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Remote estimation of gross primary productivity in soybean and maize based on total crop chlorophyll content

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ABSTRACT

The synoptic quantification of crop gross primary productivity (GPP) is essential for studying carbon budgets in croplands and monitoring crop status. In this study, we applied a recently developed model, which relates crop GPP to a product of total crop chlorophyll content and incoming photosynthetically active radiation, for the remote estimation of GPP in two crop types (maize and soybean) with contrasting canopy architectures and leaf structures. The objective of this study was to evaluate performances of twelve vegetation indices used for detecting different vegetation biophysical characteristics, in estimating GPP of rainfed and irrigated crops over a period from 2001 through 2008. Indices tested in the model exhibited strong and significant relationships with widely variable GPP in each crop (GPP ranged from 0 to 19 gC/m^2/d for soybean and 0 to 35 gC/m^2/d for maize), however, they were species-specific. Only three indices, which use MERIS red edge and NIR spectral bands (i.e. red edge chlorophyll index, MERIS Terrestrial Chlorophyll Index and red edge NDVI), were found to be able to estimate GPP accurately in both crops combined, with root mean square errors (RMSE) below 3.2 gC/m^2/d. It was also shown that two indices, red edge chlorophyll index and red edge NDVI with a red edge band around 720 nm, were non-species-specific and yielded a very accurate estimation of GPP in maize and soybean combined, with RMSEs below 2.9 gC/m^2/d and coefficients of variation below 21%.

1. Introduction

Crop gross primary productivity (GPP) is the rate at which a cropland captures and stores carbon as biomass contributing approximately 15% of global carbon dioxide fixation (Malmstrom et al., 1997). An accurate and synoptic quantification of spatially distributed GPP is essential for studying carbon budgets in croplands and monitoring crop status. Since crop productivity is a result of the interaction of solar radiation with plant canopy (e.g., Knipling, 1970), remote sensing techniques can be used as an expedient tool for GPP estimation at regional and global scales.

Recently, a new paradigm for GPP estimation in crops based on the assumption that total canopy chlorophyll (Chl) content is the main driver of crop GPP has been proposed (Gitelson, Verma, et al., 2003; Gitelson et al., 2006). This assumption is developed based on Monteith model that expressed GPP as (Monteith, 1972, 1977):

$$GPP = fAPAR_{green} \times PAR_{in} \times LUE \quad (1)$$

where PAR_{in} is the incident photosynthetically active radiation, $fAPAR_{green}$ refers to the fraction of PAR_{in} absorbed by photosynthetically active vegetation (Hall et al., 1992), and LUE is the efficiency of the absorbed radiation being converted into biomass.

It was recognized that chlorophyll (Chl) is likely to remain the universal basis for expressing photosynthetic rate in vegetation (Foyer et al., 1982). It is a main factor influencing the amount of light absorbed by vegetation, i.e. $fAPAR_{green}$ (Heath, 1969), and also directly relates to the enhanced electron transport activity, which governs LUE (Terry, 1980). Dawson et al. (2003) showed that the variation in foliar Chl content may account for some of the seasonal variability in LUE. Houborg et al. (2011) demonstrated that variations in leaf Chl content were closely correlated with temporal changes in LUE. Kergoat et al. (2008) found that foliar nitrogen content of the dominant plant species, which closely related to Chl, explained 71% of the variation in LUE. Peng et al. (2011) showed that total crop Chl content, defined as a product of total leaf area index and leaf Chl content (Ciganda et al., 2008), relates to LUE. Therefore, two key physiological properties, light capture and the efficiency of the use of absorbed light, relate significantly to total canopy Chl, which subsumes a broad range of processes and can be applied as an integrative diagnostic tool.

Medina and Lieth (1964) showed a very close relationship ($R^2 > 0.98$) between seasonal maximum biomass (i.e. the proxy of GPP) and total Chl in meadows. Marks (1971), Kira et al. (1967) and Whittaker and Marks (1975) found close relationships between net primary productivity and leaf area index (i.e. the proxy of total Chl content) in evergreen needle leaf and deciduous broadleaf species.

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A close relationship was observed between GPP and the product of total Chl content and PAR_{in} in maize (Peng & Gitelson, 2011; Peng et al., 2011), soybean (Gitelson et al., 2006) and wheat (Wu et al., 2009), and this relationship was found to be non-species-specific for maize and soybean, which are two different crop types (C3 and C4) with contrasting leaf structures and canopy architectures (Gitelson et al., 2006). Thus, total crop Chl content may be used for estimating GPP. A simple model was suggested to remotely assess GPP in crops via estimation of total crop Chl content and PAR_{in} in the form (Gitelson et al., 2006):

$$GPP = Chl \times PAR_{in}. \quad (2)$$

The methodology of this model was further justified in detail by Peng et al. (2011).

Many algorithms have been developed for the remote estimation of biophysical characteristics of vegetation. The most widespread type of algorithms used is the mathematical combination of visible and NIR reflectance bands, in the form of spectral vegetation indices. Vegetation indices (VIs), presented in Table 1 (e.g., NDVI, TVI, MTVI and WDRVI), were introduced for estimation of green leaf area index (LAI), which closely relates to total Chl content (Ciganda et al., 2008). Several VIs, such as MERIS Terrestrial Chlorophyll Index (MTCI) and Chlorophyll Indices (CI_{green} and $CI_{red\ edge}$) have been specifically proposed to estimate total Chl content (Table 1). In our previous study, we tested the relationships between total Chl content and VIs, and showed that some VIs could explain more than 87% of Chl content variation in maize (Peng et al., 2011). Gitelson et al. (2005) showed that the determination coefficient of the relationship between CI_{green} or $CI_{red\ edge}$ and total Chl in maize and soybean exceeded 0.92. Thus, these chlorophyll- and green LAI-related VIs can be used as a proxy of Chl in the model (Eq. 2) for estimating GPP in the form (Gitelson et al., 2006):

$$GPP = VI \times PAR_{in}. \quad (3)$$

This model has been successfully employed to estimate GPP in maize fields that are different in irrigation, crop management, field history and climatic conditions (Peng & Gitelson, 2011; Peng et al., 2011). The same approach was applied for the accurate estimation of GPP in wheat (Wu et al., 2009).

The objectives of this paper are (1) to test the performance of different vegetation indices to estimate GPP in soybean, and (2) to compare the ability of the algorithms, developed and calibrated for GPP estimation in maize (Peng & Gitelson, 2011), to predict GPP in soybean with no re-parameterization of its coefficients, and (3) to develop a unified algorithm for GPP estimation in two contrasting crop types such as soybean and maize.

2. Materials and methods

Three AmeriFlux sites all located within 1.6 km of each other at the University of Nebraska-Lincoln Agricultural Research and Development Center near Mead, Nebraska, USA were studied during the growing seasons 2001 through 2008. Sites 1 and 2 are 65-ha fields equipped with center pivot irrigation systems. Site 3 is of approximately the same size, but relies entirely on rainfall for moisture. Site 1 is planted in continuous maize. Site 2 and site 3 are both planted in maize–soybean rotation, and soybean was planted in even years (2002, 2004, 2006 and 2008) at a population of around 370,000 seed/ha under no-till management. An Asgrow 2703 soybean hybrid was planted in 2002, a Pioneer 93B09 soybean hybrid was planted in 2004, and a Pioneer 93M11 soybean hybrid was planted in 2006 and 2008. The details about maize fields are given in Peng and Gitelson (2011).

Each study site is equipped with an eddy covariance tower and meteorological sensors to obtain continuous measurements of CO_2 fluxes, water vapor and energy fluxes every 1 h since 2001 (details are given in Verma et al. (2005)). The study sites represented approximately 90–95% of the flux footprint during daytime and 70–90% during nighttime (e.g., Schuepp et al., 1990). Daytime net ecosystem exchange (NEE) values were computed by integrating the hourly CO_2 fluxes collected during a day when PAR_{in} exceeded 1 μmol/m^2/d. Daytime estimates of ecosystem respiration (Re) were obtained from the night CO_2 exchange and temperature relationship (e.g., Falge et al., 2002), and daytime GPP was then acquired by subtracting Re from NEE as: GPP = NEE − Re. Sign convention used here is such that flux to the surface is positive so that GPP is always positive while Re is always negative (Verma et al., 2005).

Hourly PAR_{in} was measured with point quantum sensors (LI-190, LI-COR Inc., Lincoln, NE) pointing to the sky and placed 6 m above the surface. Daytime PAR_{in} values were computed by integrating the hourly measurements during a day when PAR_{in} exceeded 1 μmol/m^2/d.

Spectral reflectance measurements at the canopy level were made using hyperspectral radiometers mounted on "Goliath", an all-terrain sensor platform (Rundquist et al., 2004). A dual-fiber optic system, with two inter-calibrated Ocean Optics USB2000 radiometers, was used to collect radiometric data in the range of 400–1100 nm with a spectral resolution of about 1.5 nm. One radiometer equipped with a 25° field-of-view optical fiber was pointed downward to measure

Table 1
Summary of vegetation indices used in this paper. ρ_{NIR}, $\rho_{red\ edge}$, ρ_{red}, ρ_{green}, ρ_{800}, ρ_{750}, ρ_{670}, and ρ_{550} are reflectances in spectral bands of NIR, red edge, red, green regions and 800 nm, 750 nm, 670 nm, 550 nm respectively.

Vegetation index	Formula	Reference
Simple Ratio (SR)	ρ_{NIR}/ρ_{red}	Jordan (1969)
Normalized Difference Vegetation Index (NDVI)	$(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red})$	Rouse et al. (1974)
Enhanced Vegetation Index 2 (EVI2)	$2.5\times(\rho_{NIR}-\rho_{red})/(1+\rho_{NIR}+2.4\times\rho_{red})$	Jiang et al. (2008)
Triangular Vegetation Index (TVI)	$0.5\times[120\times(\rho750-\rho550)-200\times(\rho670-\rho550)]$	Broge and Leblanc (2000)
Modified TVI 1(MTVI1)	$1.2\times[1.2\times(\rho800-\rho550)-2.5\times(\rho670-\rho550)]$	Haboudane et al. (2004)
Modified TVI 2 (MTVI2)	$1.5\times[1.2(\rho800-\rho550)-2.5\times(\rho670-\rho550)]/\mathrm{sqrt}((2\rho800+1)2-(6\rho800-5\mathrm{sqrt}(\rho670))-0.5)$	Haboudane et al. (2004)
Visible Atmospherically Resistant Index (VARI)	$(\rho_{green}-\rho_{red})/(\rho_{green}+\rho_{red})$	Gitelson et al. (2002)
Wide Dynamic Range Vegetation Index (WDRVI)[a]	$(\alpha\times\rho_{NIR}-\rho_{red})/(\alpha\times\rho_{NIR}+\rho_{red})$, $0<\alpha<1$	Gitelson (2004)[a]
	$(\alpha\times\rho_{NIR}-\rho_{red})/(\alpha\times\rho_{NIR}+\rho_{red})+(1-\alpha)/(1+\alpha)$, $\alpha=0.2$	
Red edge NDVI	$(\rho_{NIR}-\rho_{red\ edge})/(\rho_{NIR}+\rho_{red\ edge})$	Gitelson and Merzlyak (1994, 1997)
MERIS Terrestrial Chlorophyll Index (MTCI)	$(\rho_{NIR}-\rho_{red\ edge})/(\rho_{red\ edge}-\rho_{red})$	Dash and Curran (2004)
Green Chlorophyll Index (CI_{green})	$\rho_{NIR}/\rho_{green}-1$	Gitelson, Gritz and Merzlyak (2003), Gitelson et al. (2005)
Red edge chlorophyll index ($CI_{red\ edge}$)	$\rho_{NIR}/\rho_{red\ edge}-1$	Gitelson, Gritz and Merzlyak (2003), Gitelson et al. (2005)

[a] In the original formulation of WDRVI (Gitelson, 2004), it may be negative for low to moderate vegetation density. In this paper, we calculated WDRVI as $(0.2\times\rho_{NIR}-\rho_{red})/(0.2\times\rho_{NIR}+\rho_{red})+0.67$, which ranged from 0 to 1.67.

Table 2
a. Established relationships "daytime GPP vs. $VI \times PAR_{in}$" in 8 irrigated and rainfed soybean sites in 2002, 2004, 2006 and 2008: $GPP = f(x)$, $x = VI \times PAR_{in}$. Best fit functions, determination coefficients (R^2) and root mean square errors (RMSE) are given for twelve vegetation indices. GPP ranged from 0 to 19 $gC/m^2/d$. All algorithms and RMSE were obtained using a k-fold cross validation procedure with $k = 15$;
b. The algorithms for estimating daytime GPP in 16 irrigated and rainfed maize sites from 2001 through 2008, established in Peng and Gitelson (2011). GPP ranged from 0 to 35 $gC/m^2/d$.

VI	Best fit function	R^2	RMSE ($gC/m^2/d$)
a.			
$CI_{red\ edge}$	$GPP = 4.80\ln(x) - 37.93$	0.90	1.56
CI_{green}	$GPP = 5.13\ln(x) - 46.92$	0.88	1.72
Red edge NDVI	$GPP = -1.19E\text{-}7x^2 + 3.00E\text{-}3x - 2.70$	0.87	1.76
WDRVI	$GPP = -2.43E\text{-}8x^2 + 1.30E\text{-}3x - 0.37$	0.87	1.78
SR	$GPP = 4.33\ln(x) - 40.20$	0.85	1.91
MTVI2	$GPP = -5.70E\text{-}8x^2 + 1.90E\text{-}3x + 0.90$	0.84	1.95
EVI2	$GPP = -8.85E\text{-}8x^2 + 2.50E\text{-}3x - 1.53$	0.84	1.95
NDVI	$GPP = -3.26E\text{-}8x^2 + 1.70E\text{-}3x - 2.17$	0.83	2.02
MTCI	$GPP = -2.66E\text{-}9x^2 + 4.17E\text{-}4x - 1.33$	0.82	2.04
TVI	$GPP = -5.34E\text{-}15x^2 + 5.85E\text{-}7x - 0.33$	0.81	2.14
MTVI1	$GPP = -7.34E\text{-}12x^2 + 2.14E\text{-}5x + 0.51$	0.81	2.17
VARI	$GPP = -3.62E\text{-}8x^2 + 1.8E\text{-}3x + 6.39$	0.79	2.30
b.			
CI_{green}	$GPP = -154 + 14.7\ln(x + 27{,}900.61)$	0.92	2.24
SR	$GPP = 28.8 \times (1 - e^{-6.78e-6 \times x})$	0.92	2.32
$CI_{red\ edge}$	$GPP = -121 + 12.42\ln(x + 16082.91)$	0.93	2.55
MTCI	$GPP = -1.16E\text{-}9x^2 + 3.85E\text{-}4x - 1.60$	0.89	2.68
WDRVI	$GPP = -1.93E\text{-}8x^2 + 1.70E\text{-}3x - 0.76$	0.87	2.87
Red edge NDVI	$GPP = -3.41E\text{-}8x^2 + 2.77E\text{-}3x - 2.06$	0.86	2.93
MTVI2	$GPP = -6.75E\text{-}8x^2 + 2.92E\text{-}3x + 1.66$	0.87	3.01
EVI2	$GPP = -9.26E\text{-}8x^2 + 0.0035x - 3.08$	0.88	3.14
TVI	$GPP = -6.35E\text{-}15x^2 + 9.2E\text{-}7x + 0.23$	0.84	3.24
MTVI1	$GPP = -8.47E\text{-}12x^2 + 3.5E\text{-}5x + 1.12$	0.84	3.27
VARI	$GPP = -1.03E\text{-}7x^2 + 4.1E\text{-}3x + 10.83$	0.80	3.56
NDVI	$GPP = 1.94E\text{-}3x - 2.59$	0.79	3.65

the upwelling radiance of the crop, and the height of this radiometer was kept constant above the top of canopy (5.4 m) throughout the growing season yielding a sample area with a diameter of 2.4 m. The other radiometer was pointed upward to measure the incident irradiance simultaneously. Radiometric data was collected close to solar noon (between 11:00 and 13:00 local time), when changes in solar zenith angle were minimal, and percent reflectance was then computed based on those measured radiance and irradiance (details are given in Gitelson et al. (2006) and Viña et al. (2011)).

For each site, six randomly selected plots were established with six randomly selected sampling points. Thus, a total of 36 spectra were sampled per site at each data acquisition, and their median value was used as the site reflectance. Spectral reflectance measurements at the canopy level were carried out from May to October during the growing seasons 2001 through 2008 (18 data acquisitions in 2001, 31 in 2002, 34 in 2003, 31 in 2004, 21 in 2005, 15 in 2005, 14 in 2007 and 9 in 2008). 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).

In this study, we tested several widely used VIs for GPP estimation (Table 1). The collected reflectance spectra were resampled to spectral bands of Moderate Resolution Imaging Spectroradiometer—MODIS (green: 545–565 nm, red: 620–670 nm, and NIR: 841–876 nm) using MODIS spectral response function and SR, NDVI, EVI2, VARI, WDRVI and CI_{green} were calculated. The reflectance spectra were also resampled to spectral bands of Medium Resolution Imaging Spectrometer—MERIS (green: 555–565 nm, red: 660–670 nm, red edge: 703–712 nm and NIR: 750–760 nm) using MERIS spectral response function and TVI, MTVI1, MTVI2, MTCI, red edge NDVI and $CI_{red\ edge}$ were calculated.

In our previous study, we calibrated and validated the algorithms for estimating maize GPP by the procedure of sorting all maize samples taken from 2001 through 2008 in ascending order of GPP; data with odd numbers were used for calibration while data with even numbers for validation (Peng & Gitelson, 2011). In this study, to establish the algorithm GPP vs. $VI \times PAR_{in}$ we used a k-fold cross validation procedure (Fielding & Bell, 1997; Kohavi, 1995). Samples were randomly split into k mutually exclusive sets (k = number of total samples/10), and they were trained and tested k times. For each time, $k - 1$ sets of them were used iteratively for calibration and the remaining set for validation. The determination coefficients (R^2) and root mean square errors (RMSE) of algorithms were then estimated by averaging the values obtained from k iterations. This method

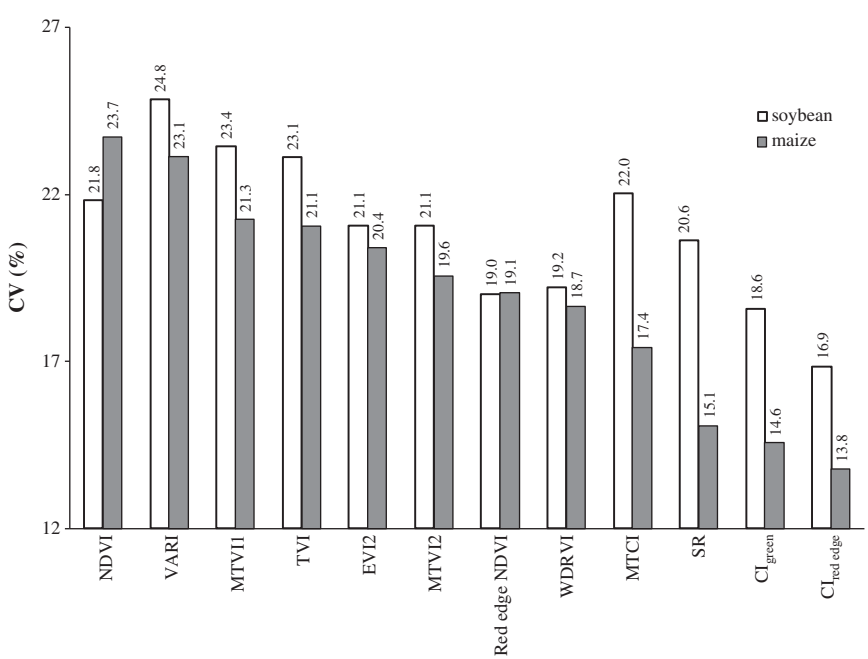

Fig. 1. Coefficients of variation (CV = RMSE/mean GPP) of the relationships, GPP vs. $VI \times PAR_{in}$, established for soybean and for maize.

reduces the dependence on a single random partition into calibration and validation datasets. By repeating the training procedure k times, all observations are used for both calibration and validation, with each observation used for validation only one time in one of k iterations.

3. Results and discussion

3.1. GPP estimation in soybean

Soybean and maize species have very different biochemical mechanisms for photosynthesis. Maize utilizes C4 carbon fixation, while soybean utilizes C3 carbon fixation. In addition, their canopy architectures are contrasting. The distribution of foliage in maize canopy is spherical, while it is planophile in soybean. Since the model (Eq. 3) was able to predict GPP accurately in maize (Peng & Gitelson, 2011; Peng et al., 2011), we tested the performance of this model for estimating GPP in soybean. Table 2a shows the best fit functions, determination coefficients (R^2), and root mean square errors (RMSE) of the relationships GPP vs. $VI \times PAR_{in}$ in eight irrigated and rainfed soybean sites in 2002, 2004, 2006 and 2008, established using a k-fold cross validation procedure with $k = 15$. All twelve VIs performed well for estimating soybean GPP, with RMSEs below 2.3 $gC/m^2/d$ (GPP ranged from 0 to 19 $gC/m^2/d$). Among the indices tested, CI_{green}, $CI_{red\ edge}$, red edge NDVI, as well as WDRVI appeared to be the best indices for estimating GPP in soybean.

When compared with the performances using those VIs for GPP estimation in maize (Table 2b), NDVI was more accurate for soybean than for maize (Fig. 1). NDVI was found to be a good indicator of low-to-moderate crop Chl and GPP, however, its sensitivity to Chl and GPP dropped drastically for moderate-to-high crop density (Gitelson et al., 2005; Gitelson et al., 2006). The maximal GPP of maize was at least 75% higher than that of soybean (35 $gC/m^2/d$ in maize vs. 19 $gC/m^2/d$ in soybean), thus, NDVI worked better for estimating low-to-moderate GPP, as in soybean, but it was less sensitive to high GPP as in maize (e.g., Asrar et al., 1984; Gitelson, 2004). As shown in Fig. 1, Chlorophyll Indices (CI_{green} and $CI_{red\ edge}$), which remain sensitive to the wide range of Chl (Gitelson, Gritz & Merzlyak, 2003; Peng et al., 2011), were consistently the most accurate for GPP estimation in both maize and soybean. SR was much less accurate in estimating GPP in soybean than in maize, since red reflectance of soybean (in the denominator of SR) is much lower than that of maize (below 2% for GPP above 16 $gC/m^2/d$), consequently soybean SR was much noisier than maize SR.

Among the eight studied soybean fields, four were under irrigated managements (site 2 in 2002, 2004, 2006 and 2008), and the other four relied entirely on rainfall (site 3 in 2002, 2004, 2006 and 2008). The soybean cultivars and climatic conditions differed from year to year. Thus, the dynamic ranges of LAI and GPP were different in eight soybean fields studied. For example, the maximum LAI was 5.1 m^2/m^2 in site 2 in 2006, but only 3.2 m^2/m^2 in site 3 in 2002. The maximum GPP was 18.7 $gC/m^2/d$ in site 2 in 2002, while 14.7 $gC/m^2/d$ in site 3 in 2004. Although the relationships GPP vs. $VI \times PAR_{in}$ varied slightly for different fields (Fig. 2 for EVI2 and Red edge NDVI), the algorithms established for all data in 8 irrigated and rainfed fields combined were quite accurate in GPP estimation with RMSEs below 2.3 $gC/m^2/d$ and R^2 above 0.79 for all indices (Table 2a).

From 2006 through 2008, site 1 was under the conservation-plow tillage operation while site 2 and site 3 were under no-till management. Since the reflectance of residues was much higher than that of the bare soil, the background reflectance was significantly lower in site 1 than in site 2 and site 3. The total canopy reflectance was more affected by the background reflectance in maize fields with spherical canopy than in soybean fields with planophile canopy. Using simulated data (Gobron et al., 1997), it was shown that some VIs (e.g., MTCI, EVI2 and $CI_{red\ edge}$) were very accurate in estimating green LAI despite very different soil backgrounds (Viña et al., in press). It is also confirmed by results of our study. For maize and soybean tilled and no-tilled fields combined, the model (Eq. 3) explained more than 79% GPP variation with RMSEs below 2.3 $gC/m^2/d$ for soybean (GPP ranged from 0 to 19 $gC/m^2/d$) and 3.6 $gC/m^2/d$ for maize (GPP ranged from 0 to 35 $gC/m^2/d$) (Table 2).

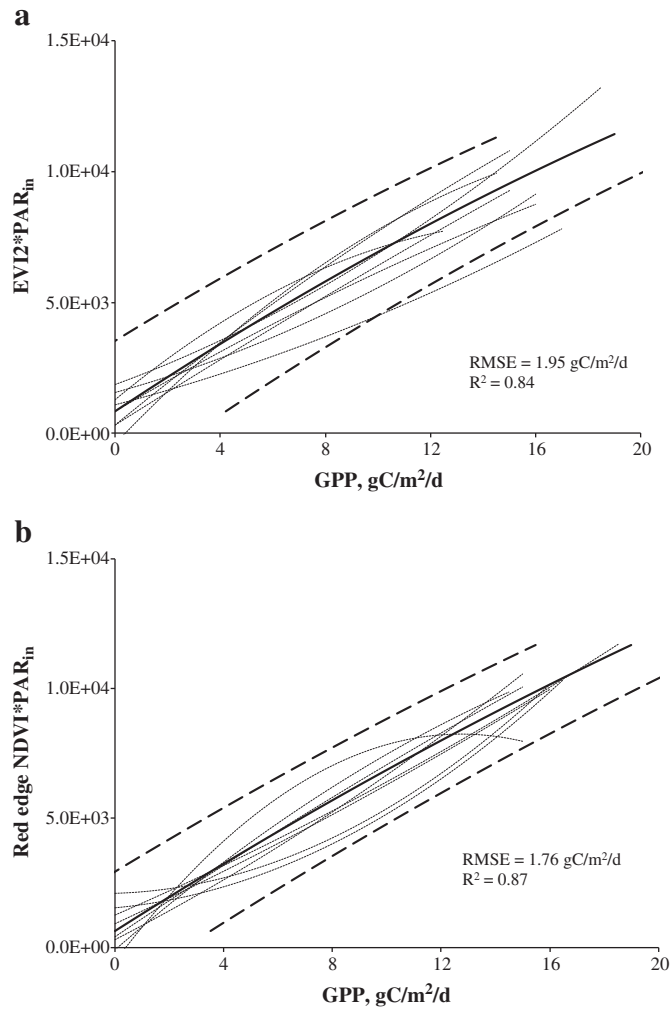

Fig. 2. Best fit functions of the relationships between GPP and the products of (a) $EVI2 \times PAR_{in}$ and (b) red edge $NDVI \times PAR_{in}$ for each of 8 different soybean fields in 2002, 2004, 2006 and 2008 (dashed lines). The solid lines are the best fit functions for all data in 8 irrigated and rainfed fields combined. The bold dashed lines represent the 95% confidential interval (i.e., two standard errors of GPP estimation).

3.2. A unified algorithm for GPP estimation in maize and soybean

Having concurrent measurements of GPP, PAR_{in} and reflectance in soybean (this study) and in maize (Peng & Gitelson, 2011), we addressed the following questions: (1) Are the algorithms developed for maize and soybean different? (2) Is it possible to develop a unified algorithm for GPP estimation in both maize and soybean?

Fig. 3 presents relationships between GPP and the product of PAR_{in} and VIs in maize and soybean. For all VIs used, the relationships for these two crops were species-specific (p-value < 0.0001), and the discrepancies became more pronounced at moderate to high GPP. For the same GPP, the value of $VI \times PAR_{in}$ for soybean was consistently higher than that for maize. The relationship between GPP and the product of total Chl content and PAR_{in} in maize and soybean was found to be non-species-specific (Gitelson et al., 2006). However, the relationship between total Chl content and VI was species-specific (Gitelson et al., 2005) with consistently higher values

of VIs for soybean than for maize with the same Chl content; it was especially pronounced for VIs using the visible and NIR bands. The reason for that is twofold:

(1) The reflectance in the visible region of the spectrum is mainly affected by leaf absorption. For the same total leaf Chl content, the reflectance in the visible region is lower in a soybean leaf than in a maize leaf, since leaf Chl content of the adaxial surface of a C3 plant (i.e. soybean) is much higher than a C4 plant (i.e. maize). As the visible light is predominantly absorbed by chloroplasts at the surface layer of a leaf (Fukshansky, 1981; Fukshansky et al., 1993; Merzlyak & Gitelson, 1995), the absorption in the visible region by a soybean leaf is higher than a maize leaf. Total canopy Chl content is the product of leaf Chl content and total leaf area, so in the visible region, the canopy reflectance of soybean is lower than of maize with the same total canopy Chl content (Fig. 4).

(2) NIR reflectance is governed by leaf/canopy scattering. NIR reflectance of a soybean leaf is higher than that of a maize leaf. In addition, for the same LAI, NIR reflectance of a planophile canopy (soybean) is much higher than that of a spherical canopy (maize)—(Fig. 4). Thus, in soybean, the visible reflectance is lower and the NIR reflectance is higher than in maize. So VIs based on NIR and visible reflectances produce consistently higher values for soybean than for maize.

Fig. 5 shows RMSEs of GPP estimation in soybean using GPP vs. $VI \times PAR_{in}$ algorithms established for maize (Peng & Gitelson, 2011)—Table 2b. It is not surprising that the algorithms with VIs based on NIR and visible bands (VARI, MTVI1, TVI, MTVI2, SR, CI_{green}, WDRVI, NDVI and EVI2) were not accurate when applied for soybean: RMSEs were above 5.3 $gC/m^2/d$ and coefficients of variation, CV = RMSE/mean GPP, were above 57%. However, the accuracy of GPP estimation in both crops was much higher and RMSEs were much lower (below 4.1 $gC/m^2/d$) when VIs based on NIR and MERIS red edge bands (red edge NDVI, MTCI and $CI_{red\ edge}$) were used. The reflectance in the red edge region is affected not only by leaf absorption but also by scattering. The absorption coefficient of Chl in the red

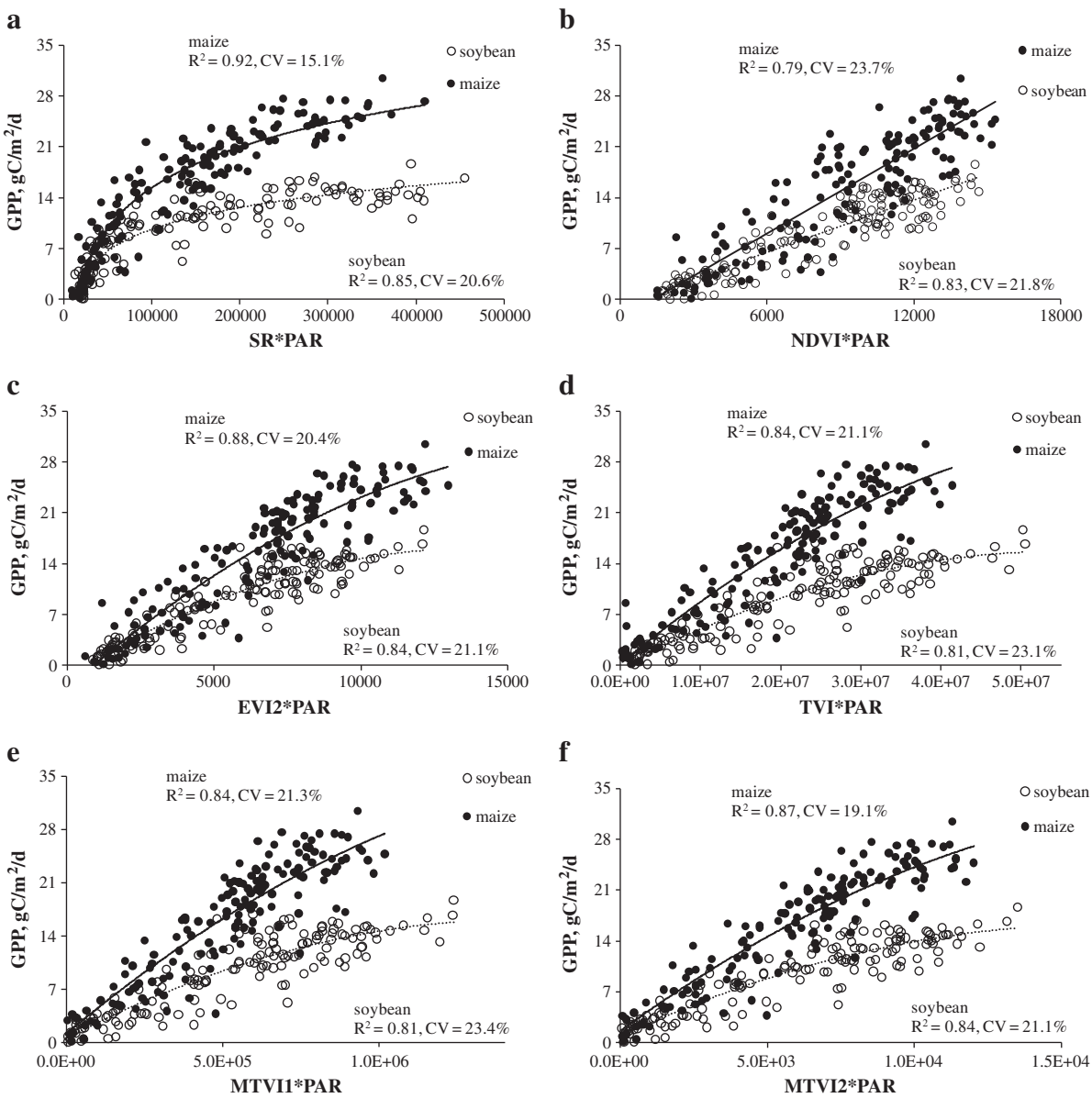

Fig. 3. Relationships of GPP vs. (a) $SR \times PAR_{in}$, (b) $NDVI \times PAR_{in}$, (c) $EVI2 \times PAR_{in}$, (d) $TVI \times PAR_{in}$, (e) $MTVI1 \times PAR_{in}$, (f) $MTVI2 \times PAR_{in}$, (g) $VARI \times PAR_{in}$, (h) $WDRVI \times PAR_{in}$, (i) $CI_{green} \times PAR_{in}$, (j) red edge $NDVI \times PAR_{in}$, (k) $CI_{red\ edge} \times PAR_{in}$, and (l) $MTCI \times PAR_{in}$ for soybean and maize. The solid lines are the best fit functions for the relationships GPP vs. $VI \times PAR_{in}$, established for maize. The dashed lines are the best fit functions for the relationships GPP vs. $VI \times PAR_{in}$, established for soybean.

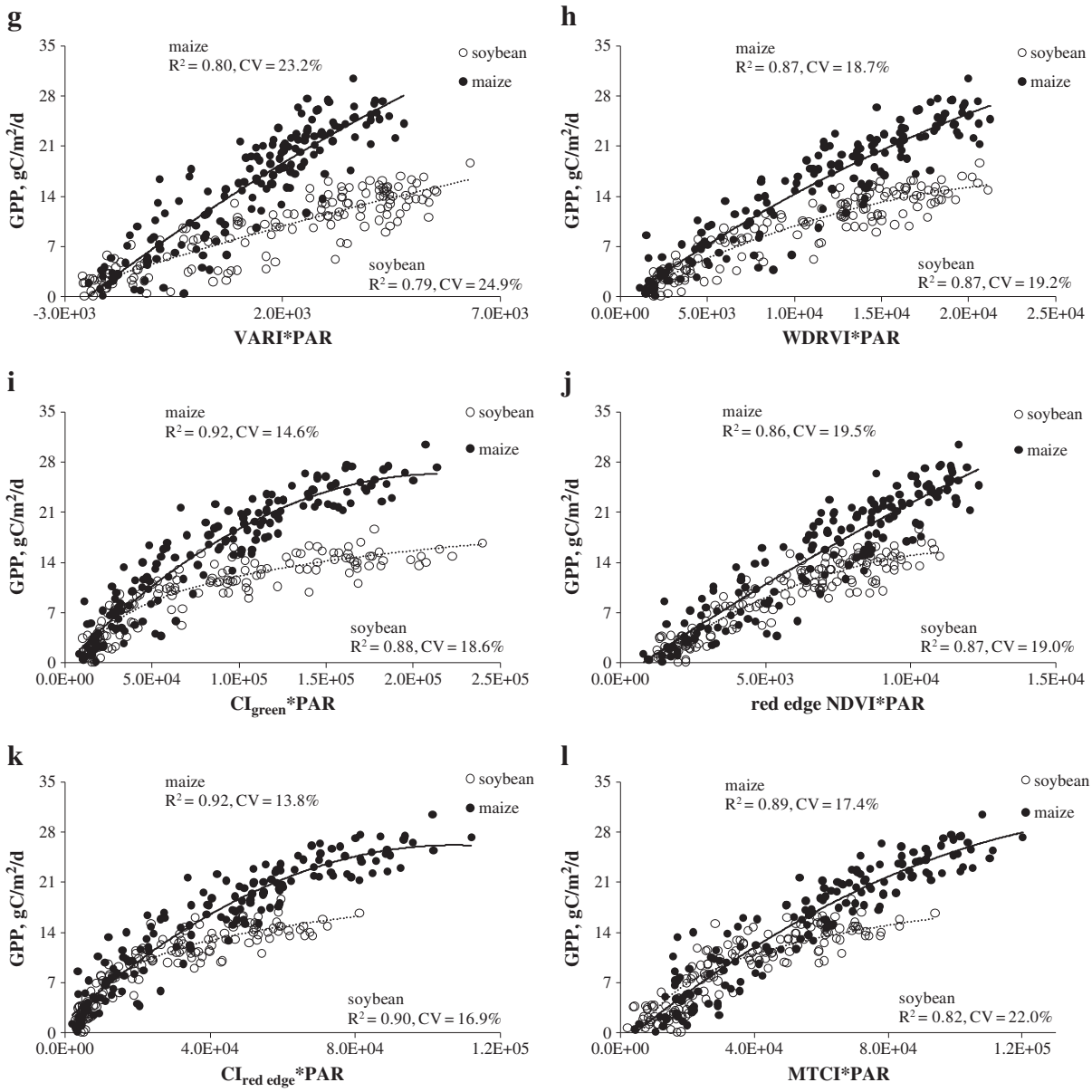

Fig. 3 (*continued*).

edge region is much lower than in the visible region. The depth of light penetration into a leaf inversely relates to the Chl absorption coefficient (Merzlyak & Gitelson, 1995), so, the red edge light penetrates deeper into a leaf and chloroplasts of the whole leaf work for light absorption. Therefore, for the same total leaf Chl content, absorption of a maize leaf in the red edge region becomes the same as absorption of a soybean leaf. On the other hand, the leaf scattering in the red edge region in soybean is higher than in maize. As a result, for the same total Chl content, soybean reflectance in the red edge region becomes higher than maize reflectance, accompanied with higher NIR reflectance in soybean than in maize (Fig. 4). Therefore, the difference in VI values for both species with the same Chl content, when using the red edge band (703 nm–710 nm), became lower than when visible bands were used. The indices using MERIS red edge band performed quite accurately estimating GPP in maize and soybean data combined with the coefficients of variation below 26% (Table 3).

There is a need to increase the accuracy of the above algorithms when applied to both maize and soybean. This issue is particularly important when using satellite data with coarse spatial resolution that do not allow for separating signals from sites with different crop species.

In order to identify the optimal red edge band for GPP estimation in both maize and soybean, we used optimization procedure to find the minimal RMSE value of the relationship GPP vs. $VI \times PAR_{in}$ for red edge NDVI and $CI_{red\ edge}$. Tuning the red edge band from 700 nm to 750 nm, we found the minimal RMSE value in the range around 720 nm (Fig. 6). As the red edge band shifts towards a longer wavelength around 720 nm, the reflectance is more affected by leaf scattering. So, in both species with the same Chl content, the difference in the red edge reflectance increases compensating for the difference in their NIR reflectances. Thus, the VIs based on longer wavelength in red edge region and NIR band become non-species-specific.

Both red edge NDVI and $CI_{red\ edge}$ with a red edge band around 720 nm were able to estimate GPP in soybean and maize with RMSEs of less than 2.9 $gC/m^2/d$ (Fig. 7). This is consistent with optimal red edge band for total Chl content estimation in maize and soybean (Gitelson et al., 2005).

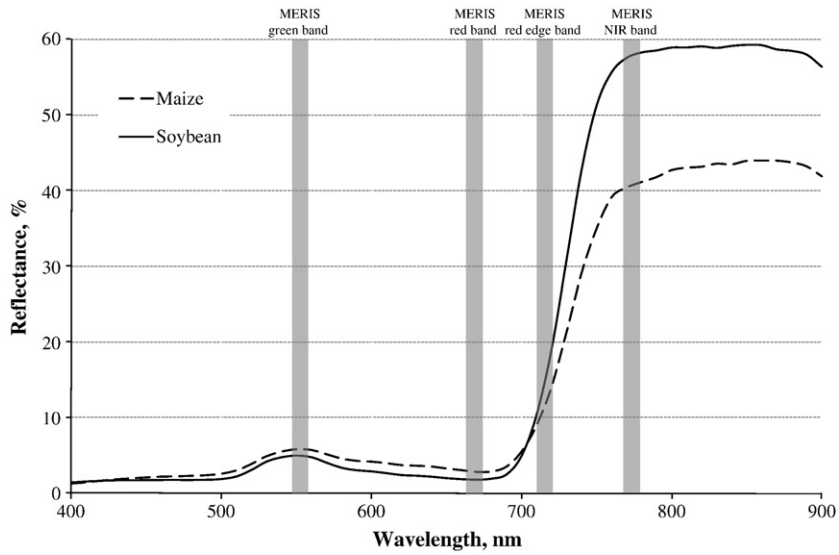

Fig. 4. Spectral reflectance of maize and soybean with the same total canopy Chl content of 2.15 g/m^2. In the visible range (the green and red), reflectance of soybean is lower than that of maize, while NIR reflectance of soybean is higher than of maize. So for the same Chl content, indices using visible and NIR bands are consistently higher for soybean than for maize. Both NIR and red edge reflectances of soybean are higher than that of maize with the same Chl content. Thus, indices with NIR and red edge reflectances were less species-specific than that with NIR and either red or green reflectances.

The choice of the vegetation index for GPP estimation depends on the spectral characteristics of the radiometers or the specific satellite sensors used. If the red edge band around 720 nm is available, as for hyperspectral radiometers such as Ocean Optics, ASD and hyperspectral imaging sensors such as AISA or HYPERION, $CI_{red\ edge}$ and red edge NDVI are recommended as non-species-specific indices that can estimate GPP accurately in both soybean and maize. If the red edge band around 700 nm is available, as in MERIS (703 nm–712 nm), HYPERION and future satellite sensors such as Sentinel-2 and Venus, $CI_{red\ edge}$, MTCI and red edge NDVI, which are least sensitive to different crop species, are recommendable to use. If the red edge band is not available, one can use CI_{green} and MTVI2 with green, red and NIR bands available as in Landsat and MODIS 500 m data. If only the red and NIR bands are available, such as in MODIS 250 m data, WDRVI, SR and EVI2 are recommended for estimating crop GPP.

The approach presented in this study is not limited to estimate crop GPP using spectral reflectance collected by radiometers mounted on a platform close to the canopy. It can be also applied to remotely sensed data collected at multiple scales from close range to satellite altitude, which allows monitoring regional or global GPP in crops. Gitelson et al. (2008) showed that the model (Eq. 3) was quite accurate in estimating GPP in maize using ETM Landsat data. The model (Eq. 3) with MTCI derived from MERIS images was able to estimate GPP accurately across a variety of land cover vegetation types (Almond et al., 2010; Harris & Dash, 2010). Wu et al. (2010, 2011) showed that GPP can be estimated using the model (Eq. 3) with MODIS data. Sakamoto et al. (2011) estimated maize GPP with high accuracy using daily shortwave radiation and MODIS-retrieved WDRVI data as proxy variables of PAR_{in} and the total chlorophyll content, respectively. Further research should test this approach using

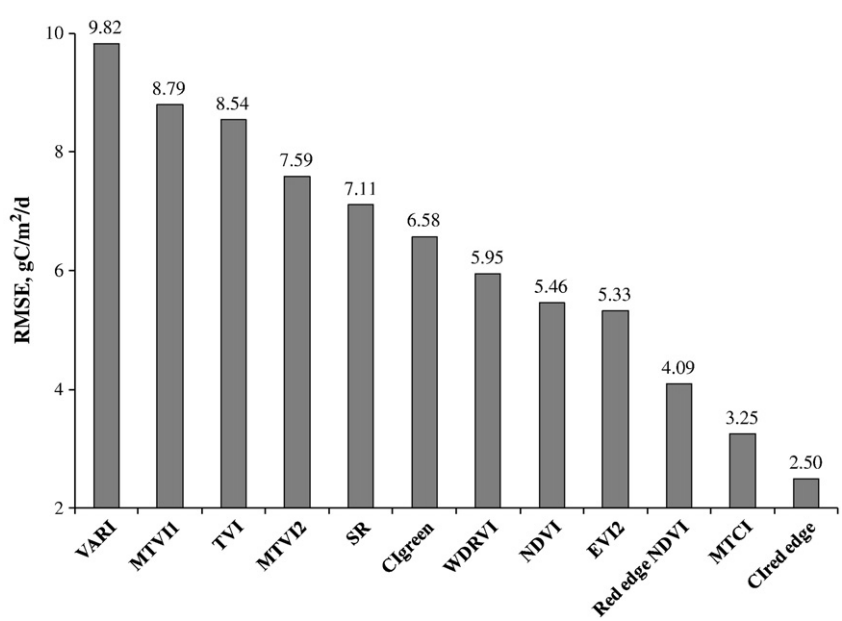

Fig. 5. Root mean square errors (RMSE) of GPP estimation in soybean using algorithms (Table 2b) established for maize.

Table 3
The algorithms based on indices using MERIS red edge band for estimating daytime GPP in 24 maize and soybean fields from 2001 through 2008: GPP = f(x), x = VI × PAR_{in}. Best fit functions, determination coefficients (R^2), root mean square errors (RMSE) and coefficients of variation were obtained using a k-fold cross validation procedure with k = 15.

VI	Best fit function	R^2	RMSE ($gC/m^2/d$)	CV (%)
Red edge NDVI	$GPP = -1.68E\text{-}8x^2 + 2.1E\text{-}3x - 1.04$	0.81	3.17	25.5
$CI_{red\ edge}$	$GPP = -1.63E\text{-}9x^2 + 4.1E\text{-}4x + 1.55$	0.85	2.74	22.1
MTCI	$GPP = -7.13E\text{-}10x^2 + 3.31E\text{-}4x - 0.75$	0.85	2.72	22.0

MERIS-derived $CI_{red\ edge}$ for GPP estimation in different vegetation types.

4. Conclusions

The model based on a product of total crop chlorophyll and PAR_{in} was tested and found capable of estimating GPP in maize and soybean that are contrasting crop species. Due to their differences in leaf structures and canopy architectures, the algorithms for GPP estimation are species-specific for maize and soybean, especially when using VIs with NIR and either red or green reflectance. However, it is possible to apply a unified algorithm for GPP estimation in both maize and soybean, by using $CI_{red\ edge}$, MTCI and red edge NDVI with MERIS spectral bands, which are least sensitive to different crop species. $CI_{red\ edge}$ and red edge NDVI with the red edge band around 720 nm were found to be non-species-specific for maize and soybean and very accurate in the estimation of GPP in maize and soybean combined, with RMSEs less than 2.9 $gC/m^2/d$ and coefficients of variation below 21%.

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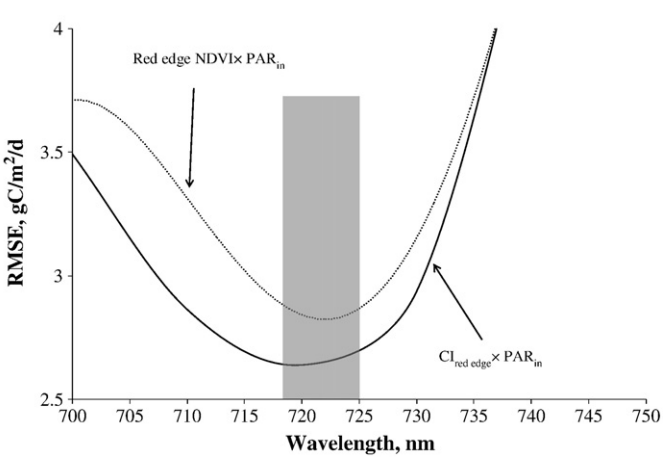

Fig. 6. Root mean square errors (RMSE) of the relationships GPP vs. VI × PAR_{in} for red edge NDVI and $CI_{red\ edge}$ calculated for soybean and maize data combined by tuning the red edge bands from 700 nm to 750 nm.

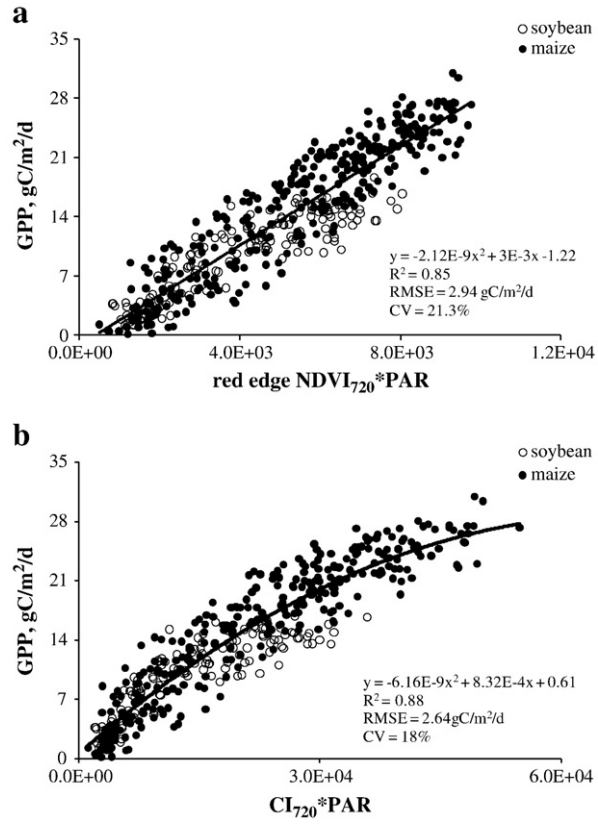

Fig. 7. Products of (a) red edge NDVI × PAR_{in}, and (b) $CI_{red\ edge}$ × PAR_{in}, plotted vs. GPP in maize (16 fields during 2001 through 2008) and soybean (8 fields in 2002, 2004, 2006 and 2008). The solid line is the best fit function for the relationship GPP vs. VI × PAR established for all soybean and maize data combined. Best fit functions, root mean square errors (RMSE), determination coefficients and coefficients of variation ($R^2$and CV), were obtained using a k-fold cross validation procedure with k = 46.

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