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Estimating green LAI in four crops: Potential of determining optimal spectral bands for a universal algorithm

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ABSTRACT

Vegetation indices (VIs) have been used previously for estimating green leaf area index (green LAI). However, it has not been verified how characteristics of the relationships between these indices and green LAI (i.e., slope, intercept, standard error) vary for different crops and whether one universal algorithm may be applied for accurate estimation of green LAI. By analyzing the data from four different crops (maize, soybean, wheat, and potato) this study aimed at: (1) determining if the previously used VIs for estimating green LAI in maize and soybean may be applicable for potato and wheat and vice versa; and (2) finding a robust algorithm for green LAI estimation that does not require re-parameterization for each crop. Spectral measurements of wheat and potato were obtained in Israel from 2004 to 2007 and of maize and soybean in the USA from 2001 to 2008, and various VIs calculated using measured reflectance were compared with green LAI measured in the field. For all four crops, ten different VIs were examined. Similarities in relationships between VIs and green LAI were found. Among the examined VIs, two variants of the chlorophyll index and wide dynamic range vegetation index with the green and red edge bands were the most accurate in estimating green LAI in all four crops. Hyperspectral reflectance data were used to determine optimal diagnostic bands for estimating green LAI in four crops using a universal algorithm. The green (530–570 nm) and red edge (700–725 nm) regions were identified for both the wide dynamic range vegetation index and chlorophyll index as having the lowest errors estimating green LAI. Since the Landsat 8 – OLI has a green spectral band and the forthcoming Sentinel-2, Sentinel-3 and VENμS have both green and red edge bands, it is expected that these VIs can be used to monitor green LAI in multiple crops using a single algorithm by means of near future satellite missions.

1. Introduction

One of the most commonly utilized vegetation biophysical characteristics is leaf area index, LAI (Bulcock and Jewitt, 2010; Fang et al., 2011). It is the ratio of leaf area (one-sided for flat leaves) per unit ground area (Watson, 1947). The green LAI is the ratio of green photosynthetically active leaf area per ground area (Daughtry et al., 1992) and is a measure of the leaf area participating in photosynthesis. There is a strong interest in developing models for the remote estimation of green LAI for use as metrics in climate (Zaroug et al., 2012), ecological (Richardson et al., 2011), and crop models (Casa et al., 2012), as well as for estimating crop vegetation status (Bobée et al., 2012), developing soil maps (Coops et al., 2012), light-use efficiency (Garbulsky et al., 2011; Claverie et al., 2012), and yield (Guindin-Garcia et al., 2012).

Vegetation indices (VIs) are widely used in remote sensing algorithms for monitoring various crop characteristics (Hatfield and Prueger, 2010; Huang et al., 2012), primarily due to their simplicity in application and ease of data processing. Most VIs are comprised of reflectances in a few wavebands that can be collected by broadband satellite sensors (e.g., Moderate Resolution

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Imaging Spectroradiometer (MODIS), Medium Resolution Imaging Spectrometer (MERIS), and Landsat among others). While narrow band and hyperspectral data can be used, it is often not necessary for green LAI estimation (Broge and Leblanc, 2001), except in cases of sparse canopies and high background reflectances (Elvidge and Chen, 1995), or to distinguish between similar classes, as is the case in monitoring crop phosphorous and potassium content (Pimstein et al., 2011) or weed identification (Shapira et al., 2013).

In general terms, a vegetation index can be defined as the derivative of reflectance with respect to wavelength, which is an indicator of the abundance and activity of absorbers in the canopy (Myneni et al., 1995). If only one major absorber, such as chlorophyll (Chl), is of interest, $d\rho/d\lambda \propto \alpha\mathrm{LAI}$, where α is a Chl absorption coefficient (Myneni et al., 1997). This is the theoretical basis for relating reflected radiation with the green LAI of the canopy, and the absorption of photosynthetically active radiation. Thus, vegetation indices relate to both vegetation Chl content and its structural properties (canopy architecture, leaf structure, etc.).

Canopy Chl content is calculated as a product of green LAI and leaf Chl content (Gitelson et al., 2005; Boegh et al., 2013). In the vegetative stage, leaf Chl increases slightly and leaf expansion, i.e. green LAI, is the main factor governing canopy Chl. In the reproductive and senescence stages, both leaf Chl and green LAI decline almost synchronously and, thus, canopy Chl relates closely to green LAI. Thus, these two vegetation biophysical characteristics are closely related – e.g., $R^2 = 0.96$ for maize, Ciganda et al. (2008); 0.86 for barley, Boegh et al. (2013). It is not surprising, then, that VIs showing such a close relation to Chl content were used for accurate estimation of green LAI and vice versa (Broge and Leblanc, 2001; Gitelson et al., 2003a,b; Boegh et al., 2013). However, only a limited number of studies have examined the relationship of various VIs with green LAI in the context of multiple crops with a wide range of leaf structures and canopy architectures (e.g. Liu et al., 2012).

It has been shown that the normalized difference vegetation index (NDVI) and other normalized difference VIs are most sensitive to low to moderate green LAI values and tend to saturate at moderate to high green LAI (Sellers, 1985; Baret and Guyot, 1991; Huete et al., 2002; Gitelson et al., 2003b). In contrast, VIs such as the simple ratio (SR; Jordan, 1969), MERIS terrestrial chlorophyll index (MTCI; Dash and Curran, 2004), enhanced vegetation index (EVI; Huete et al., 1997) and chlorophyll indices (CIs; Gitelson et al., 2003a) show an increase in sensitivity to moderate to high green LAI; however, they were found to be less sensitive to low values of green LAI (Viña et al., 2011; Nguy-Robertson et al., 2012). It also has been demonstrated that the red-edge inflection point (REIP) is a good predictor of widely variable green LAI in potato and wheat (Herrmann et al., 2011; Pimstein et al., 2007). The goals of this study were to: (1) test the performance of VIs for green LAI estimation in four different crop types: maize (*Zea mays*), potato (*Solanum tuberosum*), soybean (*Glycine max*), and wheat (*Triticum* sp.) during the vegetative growing stage; and (2) determine whether a robust algorithm for green LAI estimation, which does not require parameterization for each crop, can be devised.

2. Materials and methods

2.1. Study area

The study area for wheat and potato was located in northwestern Negev, Israel. Wheat fields consisted of rainfed and irrigated plots, while all potato fields were irrigated. Both crops were grown under several nitrogen management strategies from 2004 through 2007. The green LAI for potato ranged from 0.68 to 3.3 $m^2\,m^{-2}$ in 2006 and 0.17 to 4.1 $m^2\,m^{-2}$ in 2007. The green LAI for wheat ranged from 0.12 to 4.5 $m^2\,m^{-2}$ in 2004 and 2.77 to 6.4 $m^2\,m^{-2}$ in 2005. The nitrogen treatment for potato consisted of applications of 0, 100, 215, 335, or 400 kg N ha^{-1} in 2006 and 0, 100, 200, 300, or 400 kg N ha^{-1} in 2007 (Cohen et al., 2010). The nitrogen treatment for wheat was either 50 or 100 kg N ha^{-1} in both 2004 and 2005. There were a total of 11 and 4 field-years for potato and wheat, respectively. Specific details of this study site can be found in the papers of Pimstein et al. (2007, 2009) and Herrmann et al. (2011).

For maize and soybean, the study site was located at the University of Nebraska-Lincoln Agricultural Research and Development Center near Mead, Nebraska. This study site consists of three 65-ha fields under different management practices: continuous irrigated maize, irrigated maize/soybean rotation, or rainfed maize/soybean rotation. All crops were grown following the best management practices for eastern Nebraska. The maximal green LAI values ranged from 4.3 to 6.5 $m^2\,m^{-2}$ for maize and 3.0 to 5.5 $m^2\,m^{-2}$ for soybean. There were 16 and 8 field-years for maize and soybean respectively. Of these 24 field-years, 4 field-years of each species were rainfed. The remaining 16 field-years were irrigated. Specific details of these three sites can be found in Suyker et al. (2004), Verma et al. (2005), and Viña et al. (2011).

2.2. Field measurements

In this study, the data collected during the vegetative stage were analyzed. Since data were limited to only the vegetative stage, the LAI measurements were a good proxy of green LAI. For the sites located in Israel, LAI measurements were an average of three measurements taken in the same field of view (FOV) as the spectral measurements using a ceptometer (AccuPAR LP80, Decagon Devices, Inc., Pullman, WA, USA) programmed differently according to the manufacturer's instructions for potato and wheat. The leaf distribution parameter was set to 2.00 for potato and 0.96 for wheat. These measurements use transmittance to estimate LAI. The values of replicate plots (same treatment) were averaged to create a field level green LAI value for each sampling date.

For the study site located in Nebraska, USA, six 20 m × 20 m plots were established in each field. These plots represented all major soil and crop production zones within each field (Verma et al., 2005). The green LAI was determined from sampling 6 ± 2 plants located in one or two rows (1 m length) within each plot every 10–14 days. Rows were alternated between sampling dates to minimize edge effects. The plants collected were transported on ice to the laboratory prior to green LAI and total LAI measurements using an area meter (LI-3100, LI-COR, Inc., Lincoln, NE, USA). These measurements were made by multiplying the green leaf area or total leaf area per plant by the number of plants collected in the sample. The values calculated from each plot were averaged to provide a field-level green LAI and total LAI on each sampling date.

Canopy reflectance of potato and wheat were collected in clear sky conditions in a nadir orientation ±2 h from solar noon using a spectrometer (FieldSpec Pro FR, Analytical Spectral Devices (ASD), Boulder, CO, USA) with a spectral range of 350–2500 nm and 25° field of view (FOV). For the purpose of this study, only the visible/near-infrared regions with a spectral resolution of 1.4 nm were utilized. Measurements were an average of 20 readings taken 1.5 m above the ground with a FOV of approximately 0.35 m^2 at the start of the season. Due to crop growth, the FOV was reduced to 0.13–0.26 m^2 and 0.08 m^2 for potato and wheat, respectively. A barium sulfate ($BaSO_4$) panel was used as the white reference for potato reflectance and a standard white reference panel (Spectralon, Labsphere Inc., North Sutton, NH, USA) was utilized for wheat reflectance. A total of 54 spectra for potato and 20 for wheat were collected.

Canopy reflectance for maize and soybean were collected using an all-terrain sensor platform, with a dual-fiber system with two radiometers (USB2000, Ocean Optics, Inc., Dunedin, FL, USA;

Table 1
Vegetation indices utilized in the study. The subscript indicates the satellite, M: MODIS, S: MERIS, and band number. For the three different variants of wide dynamic range vegetation index, α was 0.1.

Index	Equation	Reference
Simple Ratio (SR)	NIR_{M2}/Red_{M1}	Jordan (1969)
Red Edge Inflection Point (REIP)	$Red\ Edge_{S9} + 45 \times \{[(Red_{S7} + NIR_{S12})/2) - Red\ Edge_{S9}]/(NIR_{S10} - Red\ Edge_{S9})\}$	Guyot and Baret (1988), Clevers et al. (2000, 2001)
Green NDVI	$(NIR_{M2} - Green_{M4})/(NIR_{M2} + Green_{M4})$	Gitelson and Merzlyak (1994)
Red Edge NDVI	$(NIR_{S12} - Red\ Edge_{S9})/(NIR_{S12} + Red\ Edge_{S9})$	Gitelson and Merzlyak (1994)
Green Chlorophyll Index (CI_{green})	$(NIR_{M2}/Green_{M4}) - 1$	Gitelson et al. (2003a,b)
Red Edge Chlorophyll Index ($CI_{red\ edge}$)	$(NIR_{S12}/Red\ Edge_{S9}) - 1$	Gitelson et al. (2003a,b)
MERIS Terrestrial Chlorophyll Index (MTCI)	$(NIR_{S10} - Red\ Edge_{S9})/(Red\ Edge_{S9} - Red_{S8})$	Dash and Curran (2004)
Wide Dynamic Range Vegetation Index (WDRVI)	$(\alpha \times NIR_{M2} - Red_{M1})/(\alpha \times NIR_{M2} + Red_{M1}) + (1-\alpha)/(1+\alpha)$	Gitelson (2004), Peng and Gitelson (2011)
Green Wide Dynamic Range Vegetation Index (Green WDRVI)	$(\alpha \times NIR_{M2} - Green_{M4})/(\alpha \times NIR_{M2} + Green_{M4}) + (1-\alpha)/(1+\alpha)$	Gitelson (2004), Peng and Gitelson (2011)
Red Edge Wide Dynamic Range Vegetation Index (Red Edge WDRVI)	$(\alpha \times NIR_{S12} - Red\ Edge_{S94})/(\alpha \times NIR_{S12} + Red\ Edge_{S9}) + (1-\alpha)/(1+\alpha)$	Gitelson (2004), Peng and Gitelson (2011)

Rundquist et al., 2004). The upward looking fiber was fitted with a cosine diffuser to measure downwelling irradiance, and the downward looking fiber measured upwelling radiance. The field of view of the downward looking sensor was kept constant along the growing season (approximately 2.4 m in diameter) by placing the fiber at a height of approximately 5.5 m above the top of the canopy. Reflectance for each date was calculated as the median value of 36 reflectance measurements collected along access roads into each of the fields. From 2001 through 2008, a total of 278 spectra for maize and 145 for soybean were collected (details are in Viña et al., 2011; Nguy-Robertson et al., 2012).

2.3. Data processing

Since green LAI of crops changes gradually during the growing season (Nguy-Robertson et al., 2012), destructive green LAI measurements for maize and soybean were interpolated using a spline function based on values of green LAI on sampling dates for each field in each year using R (R-project, V. 2.12.2). Interpolated green LAI values were then obtained for the dates when reflectance measurements did not coincide with the dates of destructive green LAI measurements. No interpolation was necessary for the estimation of green LAI for wheat and potato.

The band settings used in calculating the VIs (Table 1) are based on the resampling the reflectance spectra to the equivalent bands in the MODIS (green: 555 ± 10 nm, red: 645 ± 25 nm, and NIR: 858.5 ± 17.5 nm) and MERIS (green: 560 ± 5 nm, red: 665 ± 5 nm, red-edge: 709 ± 5 nm, and NIR: 755 ± 5, 775 ± 7.5 nm) satellite sensors. While MERIS failed, these bands are still relevant since new satellite sensors, the multi spectral instrument (MSI) and ocean land color instrument (OLCI), using the same or similar bands are scheduled to be launched in 2014 aboard the Sentinel-2 and 3 satellites (http://www.esa.int/Our_Activities/Observing_the_Earth).

The examined VIs were selected primarily due to their performance analyzed in previous studies (Herrmann et al., 2011; Viña et al., 2011; Nguy-Robertson et al., 2012). The VIs in Table 1 include those typically applied (e.g. SR) as well as modified VIs (e.g. Green WDRVI). SR, green NDVI, red edge NDVI, CI_{green}, $CI_{red\ edge}$ and MTCI were shown to be capable of estimating crop total chlorophyll content, green LAI, gross primary production and fraction of absorbed photosynthetically active radiation in maize and soybean (Gitelson, 2003b; Viña et al., 2011; Nguy-Robertson et al., 2012; Peng and Gitelson, 2012). The green WDRVI uses the green (555 ± 10 nm) band instead of red in WDRVI (Gitelson, 2004; Peng and Gitelson, 2012), which is more sensitive than the original formulation of WDRVI to green LAI at high biomass (Gitelson, 2011a, 2011b). The REIP does not use the optimized bands for a continuous reflectance spectrum (Guyot and Baret, 1988) but rather those proposed for MERIS spectral bands (Clevers et al., 2000, 2001) that have been shown to work well for green LAI estimates in wheat and potato (Herrmann et al., 2011).

The best-fit relationships between VIs and green LAI, coefficient of determination (R^2), coefficient of variation (CV), and the analysis of variance (ANOVA) among crop species were conducted in R (R-project, V. 2.12.2). The ANOVA test compared the coefficients of the best-fit relationships using all the data with those developed for each specific crop type (Ritz and Streibig, 2008). This statistical test estimates the significance of the coefficients between crops. The coefficients were more similar in the models that have higher *p*-values. This means that models with the highest *p*-values are the least species-specific. This information combined with error estimates will provide insight on which models have the highest potential for developing a unified algorithm.

3. Results and discussion

3.1. Relationships between VIs and green LAI

Vegetation indices, which were accurate in estimating green LAI in potato and wheat (Herrmann et al., 2011) as well as for maize and soybean (Gitelson et al., 2003b; Viña et al., 2011; Nguy-Robertson et al., 2012), were applied to four crops (Figs. 1 and 2). All indices tested in this study were related quite closely to green LAI with coefficients of determination (R^2) in each crop exceeding 0.80. The relationships VI vs. green LAI were essentially non-linear for green and red edge NDVI, WDRVI, and REIP (Fig. 1), and nearly linear for SR, MTCI, green WDRVI, CI_{green}, red edge WDRVI, and $CI_{red\ edge}$ (Fig. 2). The NDVI-based VIs, REIP, and WDRVI with the red spectral band all exhibited saturation at moderate to high values of green LAI for at least two or more crops. Green NDVI and red edge NDVI were consistently saturated at high green LAI in all four crops. REIP, which performed quite well for potato (Herrmann et al., 2011), was insensitive to high green LAI of maize, soybean and wheat. When green LAI was above 3 $m^2\ m^{-2}$, REIP in formulation designed for MERIS and the future satellite mission Sentinel-3, varied only 4 nm at most. This was in contrast to the findings in Herrmann et al. (2011), which demonstrated sensitivity of the REIP formulation using continuous data to high green LAI (~12 nm for green LAI ranging between 3 and 7 $m^2\ m^{-2}$). While the original formulation of WDRVI (with $\alpha = 0.1$) using a red band has been shown to be more sensitive than VIs like NDVI to high green LAI in maize (Gitelson, 2004), this study has found that for wheat and potato, WDRVI saturates at green LAI exceeding 2 $m^2\ m^{-2}$.

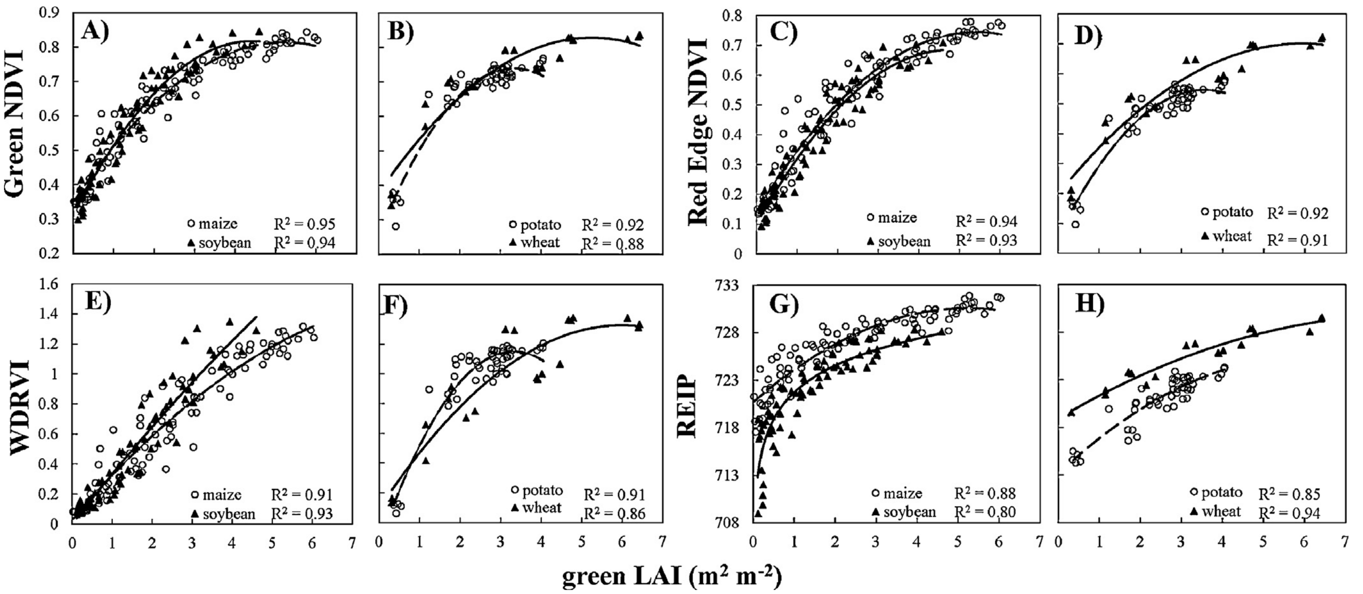

Fig. 1. Vegetation index (VI) vs. green leaf area index (green LAI) relationships for maize, soybean, potato, and wheat that exhibit strong non-linearity for at least two of the crops examined. Crops were placed in separate figures based on green LAI determination (destructive or non-destructive). Best-fit lines using 2nd order polynomials are indicated for each relationship with the coefficient of determination (R^2).

The R^2 values represent the dispersion of the points from the best-fit regression lines and provide a measure of how good the regression model is in capturing the relationship between green LAI and VI. However, the R^2 may be misleading when examining non-linear models, as presented in Fig. 1, where the sensitivity of VIs to moderate-to-high green LAI, and thus accuracy of estimation, decreased drastically (Nguy-Robertson et al., 2012; Simon et al., 2012). Hence, this study focused on the performance of the VIs presented in Fig. 2, which were found to have quite high sensitivity to green LAI in the whole range from 0 to more than 6 $m^2\,m^{-2}$: SR, CI_{green}, $CI_{red\ edge}$, green WDRVI, red edge WDRVI, and MTCI.

To provide results that should be impacted minimally by the methodology of green LAI determination in the field, two subsets of samples were studied first. One subset consisted of maize and soybean samples for which green LAI was determined destructively, and the other consisted of wheat and potato samples for which green LAI was determined via transmittance measurements. Unified algorithms for each subset were established for each VI (Table 2). Among the tested VIs, MTCI was least accurate for potato and wheat with the highest CV at 24%. The SR was the least accurate for maize and soybean with a CV above 24%. The green LAI vs. MTCI relationships had quite different slopes and intercepts for each crop appearing more species-specific with small p-values (Table 2), thus resulting in higher CV when using a universal algorithm for different species. For maize and soybean, the $CI_{red\ edge}$ (p-value = 0.26) and red edge WDRVI (p-value = 0.23) were not species-specific, while algorithms for other VIs were species-specific with p-value < 0.02. For wheat and potato, all tested VIs were species-specific. Since the sample size in potato and wheat data sets was much smaller than in the maize and soybean datasets, 74 vs. 422, respectively, the species-specific test statistics for potato and wheat may be not representative due to the limited sample size.

For the maize and soybean data sets, the red edge variants of the CI and WDRVI (e.g., $CI_{red\ edge}$ and red edge WDRVI) were more accurate (much less species-specific) than those using green variants (e.g., green WDRVI and CI_{green}). As originally was shown in Gitelson et al. (2005) and supported by Nguy-Robertson et al. (2012), algorithms for estimating biophysical characteristics such as Chl or green LAI using VIs containing a green band are species-specific while those using a red edge band may be species-independent. The reasoning for this behavior relates to both canopy architecture and leaf Chl distribution. Both soybean and potato have predominantly horizontal leaves while the leaf angle distribution in maize is spherical and wheat is uniform (De Wit, 1965; Goel and Strebel, 1984). In soybean and potato leaves, the Chl content in the adaxial side is much higher than in the abaxial side but is evenly distributed in maize and wheat leaves (Walter-Shea et al., 1991). Both factors affect light reflectance and transmittance (Seyfried and Fukshansky, 1983; Walter-Shea et al., 1991), thus making VIs retrieved from visible and NIR reflectance species-specific especially in the range of moderate-to-high green LAI. Light in the red edge spectral range penetrates much deeper into the canopy than light in the green range (Merzlyak and Gitelson, 1995). Thus, the difference in leaf structures and canopy architectures affect VIs with a red edge band less than those in the visible range of the electromagnetic spectrum. The deviation of soybean samples with maximum

Table 2
Unified algorithms for the maize and soybean dataset and for potato and wheat dataset. Lower coefficient of variation (CV, %) indicates algorithms with less dispersion from the best-fit line. Higher p-values indicated algorithms that were less species-specific.

	Maize and soybean dataset			Potato and wheat dataset		
	Green LAI = f (VI)	CV	p-value	Green LAI = f (VI)	CV	p-value
$CI_{red\ edge}$	$-0.036x^2 + 1.08x - 0.07$	19.1	0.26	$y = -0.067x^2 + 1.5x - 0.22$	17.7	2.6E−04
Red edge WDRVI	$2.1x^2 + 6.7x - 0.09$	19.1	0.27	$y = 1.6x^2 + 9.6x - 0.25$	17.7	3.5E−04
CI_{green}	$-0.018x^2 + 0.74x - 0.54$	22.3	2.8E−18	$y = -0.003x^2 + 0.64x - 0.37$	17.5	6.0E−03
Green WDRVI	$3.0x^2 + 3.9x - 0.45$	22.3	6.9E−17	$y = 5.7x^2 + 1.7x - 0.08$	17.4	0.01
SR	$-0.008x^2 + 0.40x - 0.25$	24.5	2.0E−14	$y = -0.0005x^2 + 0.20x + 0.20$	22.8	2.8E−04
MTCI	$-0.012x^2 + 0.90x - 1.1$	23.6	2.2E−10	$y = -0.11x^2 + 19x - 1.4$	24.0	8.15E−08

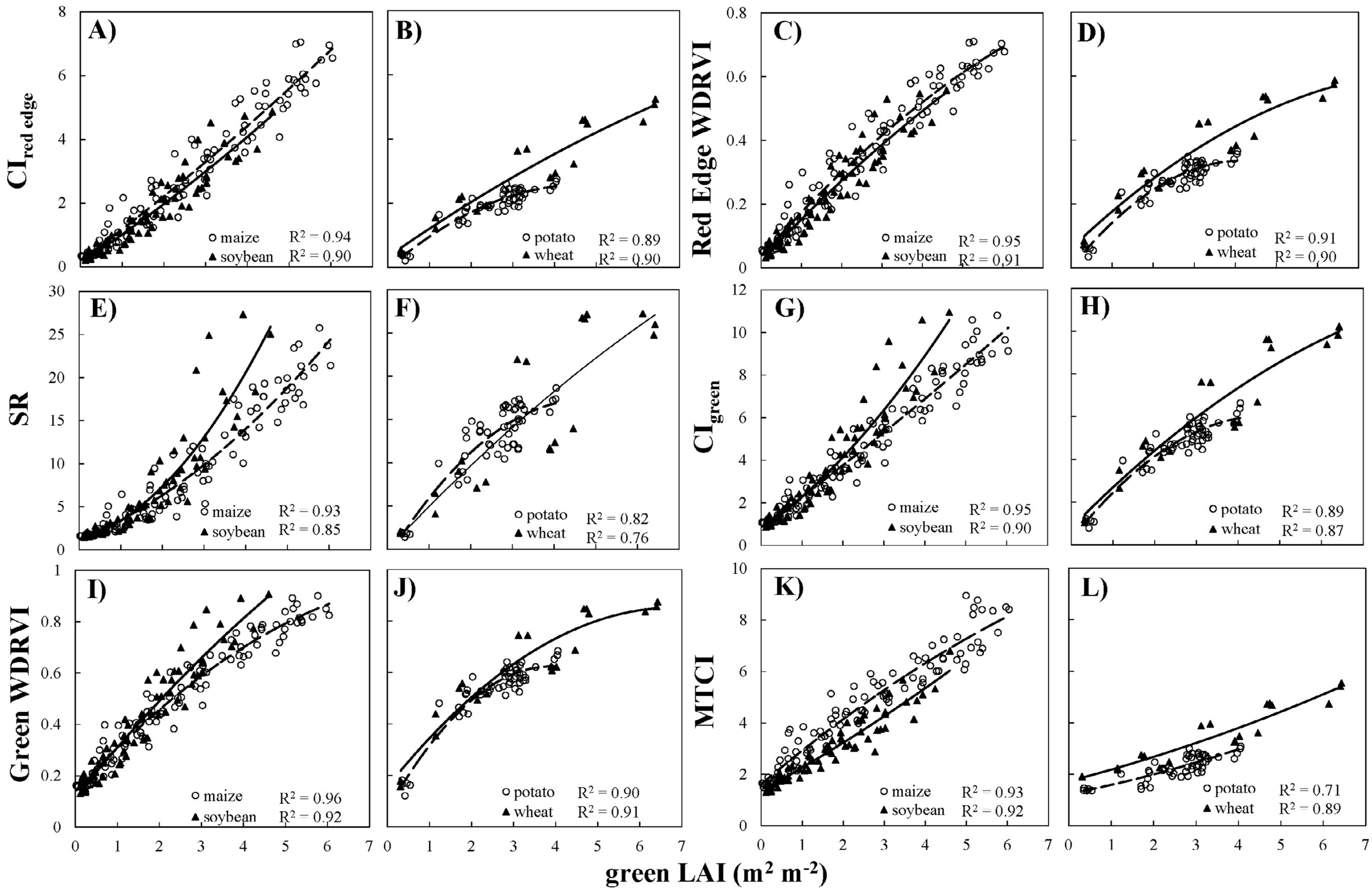

Fig. 2. Vegetation index (VI) vs. green leaf area index (green LAI) relationships for maize, soybean, potato, and wheat that were found to have quite high sensitivity to green LAI in the whole range from 0 to more than 6. Best-fit lines using 2nd order polynomials are indicated for each relationship with the coefficient of determination (R^2).

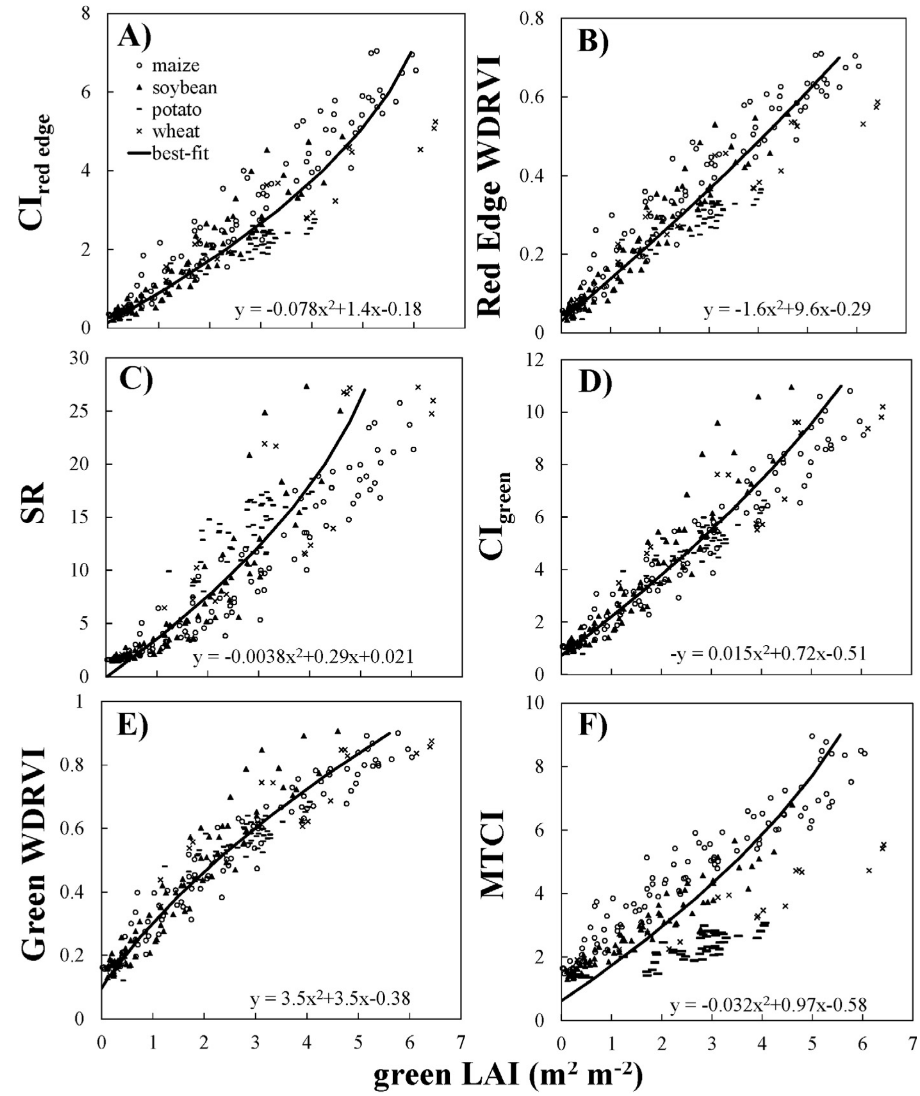

Fig. 3. The unified best-fit vegetation index (VI) vs. green leaf area index (green LAI) relationship for maize, soybean, potato, and wheat using a 2nd order polynomial.

green LAI reaching 5 $m^2\ m^{-2}$ from other crops was more obvious (Fig. 3C–E). Potato was still biased towards higher values in VIs such as SR and CI. The maximal green LAI for potato of 3 $m^2\ m^{-2}$ was not high enough for this bias to be evident, nor did it increase the error estimates greatly.

One unified algorithm was established for all four crops combined using each VI (Fig. 3) and the accuracy of green LAI estimation in each crop with no algorithm re-parameterization was determined (Fig. 4). Despite the difference in methodologies of green LAI determination in the field (destructive for maize and

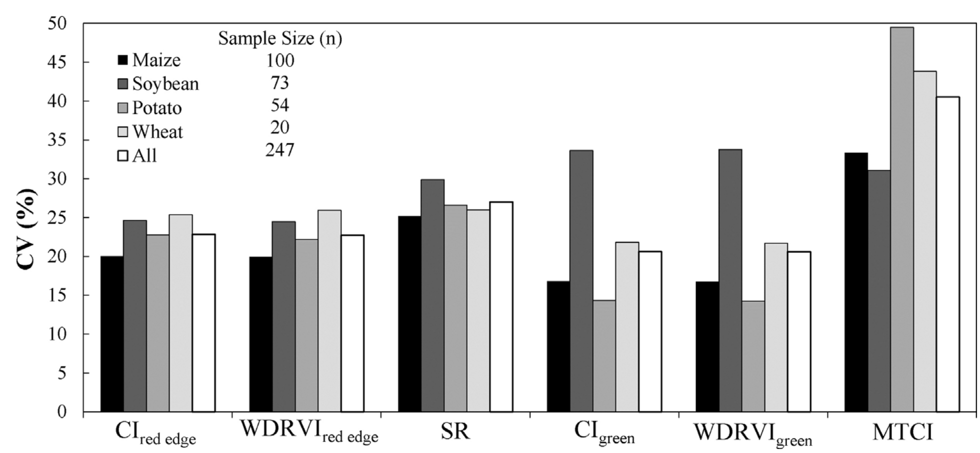

Fig. 4. Coefficient of variation (CV, %) of green LAI estimation by unified algorithms for each crop and the entire dataset.

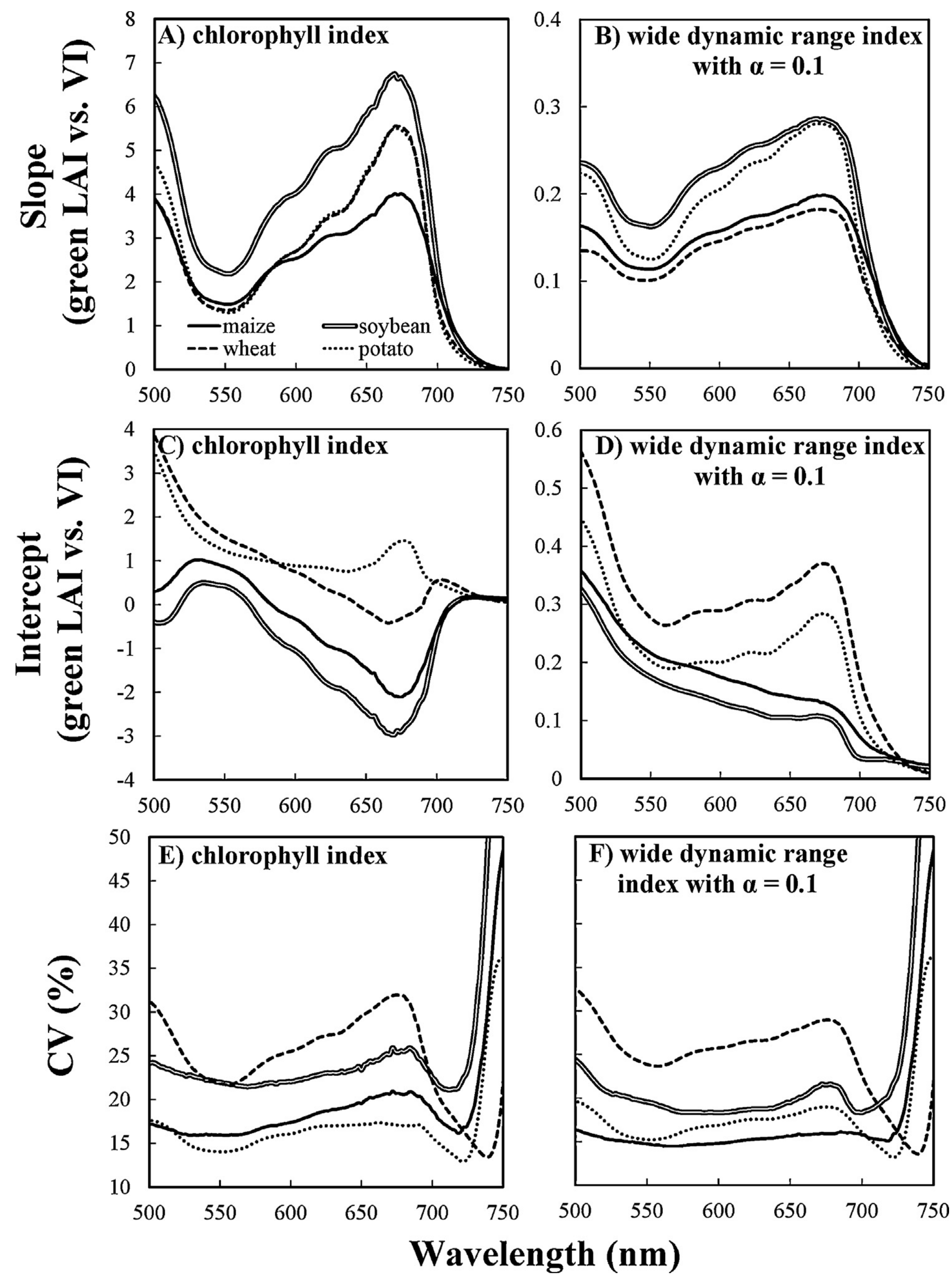

Fig. 5. The slope and intercept of the linear relationship of the green LAI vs. (A, C) Chlorophyll Index $[\rho_{NIR}/\rho_\lambda - 1]$ relationship and (B, D) Wide Dynamic Range Index $[(0.1 \times \rho_{NIR} - \rho_\lambda)/(0.1 \times \rho_{NIR} + \rho_\lambda)]$ for each crop. The coefficient of variation (CV, %) of the green LAI estimation by (E) Chlorophyll index and by (F) Wide Dynamic Range Index.

soybean and non-destructive for wheat and potato), among the six indices, the $CI_{red\ edge}$ and the red edge WDRVI had consistently lower values of the CV (below 26%) for all four crops. The CI_{green} and green WDRVI worked well for maize, potato and wheat, but had higher estimation errors in soybean (CV > 33%). SR was consistent across all four species but did not perform exceptionally well. It outperformed the green indices in soybean but had higher error in the other three crops (Fig. 4). MTCI performed poorly for all four crops with CV > 31% (Fig. 4); the difference of slopes for crops studied in US and Israel was large (Fig. 3).

3.2. Optimized spectral bands for unified algorithm

The CI and WDRVI showed potential to be used in a unified algorithm for green LAI estimation in different crops. The spectral bands of CI and WDRVI, examined above are utilized in existing (MODIS, Landsat), previously operating (MERIS), and future satellite sensors (e.g., OLCI, MSI, Venμs). However, they may not be the most optimal for a unified algorithm for all four crops. Having the hyperspectral reflectance data, this study also attempted to identify the best bands for developing potential universal algorithms for different crop species. To find optimal bands, the spectral behavior of the slope of the linear relationships between green LAI vs. CI $[(\rho_{NIR}/\rho_\lambda) - 1]$ and green LAI vs. WDRVI $[(0.1 \times \rho_{NIR} - \rho_\lambda)/(0.1 \times \rho_{NIR} + \rho_\lambda)]$ were examined for each crop. The NIR band was fixed at 841–876 nm and the second waveband (λ) varied between 500 and 750 nm. The hypothesis was that unified algorithms should have equal slopes and intercepts for different crops. When developing a universal algorithm to apply to multiple species, slopes and intercepts can provide insight into two different types of errors. Differences between species in terms of the intercept but not in the slope will introduce bias into the algorithm such that green LAI estimation for some species will always be overestimated and in others underestimated. Differences in the slope but not in the intercept will increase estimation errors at higher values of green LAI. Thus, the maximal VI value will correspond to widely different green LAI between and among species.

When λ was beyond 700 nm, slopes and intercepts of the relationships green LAI vs. VIs for all four crops were quite close across four crop species (Fig. 5A–D). However, when λ was set longer than 730 nm, the accuracy of green LAI estimation decreased with CV increasing dramatically (Fig. 5E and F), since reflectance beyond 730 nm was much more affected by leaf scattering than chlorophyll absorption. When bands in the range of 700–725 nm were used, the CV was lowest (<25%) for all four crops, thus, this region likely can be used in CI and WDRVI for a potential unified algorithm.

In addition, in the broad green spectral region (530–570 nm), the green LAI vs. CI relationships had almost equal slopes and intercepts for three crops, wheat, maize and potato (Fig. 5A and C). These results suggest that CI_{green} may be used as another choice for a unified algorithm not requiring re-parameterization for these three crops. This spectral range is included in the green band (525–600 nm) of the newly launched Landsat 8 (OLI sensor), making it possible to be used for estimating green LAI in these three crops. The MSI and OLCI sensors aboard Sentinel-2 and Sentinel-3, respectively, have bands (green, centered at 560 nm, and red edge, centered at 705 nm), that fall within the ranges found optimal for unified algorithms. The Venμs system has a band centered at 702 nm. Thus, it is hopeful that these VIs can be used to monitor multiple crops using a single algorithm in near future satellite missions.

4. Conclusions

The performance of ten vegetation indices in estimating green LAI was studied. Normalized difference-based indices were essentially non-linearly related to green LAI. REIP worked well for potato but was saturated at high values of green LAI in maize, soybean, and wheat. Six VIs, SR, CI_{green}, $CI_{red\ edge}$, green WDRVI, red edge WDRVI, and MTCI, showed comparable sensitivity to green LAI in the whole range of its variation. Of these six VIs, the chlorophyll index (CI) and wide dynamic range vegetation index (WDRVI) variants using the red edge band were identified as being the best suited for a unified algorithm. The unified algorithms based on CI_{green} and green WDRVI were able to accurately estimate green LAI in three crops, maize, potato, and wheat; however, these VIs did not estimate green LAI in soybean well. $CI_{red\ edge}$ and red edge WDRVI have the highest potential for unified algorithms that will not require re-parameterization for all four crops studied. Future research is needed using identical methodology for estimating green LAI to obtain accurate coefficients for a unified algorithm.

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