Green Leaf Area Index Estimation in Maize and Soybean: Combining Vegetation Indices to Achieve Maximal Sensitivity

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ABSTRACT

Vegetation indices (VIs), traditionally used for estimation of green leaf area index (gLAI), have different sensitivities along the range of gLAI variability. The goals of this study were to: (i) test 12 VIs for estimating gLAI in maize (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.]; (ii) estimate gLAI in both crops without the need to reparameterize the algorithms for different crops; and (iii) devise a combined VI that is maximally sensitive to gLAI along its entire range of variability. The study was performed for eight growing seasons (2001–2008) in one irrigated and one rainfed field under a maize–soybean rotation and one irrigated field under continuous maize in eastern Nebraska for a total of 24 field-years. The gLAI ranged from 0 to 6.5 m^2/m^2 in maize and 0 to 5.5 m^2/m^2 in soybean. Normalized difference indices, e.g., the normalized difference vegetation index (NDVI) were most sensitive to gLAI below 2 m^2/m^2, while ratio indices, e.g., simple ratio (SR) and chlorophyll indices (CIs), were most sensitive to gLAI above 2 m^2/m^2. For the crops evaluated, relationships between gLAI and the VIs were species specific with the exception of the red-edge NDVI and the $CI_{red\text{-}edge}$. To benefit from the different sensitivities of VIs along the entire gLAI range, we suggest combining VIs. For sensors with spectral bands in the red and near-infrared regions, the best combination was NDVI and SR (maize: coefficient of variation [CV] = 20%; soybean: CV = 23%); however, this combined index is species specific. For sensors with bands in the red-edge and near-infrared regions, the best combination was red-edge NDVI and $CI_{red\text{-}edge}$, which was capable of accurately estimating gLAI in both crops with a CV < 20% and with no reparameterization.

The leaf area index (LAI), the ratio of leaf area to ground area, typically reported as square meters per square meter, is a commonly used biophysical characteristic of vegetation (Watson, 1947). The LAI can be subdivided into photosynthetically active and photosynthetically inactive components. The former, the gLAI, is a metric commonly used in climate (e.g., Buermann et al., 2001), ecological (e.g., Bulcock and Jewitt, 2010), and crop yield (e.g., Fang et al., 2011) models. Because of its wide use and applicability to modeling, there is a need for a nondestructive remote estimation of gLAI across large geographic areas.

Various techniques based on remotely sensed data have been utilized for assessing gLAI (see reviews by Pinter et al., 2003; Hatfield et al., 2004, 2008; Doraiswamy et al., 2003; le Maire et al., 2008, and references therein). Vegetation indices, particularly the NDVI (Rouse et al., 1974) and SR (Jordan, 1969), are the most widely used. The NDVI, however, is prone to saturation at moderate to high gLAI values (Kanemasu, 1974; Curran and Steven, 1983; Asrar et al., 1984; Huete et al., 2002; Gitelson, 2004; Wu et al., 2007; González-Sanpedro et al., 2008) and requires reparameterization for different crops and species. The saturation of NDVI has been attributed to insensitivity of reflectance in the red region at moderate to high gLAI values due to the high absorption coefficient of chlorophyll. For gLAI below 3 m^2/m^2, total absorption by a canopy in the red range reaches 90 to 95%, and further increases in gLAI do not bring additional changes in absorption and reflectance (Hatfield et al., 2008; Gitelson, 2011). Another reason for the decrease in the sensitivity of NDVI to moderate to high gLAI values is the mathematical formulation of that index. At moderate to high gLAI, the NDVI is dominated by near-infrared (NIR) reflectance. Because scattering by the cellular or leaf structure causes the NIR reflectance to be high and the absorption by chlorophyll causes the red reflectance to be low, NIR reflectance is considerably greater than red reflectance: e.g., for gLAI >3 m^2/m^2, NIR reflectance is >40% while red reflectance is <5%. Thus, NDVI becomes insensitive to changes in both red and NIR reflectance.

Other commonly used VIs include the Enhanced Vegetation Index, EVI (Liu and Huete, 1995; Huete et al., 1997, 2002), its

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Abbreviations: CI, chlorophyll index; CVI, combined vegetation index; EVI, Enhanced Vegetation Index; EVI2, Enhanced Vegetation Index 2; gLAI, green leaf area index; IMZ, intensive measurement zone; LAI, leaf area index; MTCI, Medium Resolution Imaging Spectroradiometer Terrestrial Chlorophyll Index; MERIS, Medium Resolution Imaging Spectroradiometer; MODIS, Moderate Resolution Imaging Spectroradiometer; MTVI, modified triangular vegetation index; NDVI, normalized difference vegetation index; NE, noise equivalent; NIR, near infrared; OSAVI, optimized soil-adjusted vegetation index; SR, simple ratio; TVI, triangular vegetation index; VI, vegetation index; WDRVI, Wide Dynamic Range Vegetation Index.

alternative form, EVI2 (Jiang et al., 2008), and the triangular vegetation index, TVI (Broge and Leblanc, 2001). While the EVI is more sensitive to moderate to high LAI than the NDVI, it was also found to be sensitive to canopy architecture (Gao et al., 2000), and it does not relate well to LAI during the senescence stages (Wang et al., 2005). The TVI relates the difference between reflectance in the NIR and red regions to the magnitude of reflectance in the green region, thus defining a triangle in a three-dimensional spectral space. While the TVI is less affected by atmospheric properties than typical VIs, it is sensitive to differences in canopy structure and soil background (Broge and Leblanc, 2001). To minimize the sensitivities of the TVI, a soil adjustment factor has been introduced in a modified TVI, MTVI (Haboudane et al., 2004). The same study found that a second modified version (MTVI2) was accurate in estimating gLAI in different canopy structures that were simulated through radiative transfer models. Another investigation, aimed at examining gLAI in wheat (*Triticum aestivum* L.), found that MTVI2 was more sensitive than the NDVI to gLAI at higher gLAI values; however, it was sensitive to heading (i.e., flowering), which is not a component of gLAI but nevertheless affects the reflectance of crop canopies (Smith et al., 2008).

The VIs that incorporate bands in the spectral transition zone between absorption by pigments and scattering by leaves and canopies, termed the red-edge region (700–740 nm), were introduced to increase the sensitivity to moderate to high vegetation densities and estimate total chlorophyll content and gLAI (Gitelson and Merzlyak, 1994; Gitelson et al., 2003a, 2003b; Dash and Curran, 2004). Radiation in the red-edge region penetrates deeper into the leaves and canopies than radiation in the visible region due to a lower absorption coefficient in the former than in the latter. Thus, higher values of chlorophyll content and gLAI are required to decrease the sensitivity of red-edge VIs to gLAI (Dash and Curran, 2004; Ciganda et al., 2008; Gitelson, 2011). Some of the red-edge VIs constitute transformations of existing VIs, such as the red-edge NDVI (Gitelson and Merzlyak, 1994), which replaces the red band with one in the red-edge region. Others constitute semianalytical procedures for estimating pigment content in diffuse media, such as the CIs (Gitelson et al., 2003a). While the CIs were developed for estimating chlorophyll content, they also relate closely with gLAI because total canopy chlorophyll content has been shown to relate closely with the gLAI (Ciganda et al., 2008; Peng et al., 2011). Therefore, CIs are suitable for estimating gLAI (Gitelson et al., 2003b; Brantley et al., 2011) and particularly for moderate to high gLAI values. For instance, it was found that VIs utilizing the red-edge region (710–730 nm) were more accurate for estimating moderate to high gLAI in shrub canopies than normalized difference indices (Brantley et al., 2011); however, that study also found that at low to moderate gLAI values, normalized difference indices (e.g., the NDVI) perform better than the $CI_{red\text{-}edge}$. The MERIS Terrestrial Chlorophyll Index (MTCI) also contains a red-edge band and was developed for the remote estimation of total canopy chlorophyll content (Dash and Curran, 2004, 2007). It has been shown that the MTCI closely relates with gLAI (Gitelson, 2011).

For gLAI estimation using VIs, it is ideal that the VI selected is not sensitive to the canopy architecture (e.g., leaf angle distribution), leaf structure (e.g., foliar chlorophyll distribution), and heliotropism, so that the relationships gLAI vs. VI would be applicable to different vegetation types without requiring algorithm reparameterization. The VIs selected should also be insensitive to soil background and atmospheric effects.

To minimize the effects of soil background and maximize the sensitivity to foliar chlorophyll, Daughtry et al. (2000) suggested combining two VIs by taking a ratio of a VI sensitive to chlorophyll and a VI insensitive to soil background, canopy architecture, and LAI variability. Thus, a combination of indices based on the Transformed Chlorophyll Absorption Reflectance Index (TCARI), the Modified Chlorophyll Adsorption Ratio Index (MCARI), and the Optimized Soil-Adjusted Vegetation Index (OSAVI), such as TCARI/OSAVI and MCARI/OSAVI, were used to estimate the leaf chlorophyll content in crops, minimizing the effects of the soil background and the gLAI variation (Daughtry et al., 2000; Haboudane et al., 2002). The goal of these studies, however, was to remove the effect of LAI on the estimation of leaf chlorophyll content (Daughtry et al., 2000; Haboudane et al., 2002; Eitel et al., 2008, 2009); therefore, for this paper, that particular set of VIs was not considered for estimating gLAI.

Viña et al. (2011) evaluated the potential effects of soil background on the remote estimation of gLAI. For this, they used reflectance spectra of spherical and planophile canopies with different gLAI values under two contrasting soil backgrounds (i.e., dark and bright), as simulated by the New Advanced Discrete Model (Gobron et al., 1997), and used them for calculating three vegetation indices: the EVI, MTCI, and $CI_{red\text{-}edge}$. The EVI has been suggested to be less sensitive to background effects (Huete et al., 1997); however, the uncertainties of gLAI estimation due to soil background effects by all three indices were very similar. In the spherical canopy, the errors of EVI, MTCI, and $CI_{red\text{-}edge}$ were 0.25, 0.18, and 0.21 m^2/m^2, respectively, while in the planophile canopy they were 0.21, 0.20, and 0.14 m^2/m^2, respectively.

Maize and soybean plants have contrasting canopy architectures (i.e., maize has a predominantly spherical leaf angle distribution while soybean has a predominantly planophile/heliotropic leaf angle distribution) and leaf structures (i.e., maize is a monocot while soybean is a dicot) that exhibit different chlorophyll distributions along the leaf depth (de Wit, 1965; Idso and de Wit, 1970; Ehleringer and Forseth, 1980). Additionally, these two species have different physiological pathways (C_3 vs. C_4). Based on contrasting anatomical and physiological traits, these crops are representative of many crops types, and most VIs have been shown to respond to them and thus are species or crop specific (Curran and Milton, 1983; Gao et al., 2000; González-Sanpedro et al., 2008). Some indices that use red-edge bands in their formulation, however, have been shown to be less sensitive to differences among species (Gitelson et al., 2005; Gitelson, 2011; Brantley et al., 2011; Viña et al., 2011).

The objectives of this study were to: (i) test the performance of 12 VIs for estimating gLAI in maize and soybean; (ii) identify an algorithm that does not require reparameterization for estimating gLAI in both maize and soybean (C_3 vs. C_4 crops); and (iii) devise a "combined vegetation index" that is maximally sensitive to gLAI along its entire range of variability (i.e., 0 to >6 m^2/m^2) and is applicable to current operational satellite-based sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the NASA Terra and Aqua satellites or the European Space Agency's Medium Resolution Imaging Spectroradiometer (MERIS).

MATERIALS AND METHODS

The study area is located at the University of Nebraska-Lincoln (UNL) Agricultural Research and Development Center near Mead, NE. It consists of three 65-ha fields under different management practices (Table 1). The soils are deep silty clay loams including Tomek (fine, smectitic, mesic Pachic Argiudolls), Yutan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs), Filbert (fine, smectitic, mesic Vertic Argialbolls), and Fillmore (fine, smectitic, mesic Vertic Argialbolls) soil series (Suyker et al., 2004). During the years of study, Field 1 was under continuous irrigated maize, while Fields 2 and 3 were under a maize–soybean rotation, with maize during odd years and soybean during even years. Field 2 was irrigated, while Field 3 received only rainfall. Overall, there were nine maize hybrids and three soybean hybrids under different planting densities (Table 1). All crops were fertilized and treated with herbicides and pesticides following UNL's best management practices for eastern Nebraska.

It has been reported that 2003 and 2005 were especially dry years, with annual precipitation values of 650 and 607 mm, respectively, which are well below the 1026 mm of a "normal" year (Suyker and Verma, 2010). Thus, water stress occurred under low soil moisture conditions, which severely affected grain yield. For example, during dry periods in 2003, soil moisture at the 10-cm depth in the rainfed field dropped >40% compared with irrigated fields. The difference in daily gross primary production (GPP) between irrigated and rainfed fields increased during the dry periods and reached a peak value that corresponded to 40% of the maximal daily GPP value (Suyker and Verma, 2010). As a result, the ratio of grain yield in the irrigated field to that in the rainfed field was >1.8 in 2003, while in a "normal" year with higher precipitation (e.g., 2007), it was <1.3 (Suyker and Verma, 2010).

Six small (20- by 20-m) plots (henceforth referred to as intensive measurement zones, IMZs) were established in each field for performing detailed plant measurements. The IMZs represented all major soil and crop production zones within each field (Verma et al., 2005). The IMZ results were aggregated to a field mean based on a weighted average of the relative area of the stratified zones represented by each IMZ. The gLAI was calculated by sampling a 1-m length of one or two rows (6 ± 2 plants) located within each IMZ every 10 to 14 d starting at the initial growth stages (V1–V3), based on the scale by Abendroth et al. (2011), and ending at crop maturity (R5–R7) in both species. Collection rows were alternated between sampling dates to minimize edge effects. The plants collected were transported on ice (to reduce pheophytin formation) to the laboratory, where they were visually divided into green leaves, dead leaves, stems, and reproductive organs. The leaf area was measured using an area meter (LI-COR Model LI-3100), which was subsequently used to determine the gLAI (green leaf area in square meters divided by ground area in square meters) by multiplying the green leaf area per plant by the plant population (number of plants per square meter) as counted in each IMZ (i.e., not based on planting density shown in Table 1). The values calculated from all six IMZs were averaged for each sampling date to provide a field-level gLAI. During the 8 yr of the study, the mean standard error

Table 1. Species, hybrid, planting density, and maximum green leaf area index (gLAI) in the 24 field-years evaluated.

Year	Site	Species	Hybrid	Planting density	Max. gLAI	Tillage operation	Applied N
				plants/ha	m^2/m^2		kg N/ha
2001	1	maize	Pioneer 33P67	82,000	6.1	intensive tillage	196
	2	maize	Pioneer 33P67	83,314	6.1		196
	3	maize	Pioneer 33B51	62,236	3.9		128
2002	1	maize	Pioneer 33P67	81,000	6.0	no-till	214
	2	soybean	Asgrow 2703	370,644	5.5		0
	3	soybean	Asgrow 2703	370,644	3.0		0
2003	1	maize	Pioneer 33B51	77,000	5.5	no-till	233
	2	maize	Pioneer 33B51	86,667	5.5		169
	3	maize	Pioneer 33B51	64,292	4.3		90
2004	1	maize	Pioneer 33B51	84,012	5.2	no-till	293
	2	soybean	Pioneer 93B09	370,644	4.4		0
	3	soybean	Pioneer 93B09	370,644	4.5		0
2005	1	maize	DeKalb 63-75	82,374	5.2	no-till	246
	2	maize	Pioneer 33B51	83,200	4.8		170
	3	maize	Pioneer 33G68	59,184	4.3		118
2006	1	maize	Pioneer 33B53	84,012	5.3	conservation plow	210
	2	soybean	Pioneer 31N28	370,644	5.0	no-till	0
	3	soybean	Pioneer 93M11	370,644	4.5		0
2007	1	maize	Pioneer 31N30	80,697	6.3	conservation plow	272
	2	maize	Pioneer 31N28	78,740	5.7	no-till	183
	3	maize	Pioneer 33H26	62,088	4.1		125
2008	1	maize	Pioneer 31N30	84,469	6.5	conservation plow	123
	2	soybean	Pioneer 93M11	369,508	4.7	no-till	0
	3	soybean	Pioneer 93M11	369,508	3.6		0

of gLAI measurements was <0.15 m^2/m^2 (Guindin-Garcia et al., 2012). Cubic spline interpolation (using MATLAB, the MathWorks) was used to estimate values of gLAI corresponding to days of reflectance measurement when that parameter was not acquired concurrently with the destructive gLAI determination.

Canopy reflectance was collected using an all-terrain sensor platform, equipped with a dual-fiber system and two Ocean Optics USB2000 spectroradiometers, with a spectral range of 400 to 1100 nm and a spectral resolution of 1.5 nm (Rundquist et al., 2004). One fiber was fitted with a cosine diffuser to measure incoming downwelling irradiance, while the second one measured upwelling radiance. The field-of-view of the downward-pointing sensor was kept constant during the growing season (approximately 2.4 m in diameter) by placing the spectroradiometer at a height of 5.5 m above the top of the canopy. Radiometric data were collected close to solar noon (between 1100 and 1300 h local time), when changes in the solar zenith angle were minimal. Ten reflectance spectra were measured at each collection point along access roads into each of the fields, and the computed average reflectance represented each collection point. Six randomly selected plots were established per field, each with six randomly selected sampling points. Thus, a total of 36 points within these areas were sampled per field at each data acquisition, and their median per date was used as the overall field reflectance. Measurements took about 5 min per plot and about 30 min per field. The two radiometers were intercalibrated immediately before and immediately after measurement in each field. Reflectance measurements were performed during the growing season each year during the 8-yr period. This resulted in a total of 314 reflectance spectra for maize (47 in 2001, 30 in 2002, 92 in 2003, 30 in 2004, 53 in 2005, 13 in 2006, 40 in 2007, and 9 in 2008) and 145 spectra for soybean (54 in 2002, 49 in 2004, 26 in 2006, and 16 in 2008), which were representative of a wide range of gLAI variation found in maize and soybean cropping systems.

Using hyperspectral aerial imagery, acquired over the study site by an AISA Eagle hyperspectral imaging spectrometer, it was shown that the canopy reflectance in the fields was spatially homogeneous; thus, reflectance spectra taken along access roads were representative of the field (Viña et al., 2011). Therefore, the remotely estimated gLAI may be compared with the measured field-level gLAI.

The 12 VIs examined in this study (Table 2) were chosen because they are representative of VIs that are widely used (e.g., NDVI and SR); some of them minimize soil background effects (e.g., OSAVI and EVI). They were also selected because of their applicability to data collected by satellite sensors such as MODIS and MERIS. These two sensors are utilized much more frequently than hyperspectral sensors, which are expensive to operate and cover limited study areas. Because a goal of this study was to find VIs applicable to MODIS and MERIS, the collected field reflectance spectra were resampled by averaging the Ocean Optics data to simulate the spectral bands of MODIS (Band 3, green: 545–565 nm; Band 1, red: 620–670 nm; and Band 2, NIR: 841–876 nm) and of MERIS (Band 5, green: 555–565 nm; Band 7, red: 660–670 nm; Band 8, red: 677.5–685 nm; Band 9, red edge: 703.8–713.8 nm; Band 10, NIR: 750–757.5 nm; and Band 12, NIR: 771.3–786.3 nm).

Best-fit relationships between the VIs and gLAI were determined using Eureqa (Schmidt and Lipson, 2009; http://

Table 2. Formulations of the vegetation indices examined.

Index	Equation	Equation in bands of MODIS or MERIS	Reference
Simple ratio	near-infrared (NIR)/red	MODIS 2/MODIS 1	Jordan, (1969)
Normalized difference vegetation index (NDVI)	(NIR – red)/(NIR + red)	(MODIS 2 – MODIS 1)/(MODIS 2 + MODIS 1)	Rouse et al. (1973)
Green NDVI	(NIR – green)/(NIR + green)	(MODIS 2 – MODIS 4)/(MODIS 2 + MODIS 4)	Gitelson and Merzlyak, (1994)
Red-edge NDVI	(NIR – red edge)/(NIR + red edge)	(MERIS 12 – MERIS 9)/(MERIS 12 + MERIS 9)	Gitelson and Merzlyak, (1994)
Optimized Soil-Adjusted Vegetation Index	(NIR – red)/(red + NIR + 0.16)	(MODIS 2- MODIS 1)/ (MODIS1 + MODIS 2 + 0.16)	Rondeaux et al. (1996)
Green chlorophyll index	(NIR/green) – 1	(MODIS 2/MODIS 4) – 1	Gitelson et al. (1996)
Red-edge chlorophyll index	(NIR/red edge) – 1	(MERIS 12/MERIS 9) – 1	Gitelson et al. (1996)
Triangular vegetation index (TVI)	0.5[120(NIR – green) – 200(red – green)]	0.5[120(MERIS 10 – MERIS 5) – 200(MERIS 7 – MERIS 5)	Broge and Leblanc (2001)
MERIS Terrestrial Chlorophyll Index	(NIR – red edge)/(red edge – red)	(MERIS 10- MERIS 9)/ (MERIS 9 + MERIS 8)	Dash and Curran, (2004)
Wide Dynamic Range Vegetation Index (WDRVI)†	[α(NIR) – red]/[α(NIR) + red]	[α(MODIS 2) – MODIS 1]/[α(MODIS 2) + MODIS 1]	Gitelson, (2004)
Modified TVI 2	1.5[1.2(NIR – green) – 2.5(red – green)]/$\sqrt{}${(2NIR + 1)^2 – [6NIR – 5$\sqrt{}$(red)] – 0.5}	1.5[1.2(MODIS 2 – MODIS 4) – 2.5(MODIS 1 – MODIS 4)]/$\sqrt{}${[2(MODIS 2) + 1]^2 – [6(MODIS 2) – 5$\sqrt{}$(MODIS 1)] – 0.5}	Haboudane et al. (2004)
Enhanced Vegetation Index 2	2.5(NIR – red)/(NIR + 2.4red + 1)	2.5(MODIS 2 – MODIS 1)/[MODIS 2 + 2.4(MODIS 1) + 1]	(Jiang et al. (2008)

† This study utilized scaled WDRVI in the form [α(MODIS band 2) – MODIS band 1]/[α(MODIS band 2) + MODIS band 1] + (1 – α)/(1 + α) (Peng et al., 2011).

creativemachines.cornell.edu/eureqa), an algorithm search engine that identifies and ranks potential regression models that best correspond to the input data. Users input the desired relationship, e.g., VI = *f*(gLAI), along with potential operations (e.g., addition, subtraction, exponential, power, etc.) and an error metric (e.g., minimize absolute error, R^2, etc.). In our case, the fitness metric used to rank the best-fit functions constituted the minimization of the root mean square error (RMSE). The inverse of these relationships (i.e., gLAI vs. VI) was utilized for gLAI estimation using VIs. After determining the best-fit relationships, a *k*-fold (k = 10) cross-validation procedure (Kohavi, 1995) was utilized to determine the estimates of model coefficients, R^2, RMSE, and CV using the statistical package R (Version 2.12.2, R Development Core Team, 2011). The CV is the RMSE of the gLAI vs. VI relationship divided by the mean value of gLAI. The data or subgroups (i.e., different crops: maize or soybean) were randomly divided into 10 sets using a random sequence generator (http://www.random.org/), nine of which were used iteratively for calibration and the remaining set for validation.

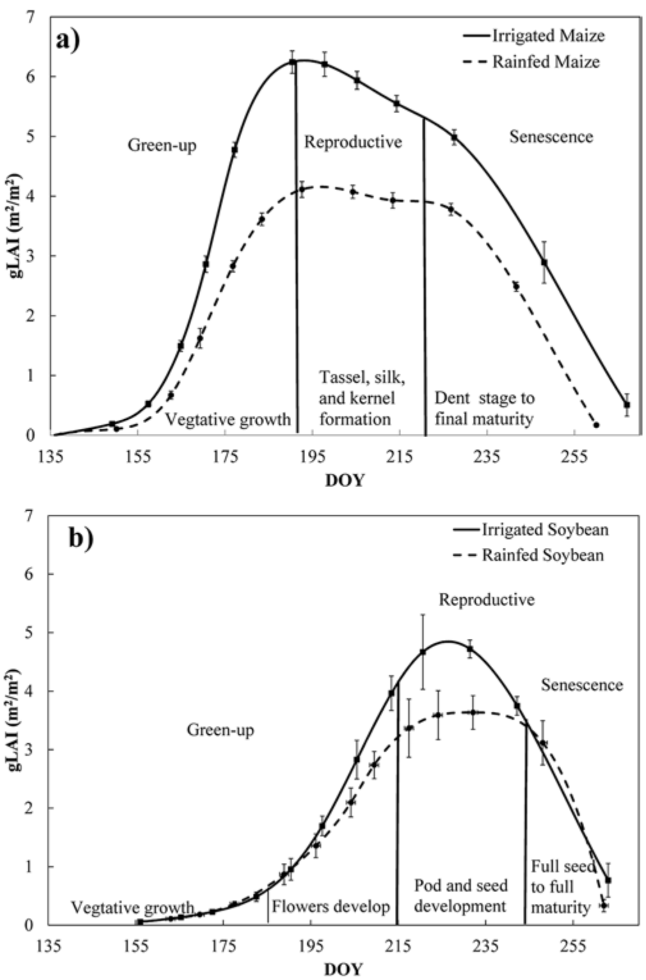

Fig. 1. Temporal dynamics of green leaf area index (gLAI) in (a) maize in 2007 and (b) soybean in 2008, in both irrigated (solid line) and rainfed (dashed line) fields. Major crop growth stages (vegetative, reproductive, and senescence) are indicated. Bars represent one standard error of destructive gLAI determination at six intensive measurement zones in each field; DOY is Day of the Year.

It is important to note that the R^2 values, as well as the RMSE and CV of gLAI estimation, represent the dispersion of the points from the best-fit regression lines. They constitute measures of how good the regression model (best-fit function) is in capturing the relationship between gLAI and VI. When the best-fit function is nonlinear, however, the R^2 as well as the RMSE and CV values may be misleading. To determine the accuracy of gLAI estimation, we used the noise equivalent (NE) of gLAI (Govaerts et al., 1999; Viña and Gitelson, 2005), which was calculated as

$$\mathrm{NE}\,\Delta\mathrm{gLAI} = \frac{\mathrm{RMSE}\left(\mathrm{VI\ vs.\ gLAI}\right)}{\mathrm{d}\left(\mathrm{VI}\right)/\mathrm{d}\left(\mathrm{LAI}\right)} \quad [1]$$

where d(VI)/d(gLAI) is the first derivative of the VI with respect to gLAI, and RMSE(VI vs. LAI) is the RMSE of the VI vs. gLAI relationship. The NE ΔgLAI provides a measure of how well the VI responds to gLAI across its entire range of variation. The NE ΔgLAI takes into account not only the RMSE of gLAI estimation but also accounts for the sensitivity of the VI to gLAI, thus providing a metric accounting for both the scattering of the points from the best-fit function and the slope of the best-fit function.

To test the applicability of VIs to estimate the gLAI of different crops with no algorithm reparameterization, we performed an ANOVA test between the coefficients of the best-fit function for both species (maize and soybean) combined vs. the coefficients obtained for each individual crop (Ritz and Streibig, 2008).

RESULTS AND DISCUSSION

While both maize and soybean undergo two major stages of development (green-up and reproduction), the temporal dynamics of their gLAIs are very different (Fig. 1). In maize, the green-up period is 20 d longer than in soybean. Maize remained in the vegetative stage as gLAI increased until it reached the maximum gLAI, which occurred when silking began. There was a decrease in gLAI of about 1 m^2/m^2 during kernel development. Then, during the final stage before maturity (dent), gLAI dropped to nearly 0 m^2/m^2 (Fig. 1a). In contrast, soybean flowered before the maximum gLAI was reached, which occurred during pod and seed development, and gLAI decreased once the plant reached full seed (Fig. 1b). The ranges of maize and soybean gLAI variability were also different. In irrigated maize, the maximum gLAI reached 6.5 m^2/m^2, while in soybean it did not exceed 5.5 m^2/m^2. For both crops, gLAI maxima in rainfed fields were typically lower than in irrigated fields (Fig. 1; Table 1). Thus, the maximum gLAI differed on per-crop (i.e., maize vs. soybean) and water-status (i.e., irrigated vs. rainfed) bases.

All best-fit functions established between gLAI and VI for either maize (Table 3) or soybean (Table 4) were nonlinear, but the shapes of the relationships VI vs. gLAI differed among VIs (Fig. 2). For example, NDVI reached an asymptote at around 0.7 when gLAI was between 2 and 3 m^2/m^2 and became almost invariant for gLAI > 4 m^2/m^2 in both maize and soybean (Fig. 2b). This saturation of the NDVI (Fig. 2b) reduced its functionality for gLAI estimation at moderate to high gLAI values because it generated large uncertainty in

Table 3. Best-fit functions of the relationships between green leaf area index (gLAI) and vegetation indices (VIs) obtained using a cross-validation procedure for maize; x = VI, y = gLAI, , and the RMSE is the root mean squared error of the gLAI estimation.

Index	Equation	R^2	RMSE
			m^2/m^2
Simple ratio	$y = x^{0.654} - 1.24$	0.86	0.66
Normalized difference vegetation index (NDVI)	$y = \log_{0.6}[-(x - 0.943)/0.731]$	0.87	0.64
Green NDVI	$y = -\{[\ln(0.876 - x) + 0.66]/0.409\}$	0.87	0.63
Red-edge NDVI	$y = \log_{0.716}(0.88 - x) - 0.623$	0.90	0.54
Optimized soil-adjusted vegetation index	$y = -[1.49 \ln(x) + 2.71]/\ln(x)$	0.81	0.78
Green chlorophyll index	$y = [(x - 0.931)/1.44]^{0.971}$	0.89	0.59
Red-edge chlorophyll index	$y = [(x - 0.15)/0.642]^{0.775}$	0.90	0.55
Triangular vegetation index (TVI)	$y = (x/8.85)^{1.73}$	0.65	1.05
MERIS Terrestrial Chlorophyll Index	$y = (x - 1.49)^{0.926}$	0.85	0.69
Wide Dynamic Range Vegetation Index, α = 0.2	$y = \log_{0.775}(1.61 - x) + 1.61$	0.88	0.60
Modified TVI 2	$y = \log_{0.81}(1.05 - x)$	0.67	1.01
Enhanced Vegetation Index 2	$y = (x + 0.863)^{4.08} - 0.863$	0.63	1.07

Table 4. Best-fit functions of the relationships between green leaf area index (gLAI) and vegetation indices (VIs) obtained using a cross-validation procedure for soybean; x = VI, y = gLAI, , and the RMSE is the root mean squared error of gLAI estimation.

Index	Equation	R^2	RMSE
			m^2/m^2
Simple ratio	$y = [(x - 1.39)^{0.698}]/2$	0.89	0.51
Normalized difference vegetation index (NDVI)	$y = \log_{0.37}(x^{-0.526} - 1.03)$	0.90	0.48
Green NDVI	$y = \sqrt{[(0.964 - x)^{-1.48} - 2.35]}$	0.89	0.51
Red-edge NDVI	$y = \ln[(0.805 - x)^{1/-0.52} - 0.82]$	0.91	0.46
Optimized soil-adjusted vegetation index	$y = -[0.916 \ln(1/x) - 1.79]/\ln(1/x)$	0.84	0.60
Green chlorophyll index	$y = [(x - 1.08)/1.38]^{0.767}$	0.90	0.49
Red-edge chlorophyll index	$y = (x/0.86)^{0.854}$	0.91	0.46
Triangular vegetation index (TVI)	$y = \exp(x/17.2) - 1.06$	0.60	0.95
MERIS Terrestrial Chlorophyll Index	$y = (x - 1.03)^{0.981}$	0.80	0.67
Wide Dynamic Range Vegetation Index, α = 0.2	$y = -\{[\ln(1.79 - x) - 0.532]/0.3\}$	0.90	0.47
Modified TVI 2	$y = x^{1.61}/0.172$	0.82	0.64
Enhanced Vegetation Index 2	$y = \exp(x/0.472) - 1.3$	0.76	0.75

model inversions: almost the same value of VI corresponded to gLAI ranging from 4 to >6 m^2/m^2. Several other normalized difference indices (green NDVI, red-edge NDVI, EVI2, and WDRVI with $\alpha = 0.2$), TVI, and MTVI2 also showed different degrees of decreased sensitivity at moderate to high gLAI values (Fig. 2c, 2d, 2e, 2h, 2j, 2k, and 2l). The SR had an exponential relationship, with lower sensitivity to gLAI < 1 m^2/m^2 than to higher gLAI values (Fig. 2a). For gLAI > 1 m^2/m^2, the relationship between SR and gLAI was nearly linear. The relationships for CIs and the MTCI exhibited a similar shape, with an increase in slope at moderate to high gLAI (Fig. 2f, 2g, and 2i).

In this study, we found that among the 12 VIs examined, only the red-edge NDVI (ANOVA: $P = 0.36$, $n = 423$, $F = 1.09$) and the $CI_{red\text{-}edge}$ (ANOVA: $P = 0.11$, $n = 423$, $F = 1.65$) can be applied for maize and soybean with no reparameterization of the algorithm. Best-fit functions of the relationships gLAI vs. red-edge NDVI and $CI_{red\text{-}edge}$ for both maize and soybean are presented in Table 5. All other VIs were crop specific (ANOVA: $P < 0.001$, $n = 423$, $F > 4.5$).

As noted above, R^2 and RMSE may be misleading when comparing nonlinear and linear relationships. For example, although the relationship NDVI vs. gLAI resulted in high R^2 values, the slope of the relationship decreased as gLAI exceeded 3 m^2/m^2 and became close to zero at gLAI values >3.5 m^2/m^2 for soybean and >4 m^2/m^2 for maize (Fig. 2b). With the decrease in sensitivity of VIs to gLAI (i.e., when gLAI exceeds 3 m^2/m^2), the scattering of the points from the best-fit functions drops, as can be seen for NDVI, green NDVI, red-edge NDVI, and OSAVI (Fig. 2b, 2c, 2d, and 2e for soybean). Thus, most of the VIs had similar R^2 and RMSE (Tables 3 and 4) but very different shapes of the relationships VI vs. gLAI (e.g., increasing exponential decay for NDVI vs. exponential growth for SR). Therefore, a different accuracy metric, specifically the NE ΔgLAI, was needed to compare the performance of VIs in estimating gLAI along its entire range of variation.

Figure 3 displays values of the NE ΔgLAI for normalized difference VIs, MTCI, and ratio indices (SR and CIs). The TVI and MTVI2 were not included in this analysis because their NE ΔgLAI values were always greater than those of normalized

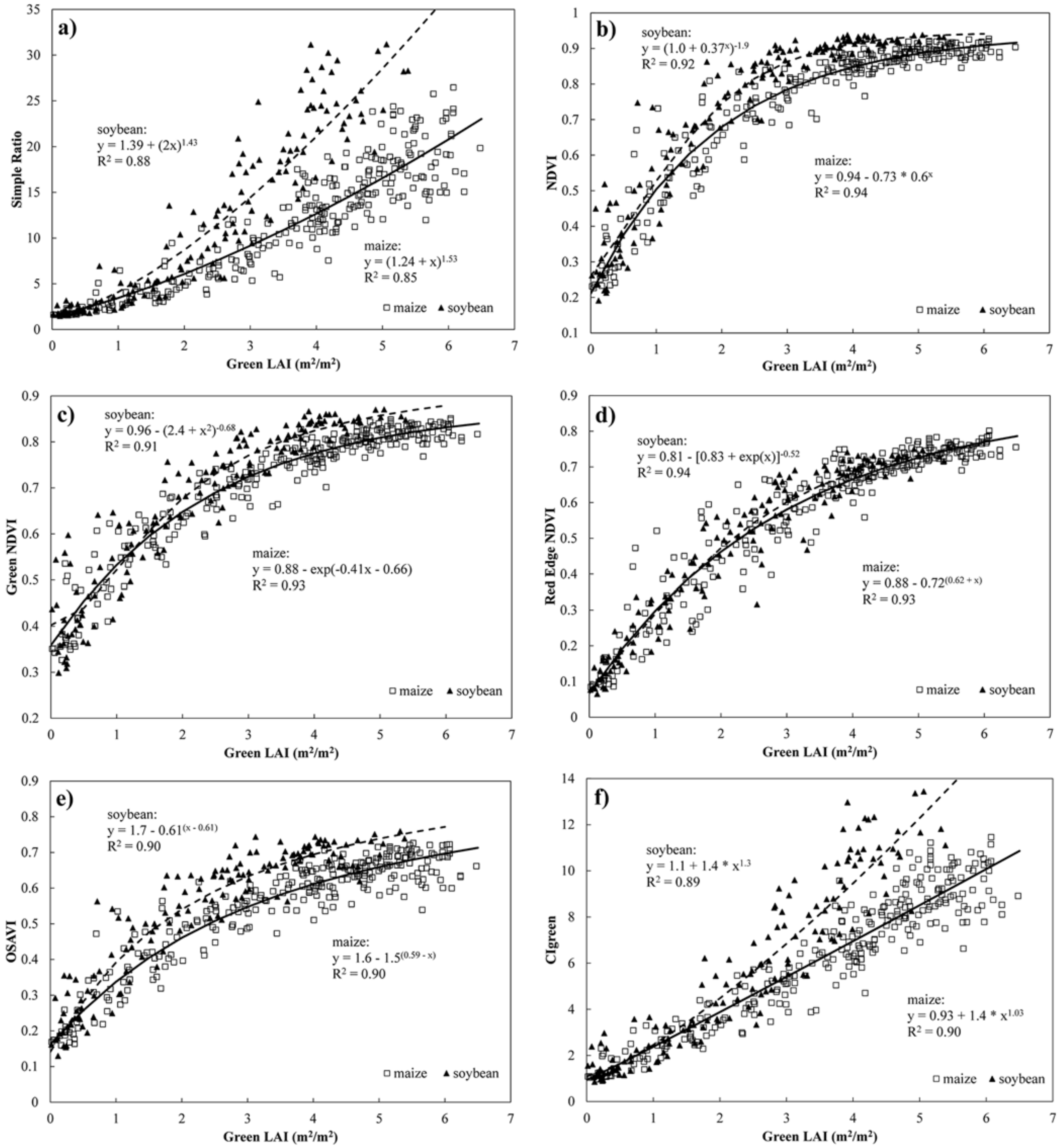

Fig. 2. Vegetation indices (VIs) plotted vs. green leaf area index (LAI): (a) simple ratio, (b) normalized difference vegetation index (NDVI), (c) green NDVI, (d) red-edge NDVI, (e) optimized soil-adjusted vegetation index (OSAVI), (f) chlorophyll index green (CI_{green}), (g) chlorophyll index red edge (CI_{red_edge}), (h) triangular vegetation index (TVI), (i) MERIS Terrestrial Chlorophyll Index (MTCI), (j) Wide Dynamic Range Vegetation Index (WDRVI) α = 0.2, (k) modified TVI 2 (MTVI2), and (l) Enhanced Vegetation Index 2 (EVI2). In all panels, solid line is best-fit function for maize, dashed line is best-fit function for soybean. The inverse of these green LAI vs. VI relationships along with their summary statistics are shown in Tables 3 and 4. Continued on the next page. ⟶

difference indices at low to moderate gLAI and also were always greater than those of SR, CIs, and MTCI at moderate to high gLAI. Therefore, TVI and MTVI2 did not meet the criteria for determining the best indices for low to moderate, for moderate to high, or for the entire range of gLAI.

The normalized difference VIs had asymptotic relationships with gLAI (Fig. 2b, 2c, 2d, 2h, and 2l); thus, the NE ΔgLAI was lowest at gLAI <2.5 m^2/m^2 for maize and <2 m^2/m^2 for soybean (Fig. 3). The SR and CIs had exponential relationships with gLAI (Fig. 2a, 2f, and 2g); thus, the lowest values of NE ΔgLAI were at gLAI >3 m^2/m^2 (Fig. 3). Therefore, the normalized difference VIs were more accurate in estimating low to moderate gLAI while the ratio indices, SR and CIs, were more accurate in estimating moderate to high gLAI.

While the relationship of MTCI with gLAI was asymptotic, the slope of the relationship was almost constant across a

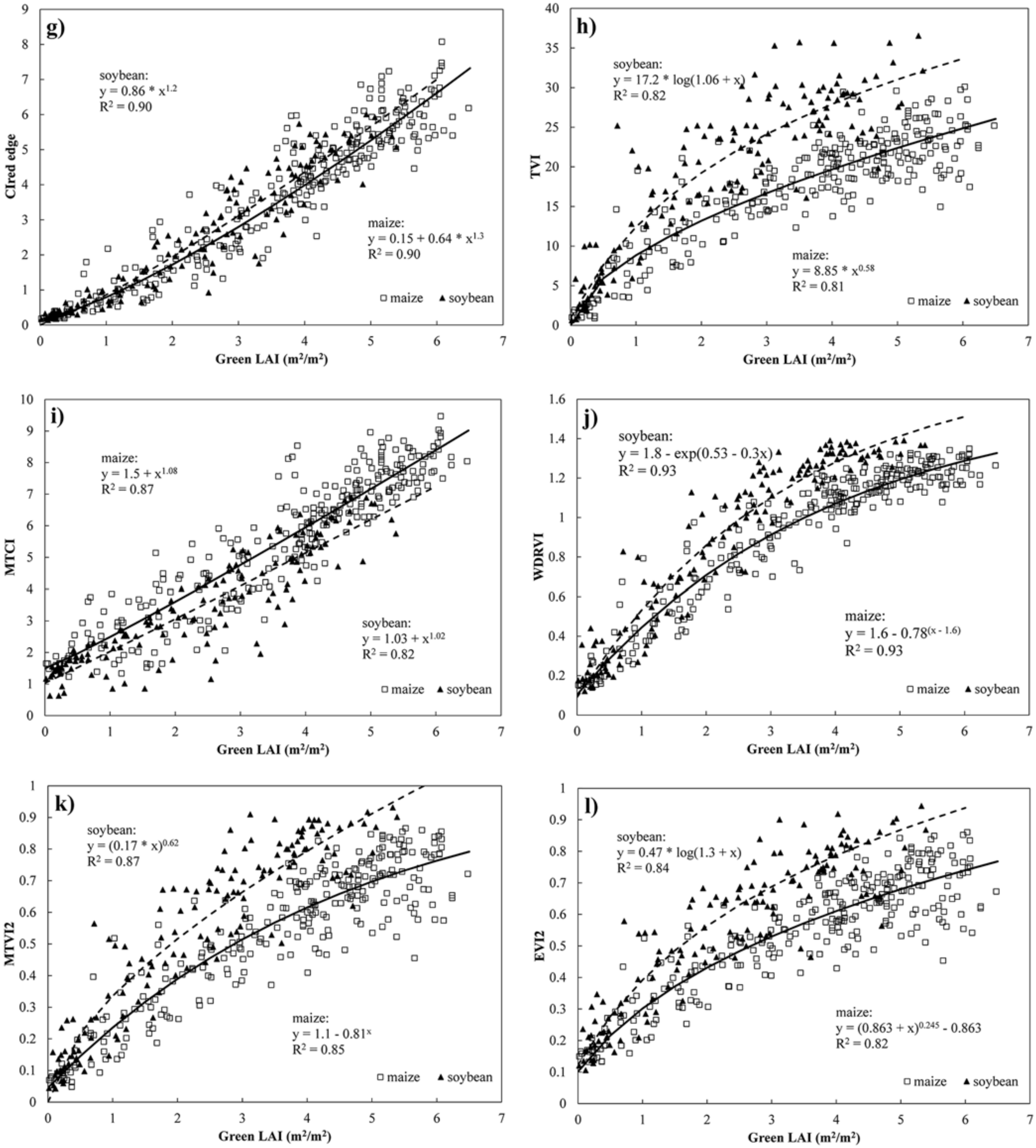

Fig. 2, continued.

Table 5. Best-fit functions of the relationships between green leaf area index (gLAI) and vegetation indices (VIs) for both maize and soybean combined; x = VI, y = gLAI, and RMSE is the root mean squared error of the gLAI estimation.

Index	Equation	R^2	RMSE
			m^2/m^2
Red-edge normalized difference vegetation index	$y = (0.155/x - 0.173)^{-0.542} - 0.739$	0.90	0.56
Red-edge chlorophyll index	$y = x^{0.898}/0.904$	0.91	0.54

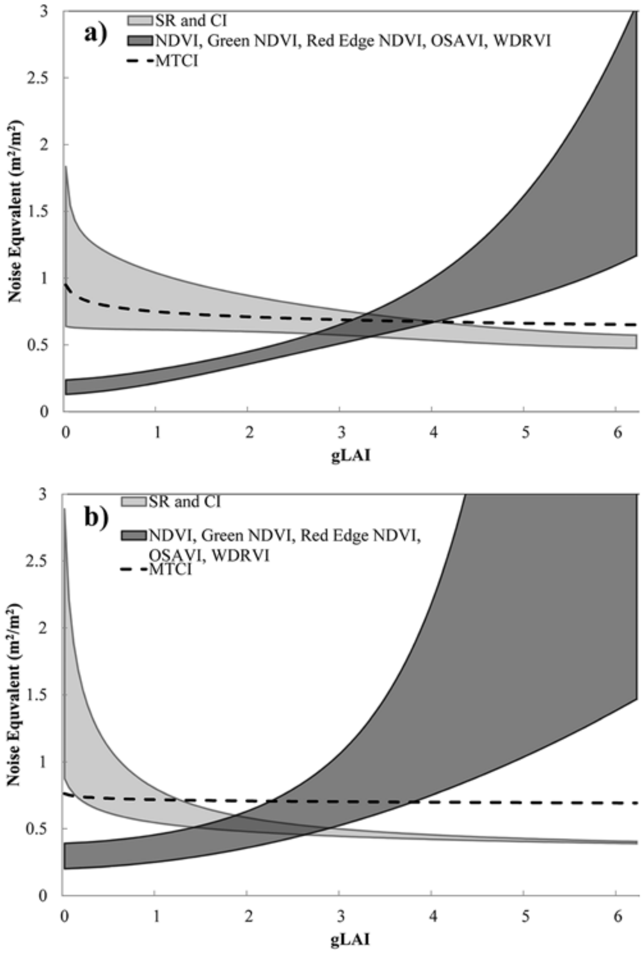

Fig. 3. Minimal and maximal values of the noise equivalent of the green leaf area index (gLAI) for (a) maize and (b) soybean for groupings of vegetation indices demonstrating increase of NE (decrease in accuracy) at moderate to high gLAI (normalized difference vegetation index [NDVI], green NDVI, red-edge NDVI, optimized soil-adjusted vegetation index [OSAVI], and Wide Dynamic Range Vegetation Index [WDRVI]), high NE at low to moderate gLAI (simple ratio [SR] and green and red-edge chlorophyll indices [CI]), and almost invariant NE throughout the entire dynamic range (MERIS Terrestrial Chlorophyll Index [MTCI]).

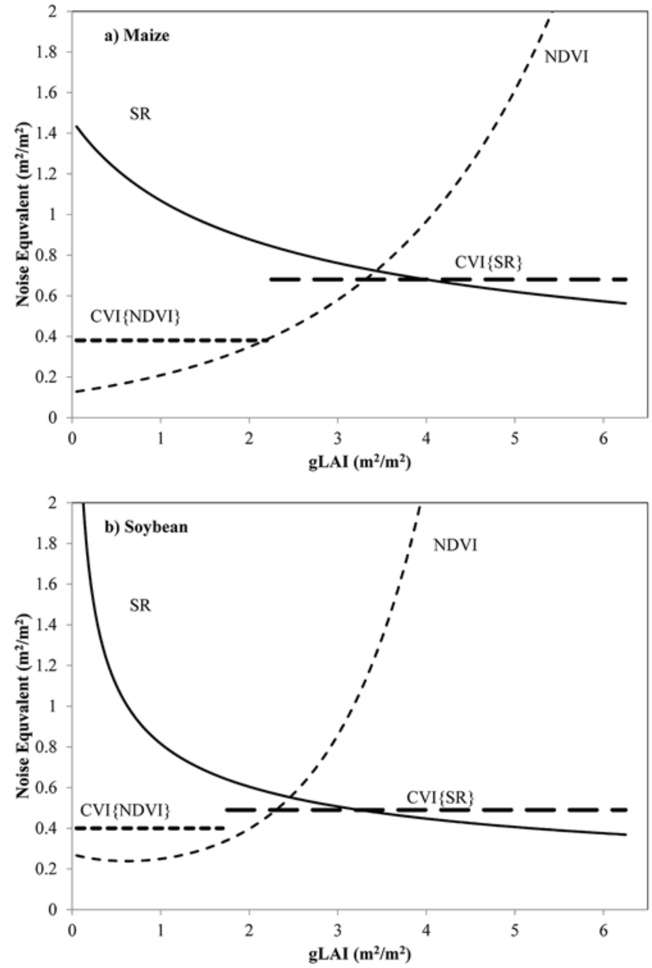

Fig. 4. Noise equivalent of the green leaf area index (gLAI) of the normalized difference vegetation index (NDVI), simple ratio (SR), and suggested combined vegetation index CVI{NDVI, SR} for (a) maize and (b) soybean; NDVI < 0.7 is the first index and SR is the second index.

wide range of gLAI variation (Fig. 2i). Therefore, for MTCI, NE ΔgLAI varied little throughout the entire range of gLAI (Fig. 3). In the range of gLAI <2.5 m^2/m^2, the MTCI had lower accuracy than normalized difference VIs and almost the same accuracy as the SR and CIs. In the range of gLAI > 2.5 m^2/m^2, however, it had lower accuracy than the SR and CIs. Thus, it did not outperform normalized difference VIs or the SR and CIs in their respective regions of highest sensitivity to changes in gLAI.

At moderate to high gLAI, the NE ΔgLAI values of the normalized difference indices in soybean were higher than those in maize. This may be explained by the very different canopy architectures and leaf structures of these crops. For the same amount of foliar chlorophyll content, the chlorophyll content on the adaxial side of soybean leaves is higher than in maize leaves, causing a higher absorption in the red range and thus lower reflectance of soybean canopies: 2% for leaf chlorophyll >500 mg/m^2 in soybean leaves (Gitelson et al., 2005) compared with 3 to 5% in maize leaves. Thus, soybean canopy reflectance in the red range is lower than that of a maize canopy. In addition, for the same gLAI, canopy reflectance of soybean in the NIR region was higher than that of maize: for gLAI around 5 m^2/m^2, NIR reflectance was 60% in soybean vs. 40% in maize (Peng and Gitelson, 2011). Thus, for the same gLAI, especially within the moderate to high range, the NIR/red reflectance ratio is higher in soybean than in maize. Therefore, the value of gLAI above which the normalized difference indices became insensitive to gLAI was lower in soybean than in maize.

Analysis of the NE ΔgLAI of the VIs (Fig. 3) showed that for gLAI <2.5 m^2/m^2, normalized difference VIs had the lowest NE ΔgLAI and thus highest accuracy of gLAI estimation, while the SR and CIs had the highest accuracy for gLAI >3 m^2/m^2 and were the best suited for estimation of moderate to high gLAI. Therefore, there was no single index that had the lowest uncertainties of gLAI estimation across the entire range of gLAI variation. To obtain the highest possible accuracy (i.e., lowest NE ΔgLAI) across the entire range of gLAI, we suggest using more than one VI in combination, i.e., a combined vegetation index (CVI).

A CVI is comprised of two VIs that are the most accurate in gLAI estimation at different ranges of gLAI: the first index

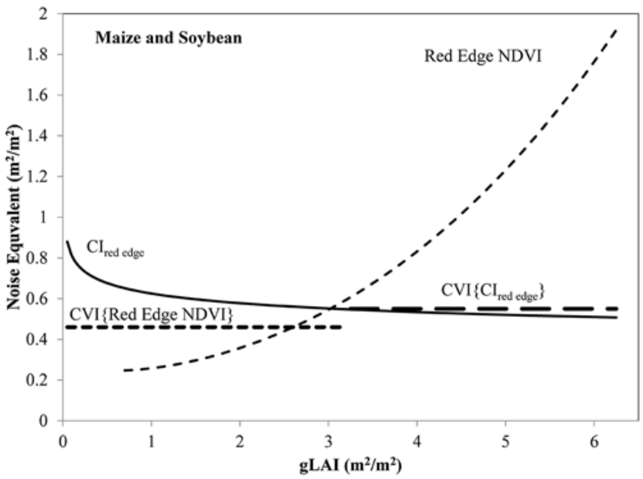

Fig. 5. Noise equivalent of the green leaf area index (gLAI) of the red-edge normalized difference vegetation index (NDVI), red-edge chlorophyll index (CIred-edge) and suggested combined vegetation index CVI{red-edge NDVI, CIred-edge} for maize and soybean combined; red-edge NDVI < 0.6 is the first index and CIred-edge is the second index.

for low to moderate gLAI (<2.5 m^2/m^2) and the second index for moderate to high gLAI (>2.5 m^2/m^2). While it is possible to scale the VIs in a CVI to create a linear relationship, any scaled algorithm will be data-set dependent and may result in a decrease in the sensitivity of the VI to gLAI. For both MODIS and MERIS data containing the red and NIR bands, we suggest using NDVI as the first index and SR as the second index: CVI{NDVI, SR}. An NDVI value around 0.7 has been previously reported as a typical point where the NDVI vs. gLAI relationship becomes saturated (Myneni et al., 1995; Gitelson et al., 2003b). Therefore, we selected NDVI = 0.7 as a threshold for both maize and soybean. In the range of NDVI from 0 to 0.7, the best-fit functions of NDVI vs. gLAI for both crops were linear, and thus the NE ΔgLAI was constant and as low as 0.38 m^2/m^2 for maize (Fig. 4a) and 0.4 m^2/m^2 for soybean (Fig. 4b).

As gLAI exceeded 2.5 m^2/m^2, NE ΔgLAI of the SR decreased and the accuracy of gLAI estimation increased for both species (Fig. 4a and 4b). When the SR was above 5.7 (corresponding to NDVI = 0.7), the best-fit function of SR vs. gLAI was linear, and thus NE ΔgLAI was constant at 0.68 m^2/m^2 for maize (Fig. 4a) and 0.49 m^2/m^2 for soybean (Fig. 4b). A CVI comprised of two indices (NDVI and SR and thus using only the red and NIR bands) was able to estimate gLAI ranging from 0 to >6 m^2/m^2 with a RMSE < 0.72 m^2/m^2 and a CV of 20% for maize, and a RMSE < 0.54 m^2/m^2 and a CV of 23% for soybean. The algorithms relating gLAI and CVI{NDVI, SR} for maize and soybean required different coefficients (Table 6), however, and thus were crop specific.

Alternatively, we suggest using the red-edge NDVI as the first CVI index and the $CI_{red\text{-}edge}$ as the second CVI index, i.e., CVI{red-edge NDVI, $CI_{red\text{-}edge}$} (Fig. 5) for data acquired by sensor systems containing red-edge and NIR bands (e.g., MERIS, Sentinel, and HYPERION). This combined index was not crop specific, at least for the species evaluated (i.e., maize and soybean), which have contrasting leaf and canopy structures. Therefore, this CVI does not require reparameterization because the same algorithm coefficients can be applied to estimate gLAI in both crops (Table 6). Based on the NE ΔgLAI results, presented in Fig. 5, we suggest using a threshold of red-edge NDVI = 0.6. For the range of red-edge NDVI of 0 to 0.6, the NE ΔgLAI was 0.46 m^2/m^2, and for $CI_{red\text{-}edge}$ > 3 (corresponding to the red-edge NDVI value of 0.6), the NE ΔgLAI was 0.55 m^2/m^2 (Fig. 5). For both species, CVI{red-edge NDVI, $CI_{red\text{-}edge}$} was able to estimate gLAI across its entire range of variation (i.e., 0 to >6 m^2/m^2), with a RMSE < 0.60 m^2/m^2 and a CV of 19%.

In applications where prior knowledge about crop type is available, using sensor systems containing red and NIR bands with spatial resolutions high enough to reduce the effects of mixed pixels, the CVI{NDVI,SR} is adequate. In many cases, however, there is uncertainty about the crop type present within a pixel (e.g., coarse spatial resolutions, mixed pixels, areas of crop rotation without prior knowledge of planted crops). Thus, the CVI{red-edge NDVI, $CI_{red\text{-}edge}$}, having a unified algorithm for crops with different leaf and canopy structures (e.g., maize and soybean), brings an objective estimation of total gLAI, even in the case of mixed pixels and crops at different phenological stages.

We acknowledge that further research is needed to evaluate the CVI{red-edge NDVI, $CI_{red\text{-}edge}$} in other crops. It is also important to investigate the reliability of the CVIs developed when applied to estimating gLAI in other vegetation types, such as grasslands and forests. Additionally, the calibration equations for the CVIs built with simulated MODIS and MERIS bands obtained from close-range hyperspectral data should be tested against actual MODIS and MERIS data. It is likely, however, that these equations are reliable because it has been shown that the coefficients of the relationships between gLAI and WDRVI, when taken at close range, remained the same as those applied to MODIS 250-m data due to accurate atmospheric correction of the MODIS 250-m surface reflectance product (Gitelson et al., 2007; Guindin-Garcia et al., 2012).

The approach presented in this study is not limited to gLAI; it may also be used for the remote estimation of other

Table 6. Best-fit functions for combined vegetation indices (CVIs) as used to estimate the green leaf area index (gLAI). A CVI is the combination of two vegetation indices where the first index (i.e., normalized difference vegetation index, NDVI, or red-edge NDVI) is most sensitive to low-to-moderate gLAI and the second index (i.e., simple ratio, SR, or red-edge chlorophyll index, $CI_{red\text{-}edge}$) are most sensitive to moderate-to-high gLAI. The threshold for NDVI was set at 0.7 and for red-edge NDVI at 0.6.

Index	Crop	First index below threshold	Second index above threshold	CV
				%
CVI{NDVI, SR}	maize	(NDVI – 0.28)/0.18	(SR + 1.0)/3.5	20
CVI{NDVI, SR}	soybean	(NDVI – 0.27)/0.22	(SR + 3.2)/6.2	23
CVI{red-edge NDVI, $CI_{red\text{-}edge}$}	maize and soybean	(red-edge NDVI – 0.13)/0.14	($CI_{red\text{-}edge}$ – 0.63)/0.95	20

biophysical characteristics, such as vegetation cover, fraction of absorbed photosynthetically active radiation, and gross primary production. The CVIs presented in this study, however, may not constitute the best VI combinations for measuring these other vegetation characteristics. Therefore, future studies are needed to investigate which VI combinations are the most appropriate for assessing other biophysical characteristics of vegetation.

CONCLUSIONS

Twelve VIs, calculated from simulated spectral bands of MODIS and MERIS satellite sensor systems, were evaluated for remotely assessing gLAI in two crop species with contrasting leaf structures and canopy architectures. All VIs investigated had essentially nonlinear relationships with gLAI, although with different sensitivities along the range of gLAI variability evaluated. On this basis, we suggest combining VIs that exhibit high sensitivity to changes in green LAI at particular ranges (i.e., low to moderate and moderate to high). When combined, these indices constitute suitable and accurate remotely sensed surrogates of gLAI across its entire range of variability. Specifically, we suggest combining the NDVI and the SR, CVI{NDVI, SR}, to be used in the case of sensors with spectral bands in the red and NIR (e.g., MODIS 250 m and Landsat TM and ETM+), although this combined index is crop specific and requires reparameterization of the algorithm for each crop. Alternatively, if a band in the red-edge region is available (e.g., MERIS, Sentinel, or HYPERION), we suggest combining the red-edge NDVI and the $CI_{red\text{-}edge}$, CVI{red-edge NDVI, $CI_{red\text{-}edge}$}. Because it was not crop specific, this combined index was capable of estimating gLAI with high accuracy, thus providing a suitable procedure for remotely estimating gLAI of crops with contrasting canopy architectures and leaf structures.

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REFERENCES

Abendroth, L.J., R.W. Elmore, M.J. Boyeer, and S.K. Marlay. 2011. Corn growth and development. Publ. PMR 1009. Iowa State Univ. Ext., Ames.

Asrar, G., M. Fuchs, E.T. Kanemasu, and J.L. Hatfield. 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agron. J. 76:300–306. doi:10.2134/agronj1984.00021962007600020029x

Brantley, S.T., J.C. Zinnert, and D.R. Young. 2011. Application of hyperspectral vegetation indices to detect variations in high leaf area index temperate shrub thicket canopies. Remote Sens. Environ. 115:514–523. doi:10.1016/j.rse.2010.09.020

Broge, N.H., and E. Leblanc. 2001. Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. Remote Sens. Environ. 76:156–172. doi:10.1016/S0034-4257(00)00197-8

Buermann, W., J. Dong, X. Zeng, R.B. Myneni, and R.E. Dickinson. 2001. Evaluation of the utility of satellite-based vegetation leaf area index data for climate simulations. J. Climate 14:3536–3550. doi:10.1175/1520-0442(2001)0142.0.CO;2

Bulcock, H.H., and G.P.W. Jewitt. 2010. Spatial mapping of leaf area index using hyperspectral remote sensing for hydrological applications with a particular focus on canopy interception. Hydrol. Earth Syst. Sci. 14:383–392. doi:10.5194/hess-14-383-2010

Ciganda, V., A.A. Gitelson, and J. Schepers. 2008. Vertical profile and temporal variation of chlorophyll in maize canopy: Quantitative “crop vigor” indicator by means of reflectance-based techniques. Agron. J. 100:1409–1417. doi:10.2134/agronj2007.0322

Curran, P.J., and E.J. Milton. 1983. The relationships between the chlorophyll concentration, LAI and reflectance of a simple vegetation canopy. Int. J. Remote Sens. 4:247–255. doi:10.1080/01431168308948544

Curran, P.J., and M.D. Steven. 1983. Multispectral remote sensing for the estimation of green leaf area index [and discussion]. Philos. Trans. R. Soc. Ser. A 309:257–270. doi:10.1098/rsta.1983.0039

Dash, J., and P.J. Curran. 2004. The MERIS terrestrial chlorophyll index. Int. J. Remote Sens. 25:5403–5413. doi:10.1080/0143116042000274015

Dash, J., and P.J. Curran. 2007. Evaluation of the MERIS terrestrial chlorophyll index (MTCI). Adv. Space Res. 39:100–104. doi:10.1016/j.asr.2006.02.034

Daughtry, C.S.T., C.L. Walthall, M.S. Kim, E.B. de Colstoun, and J.E. McMurtrey III. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sens. Environ. 74:229–239. doi:10.1016/S0034-4257(00)00113-9

de Wit, C.T. 1965. Photosynthesis of leaf canopies. Agric. Res. Rep.663. Inst. for Biol. and Chem. Res. on Field Crops and Herbage, Wageningen, the Netherlands.

Doraiswamy, P.C., S. Moulin, and P.W. Cook. 2003. Crop yield assessment from remote sensing. Photogramm. Eng. Remote Sens. 69:665–674.

Ehleringer, J., and I. Forseth. 1980. Solar tracking by plants. Science 210:1094–1098. doi:10.1126/science.210.4474.1094

Eitel, J.U.H., D.S. Long, P.E. Gessler, and E.R. Hunt. 2008. Combined spectral index to improve ground-based estimates of nitrogen status in dryland wheat. Agron. J. 100:1694–1702. doi:10.2134/agronj2007.0362

Eitel, J.U.H., D.S. Long, P.E. Gessler, E.R. Hunt, and D.J. Brown. 2009. Sensitivity of ground-based remote sensing estimates of wheat chlorophyll content to variation in soil reflectance. Soil Sci. Soc. Am. J. 73:1715–1723. doi:10.2136/sssaj2008.0288

Fang, H., S. Liang, and G. Hoogenboom. 2011. Integration of MODIS LAI and vegetation index products with the CSM–CERES-Maize model for corn yield estimation. Int. J. Remote Sens. 32:1039–1065. doi:10.1080/01431160903505310

Gao, X., A.R. Huete, W. Nif, and T. Miura. 2000. Optical–biophysical relationships of vegetation spectra without background contamination. Remote Sens. Environ. 74:609–620. doi:10.1016/S0034-4257(00)00150-4

Gitelson, A.A. 2004. Wide Dynamic Range Vegetation Index for remote quantification of biophysical characteristics of vegetation. J. Plant Physiol. 161:165–173. doi:10.1078/0176-1617-01176

Gitelson, A.A. 2011. Remote sensing estimation of crop biophysical characteristics at various scales. In: P.S. Thenkabail et al., editors, Hyperspectral remote sensing of vegetation. CRC Press, Boca Raton, FL. p. 1–36.

Gitelson, A.A., Y. Gritz, and M.N. Merzlyak. 2003a. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. J. Plant Physiol. 160:271–282. doi:10.1078/0176-1617-00887

Gitelson, A.A., Y.J. Kaufman, and M.N. Merzlyak. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sens. Environ. 58:289–298. doi:10.1016/S0034-4257(96)00072-7

Gitelson, A.A., and M.N. Merzlyak. 1994. Spectral reflectance changes associated with autumn senescence of *Aesculus hippocastanum* L. and *Acer platanoides* L. leaves: Spectral features and relation to chlorophyll estimation. J. Plant Physiol. 143:286–292. doi:10.1016/S0176-1617(11)81633-0

Gitelson, A.A., A. Viña, T.J. Arkebauer, D.C. Rundquist, G.P. Keydan, and B. Leavitt. 2003b. Remote estimation of leaf area index and green leaf biomass in maize canopies. Geophys. Res. Lett. 30(5):1248. doi:10.1029/2002GL016450

Gitelson, A.A., A. Viña, V. Ciganda, D.C. Rundquist, and T.J. Arkebauer. 2005. Remote estimation of canopy chlorophyll content in crops. Geophys. Res. Lett. 32(8):L08403. doi:10.1029/2005GL022688

Gitelson, A.A., B.D. Wardlow, G.P. Keydan, and B. Leavitt. 2007. An evaluation of MODIS 250-m data for green LAI estimation in crops. Geophys. Res. Lett. 34(20):L20403. doi:10.1029/2007GL031620

Gobron, N., B. Pinty, M.M. Verstraete, and Y. Govaerts. 1997. A semidiscrete model for the scattering of light by vegetation. J. Geophys. Res. 102(D8):9431–9446. doi:10.1029/96JD04013

González-Sanpedro, M.C., T. Le Toan, J. Moreno, L. Kergoat, and E. Rubio. 2008. Seasonal variations of leaf area index of agricultural fields retrieved from Landsat data. Remote Sens. Environ. 112:810–824. doi:10.1016/j.rse.2007.06.018

Govaerts, Y.M., M.M. Verstraete, B. Pinty, and N. Gobron. 1999. Designing optimal spectral indices: A feasibility and proof of concept study. Int. J. Remote Sens. 20:1853–1873. doi:10.1080/014311699212524

Guindin-Garcia, N., A.A. Gitelson, T.J. Arkebauer, J. Shanahan, and A. Weiss. 2012. An evaluation of MODIS 8- and 16-day composite products for monitoring maize green leaf area index. Agric. Forest Meteorol. 161:15–25. doi:10.1016/j.agrformet.2012.03.012

Haboudane, D., J.R. Miller, E. Pattey, P.J. Zarco-Tejada, and I.B. Strachan. 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote Sens. Environ. 90:337–352. doi:10.1016/j.rse.2003.12.013

Haboudane, D., J.R. Miller, N. Tremblay, P.J. Zarco-Tejada, and L. Dextraze. 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sens. Environ. 81:416–426. doi:10.1016/S0034-4257(02)00018-4

Hatfield, J.L., A.A. Gitelson, J.S. Schepers, and C.L. Walthall. 2008. Application of spectral remote sensing for agronomic decisions. Agron. J. 100:S-117–S-131. doi:10.2134/agronj2006.0370c

Hatfield, J.L., J.H. Prueger, and W.P. Kustas. 2004.Remote sensing of dryland crops. In: S.L. Ustin, editor, Manual of remote sensing. Vol. 4. Remote sensing for natural resource management and environmental monitoring. 3rd ed. John Wiley & Sons, Hoboken, NJ. p. 531–568.

Huete, A.R., K. Didan, T. Miura, E. Rodriguez, X. Gao, and L. Ferreira. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83:195–213. doi:10.1016/S0034-4257(02)00096-2

Huete, A.R., H.Q. Liu, K. Batchily, and W. van Leeuwen. 1997. A comparison of vegetation indices over a global set of TM images for EOS–MODIS. Remote Sens. Environ. 59:440–451. doi:10.1016/S0034-4257(96)00112-5

Idso, S.B., and C.T. de Wit. 1970. Light relations in plant canopies. Appl. Opt. 9:177–184. doi:10.1364/AO.9.000177

Jiang, Z., A.R. Huete, K. Didan, and T. Miura. 2008. Development of a two-band enhanced vegetation index without a blue band. Remote Sens. Environ. 112:3833–3845. doi:10.1016/j.rse.2008.06.006

Jordan, C.F. 1969. Derivation of leaf-area index from quality of light on the forest floor. Ecology 50:663–666. doi:10.2307/1936256

Kanemasu, E.T. 1974. Seasonal canopy reflectance patterns of wheat, sorghum, and soybean. Remote Sens. Environ. 3:43–47. doi:10.1016/0034-4257(74)90037-6

Kohavi, R. 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. In: C.S. Mellish, editor, Proceedings of the 14th International Joint Conference on Artificial Intelligence, Montreal, QC, Canada. 20–25 Aug. 1995. Vol. 2. Morgan Kaufmann, San Francisco. p. 1137–1143.

le Maire, G., C. François, K. Soudani, D. Berveiller, J.Y. Pontailler, and N. Bréda. 2008. Calibration and validation of hyperspectral indices for the estimation of broadleaved forest leaf chlorophyll content, leaf mass per area, leaf area index and leaf canopy biomass. Remote Sens. Environ. 112:3846–3864. doi:10.1016/j.rse.2008.06.005

Liu, H.Q., and A.R. Huete. 1995. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE Trans. Geosci. Remote Sens. 33:457–465. doi:10.1109/36.377946

Myneni, R.B., F.G. Hall, P.J. Sellers, and A.L. Marshak. 1995. The interpretation of spectral vegetation indexes. IEEE Trans. Geosci. Remote Sens. 33:481–486. doi:10.1109/36.377948

Peng, Y., and A.A. Gitelson. 2011. Application of chlorophyll-related vegetation indices for remote estimation of maize productivity. Agric. For. Meteorol. 151:1267–1276. doi:10.1016/j.agrformet.2011.05.005

Peng, Y., A.A. Gitelson, G.P. Keydan, D.C. Rundquist, and W. Moses. 2011. Remote estimation of gross primary production in maize and support for a new paradigm based on total crop chlorophyll content. Remote Sens. Environ. 115:978–989. doi:10.1016/j.rse.2010.12.001

Pinter, P.J., Jr., J.L. Hatfield, J.S. Schepers, E.M. Barnes, M.S. Moran, C.S. Daughtry, and D.R. Upchurch. 2003. Remote sensing for crop management. Photogramm. Eng. Remote Sens. 69:647–664.

R Development Core Team. 2011. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna. http://www.R-project.org/

Ritz, C., and J.C. Streibig. 2008. Grouped data. p. 109–131. In: C. Ritz and J.C. Streibig, editors, Nonlinear regression with R. Springer, New York.

Rondeaux, G., M. Steven, and F. Baret. 1996. Optimization of soil-adjusted vegetation indices. Remote Sens. Environ. 55:95–107. doi:10.1016/0034-4257(95)00186-7

Rouse, J.W., R.H. Haas, J.A. Schell, and D.W. Deering. 1974. Monitoring vegetation systems in the Great Plains with ERTS. In: S.C. Freden and M.A. Becker, editors, Third Earth Resources Technology Satellite Symposium, Greenbelt, MD. 10–14 Dec. 1973. NASA, Washington, DC. p. 309–317.

Rundquist, D.C., R. Perk, B. Leavitt, G.P. Keydan, and A.A. Gitelson. 2004. Collecting spectral data over cropland vegetation using machine-positioning versus hand-positioning of the sensor. Comput. Electron. Agric. 43:173–178. doi:10.1016/j.compag.2003.11.002

Schmidt, M., and H. Lipson. 2009. Distilling free-form natural laws from experimental data. Science 324:81–85. doi:10.1126/science.1165893

Smith, A.M., G. Bourgeois, P.M. Teillet, J. Freemantle, and C. Nadeau. 2008. A comparison of NDVI and MTVI2 for estimating LAI using CHRIS imagery: A case study in wheat. Can. J. Remote Sens. 34:539–548. doi:10.5589/m08-071

Suyker, A.E., and S.B. Verma. 2010. Coupling of carbon dioxide and water vapor exchanges of irrigated and rainfed maize–soybean cropping systems and water productivity. Agric. For. Meteorol. 150:553–563. doi:10.1016/j.agrformet.2010.01.020

Suyker, A.E., S.B. Verma, G. Burba, T.J. Arkebauer, D.T. Walters, and K.G. Hubbard. 2004. Growing season carbon dioxide exchange in irrigated and rainfed maize. Agric. For. Meteorol. 124:1–13. doi:10.1016/j.agrformet.2004.01.011

Verma, S.B., A. Dobermann, K.G. Cassman, D.T. Walters, J.M. Knops, T.J. Arkebauer, et al. 2005. Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. Agric. For. Meteorol. 131:77–96. doi:10.1016/j.agrformet.2005.05.003

Viña, A., and A.A. Gitelson. 2005. New developments in the remote estimation of the fraction of absorbed photosynthetically active radiation in crops. Geophys. Res. Lett. 32(17):L17403. doi:10.1029/2005GL023647

Viña, A., A.A. Gitelson, A.L. Nguy-Robertson, and Y. Peng. 2011. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. Remote Sens. Environ. 115:3468–3478. doi:10.1016/j.rse.2011.08.010

Wang, Q., S. Adiku, J. Tenhunen, and A. Granier. 2005. On the relationship of NDVI with leaf area index in a deciduous forest site. Remote Sens. Environ. 94:244–255. doi:10.1016/j.rse.2004.10.006

Watson, D.J. 1947. Comparative physiological studies on the growth of field crops: I. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. Ann. Bot. 11:41–76.

Wu, J., D. Wang, and M. Bauer. 2007. Assessing broadband vegetation indices and QuickBird data in estimating leaf area index of corn and potato canopies. Field Crops Res. 102:33–42. doi:10.1016/j.fcr.2007.01.003