoretical range of NSI values that correspond to particular N stress levels, and should be used only after determining the ability of a spectral index/model to predict N stress. Described in other words, a spectral index/model with a high CV simply means that it has a larger range in NSI values (i.e., there is less saturation over the range of NSI values).

3.2.4. Accuracy assessment

Among the spectral indices, the highest overall accuracy and $\widehat{K}$ was observed for DCNI in RB (overall accuracy = 78% and $\widehat{K} = 64\%$), and for MERIS Terrestrial Chlorophyll Index (MTCI) in AR (overall accuracy = 79% and $\widehat{K} = 66\%$; Table 8). MTCI was the most consistent across cultivars in providing high r^2 values, low RMSECVs, and high accuracies/$\widehat{K}$. MTCI had relatively similar accuracies and $\widehat{K}$ as the PLS models that used first derivative reflectance as the independent input variables. Performing an accuracy assessment based on leaf N concentration provides insight into the ability of a spectral index/model to classify a crop into different stress levels. This is useful information if spectral indices/models are to be used for variable-rate application decisions at a commercial scale (Cohen et al., 2010). The spectral indices/models with the highest accuracies and $\widehat{K}$ are not necessarily those that have the highest r^2 or lowest RMSECV values, but rather are those most closely related to the variable being compared against (i.e., leaf N concentration in this study).

Averaged across cultivars, the overestimated and underestimated stress were 14% and 11% for MTCI, respectively, and were 5% and 18% for the PLS model, respectively. Of these N stress predictors, MTCI was the only one that did not have a substantially higher percentage of underestimated stress than overestimated

Table 7
Coefficient of Variation (CV) for leaf N concentration and selected spectral indices/models for Russet Burbank and Alpine Russet potato cultivars at different Days After Emergence (DAE) in 2010 and 2011. The CVs are ratios between mean values and standard deviations, and therefore are similar whether or not a Nitrogen Sufficiency Index (NSI) transformation has been applied.

Measurement or spectral index/model	Russet Burbank						Alpine Russet					
	2010		2011		AVG	Relative fluctuation	2010		2011		AVG	Relative fluctuation
	47 DAE	83 DAE	43 DAE	66 DAE			47 DAE	83 DAE	43 DAE	66 DAE		
	(%)						(%)					
Plant measurements												
Leaf N	14	13	15	14	14	0.18	10	19	12	13	14	0.64
Broadband indices												
NG	15	14	14	14	14	0.10	14	14	15	12	14	0.23
Narrowband indices												
DCNI	15	15	13	15	14	0.19	11	19	8	12	12	0.88
MTCI	20	23	21	21	21	0.17	18	25	18	18	20	0.39
NDI2	9	9	9	10	9	0.08	8	11	7	8	8	0.51
NDVI	4	8	4	4	5	1.00	3	6	5	3	4	0.73
NDVI1	25	28	27	26	26	0.13	24	30	25	23	25	0.30
SR8	24	21	21	21	22	0.13	20	26	16	17	20	0.47
Partial least squares regression												
PLS RD[a]	8	10	7	7	8	0.29	11	6	8	9	9	0.53

[a] Partial least squares regression using the reflectance derivative as input for its independent variables.

Table 8
Comparison of classification results using an accuracy assessment between leaf N concentration and measurements or spectral indices/models for Russet Burbank and Alpine Russet potato cultivars. All measures of accuracy are reported across all image dates.

Measurement or spectral index/model	Russet Burbank (n = 80)					Alpine Russet (n = 80)				
	Overall accuracy	KHAT ($\hat{K}$)	Overestimated stress	Underestimated stress	High cost errors	Overall accuracy	KHAT ($\hat{K}$)	Overestimated stress	Underestimated stress	High cost errors
	(%)									
Broadband indices										
NG	75	60	11	14	0	73	56	9	19	0
Narrowband indices										
DCNI	78	64	10	13	0	70	52	9	21	0
MTCI	73	57	18	10	3	79	66	10	11	1
NDI2	74	57	6	20	0	59	31	5	36	0
NDVI	51	13	3	46	3	49	8	0	51	9
NDVI1	71	55	19	10	4	74	59	16	10	4
SR8	66	48	24	10	3	76	63	14	10	0
Partial least squares regression										
PLS RD[a]	79	65	5	16	0	76	62	5	19	0

[a] PLS = Partial least squares regression using reflectance derivative as input for its independent variables.

stress. Instead, MTCI slightly overestimated the N stress classes. For N fertilizer recommendations, it is perhaps better to have a slightly higher percentage of overestimated stress than underestimated stress since a grower may run the risk of losing yield if fertilizer is applied below the optimum rate due to misclassified areas of underestimated stress.

The CV of a spectral index/model was directly related to the results of its accuracy assessment, especially regarding overestimated and underestimated stress (Tables 7 and 8). Assuming a fixed NSI threshold and similar prediction accuracies between two spectral indices/models, an index/model with a higher CV will tend to overestimate N stress and one with a lower CV will tend to underestimate N stress. This suggests that the CVs of spectral indices/models are important for determining N threshold levels and should be considered when making fertilizer recommendations. For N threshold levels to be universal across spectral indices/models for fertilizer recommendations, the spectral indices/models must be standardized based on their CVs.

4. Conclusions

Across image dates and over growing seasons for both cultivars, the PLS models, were the best predictors of leaf N concentration in potatoes (i.e., they had the highest r^2 and lowest RMSECV values). To be used in a commercial setting, the latent variables (including the scores and loadings) should be understood for the sensor and the environmental conditions for which the PLS model is developed. Of the indices evaluated, MTCI was found to be the most promising spectral index for determining N stress level for variable rate application of N fertilizer over a broad range of conditions, but PLS holds promise for the future if challenges such as sensor cost and sensor size can be overcome.

Normalization of leaf N concentration or spectral indices/models by applying the N Sufficiency Index (NSI) made them insensitive to external factors such as cultivar, which makes them more useful over a broader range of environmental conditions. Because canopy-scale spectral data are affected by biomass/leaf area index in addition to plant biophysical parameters (Daughtry et al., 2000), many of the spectral indices/models were able to distinguish between the N treatments better than leaf N concentration according to a means separation analysis. For NSIs to be useful for variable rate fertilizer management, the user must be aware of the variability imposed by the spectral index/model relative to the variability of leaf N concentration (or the measurement that the spectral data is being based on). Without doing so increases the risk of underestimating or overestimating the actual N stress level.

Future research should investigate: (i) the relationship between canopy-scale hyperspectral data and the Nitrogen Nutrition Index (NNI) to better understand plant N stress, (ii) the behavior of PLS models under different environmental conditions (e.g., growth stages and cultivars), and (iii) the relationships in variability among plant measurements and spectral indices/models.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2014.12.018.

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