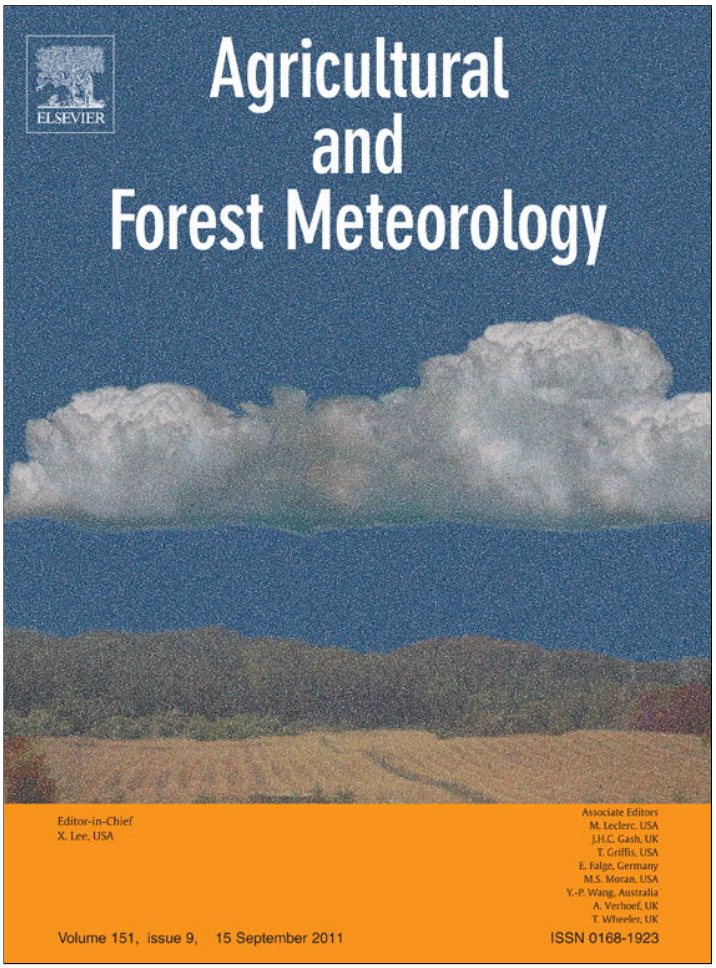

Agricultural and Forest Meteorology 151 (2011) 1267–1276

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Application of chlorophyll-related vegetation indices for remote estimation of maize productivity

Yi Peng, Anatoly A. Gitelson*

Center for Advanced Land Management Information Technologies, School of Natural Resources, University of Nebraska-Lincoln, Lincoln, NE 68588-0973, USA

ARTICLE INFO

Article history:
Received 22 March 2011
Received in revised form 6 May 2011
Accepted 10 May 2011

Keywords:
Gross primary production
Chlorophyll content
Vegetation indices

ABSTRACT

Crop gross primary productivity (GPP) is an important characteristic for evaluating crop nitrogen content and yield, as well as the carbon exchange. Based on the close relationship observed between GPP and total chlorophyll content in crops, we applied a model that relies on a product of chlorophyll-related vegetation index and incoming photosynthetically active radiation for remote estimation of GPP in maize. In this study, we tested the performance of this model for maize GPP estimation based on spectral reflectance collected at a close range, 6 m above the top of the canopy, over a period of eight years from 2001 through 2008. Fifteen widely used chlorophyll-related vegetation indices were employed for GPP estimation in irrigated and rainfed maize, and accuracy and uncertainties of the models were compared. We also explored the possibility of using a unified algorithm in estimating maize GPP in fields that are different in irrigation, field history and climatic conditions. The results showed that vegetation indices that closely relate to total canopy chlorophyll content and/or green leaf area index were accurate in GPP estimation. Both green and red edge Chlorophyll Indices, MERIS Terrestrial Chlorophyll Index as well as Simple Ratio were the best approximations of the widely variable GPP in maize under different crop managements and climatic conditions. They were able to predict daily GPP reaching 30 gC/m^2/d with RMSE below 2.75 gC/m^2/d.

1. Introduction

With the rising demand for agricultural products and commodities all over the world, croplands play an increasingly important role in global ecosystem balance, as well as human sustainable development. It is reported that approximately 24% of Earth's terrestrial surface is occupied by cultivated systems (Cassman and Wood, 2005). Gross primary production (GPP) of crops is the rate at which a cropland captures and stores carbon as biomass. Crop GPP has been estimated to contribute 15% of global carbon dioxide fixation through photosynthesis (Malmstrom et al., 1997). Therefore, there is a growing interest in crop GPP estimation especially on a regional and global scale, particularly in maize croplands that almost dominate agricultural land use in the north-central USA. An accurate and synoptic quantification of spatially distributed GPP of maize is essential for monitoring crop growth and carbon exchange of this region.

Field studies use tower eddy covariance systems to calculate seasonal and inter-annual dynamics of GPP in crops. Such micrometeorological approaches provide reliable and accurate estimates of GPP, based on measurements of the entire net CO_2 flux between the land surface and the atmosphere (e.g., Verma et al., 2005). However, it measures CO_2 fluxes over a limited area, although at a high temporal resolution. The up-scaling beyond these small footprints is needed for regional and global carbon budget evaluations as well as for estimating crop yield. Since crop productivity is a result of the interaction of solar radiation with plant canopy, remote sensing technique can be used as an expedient tool for GPP estimation over large areas.

The GPP estimate is based on a concept originally developed by Monteith (1972), suggesting that the GPP of stress-free plants is linearly related to the product of the incoming photosynthetically active radiation (PAR_{in}), the fraction of PAR absorbed by photosynthetically active elements of plants ($fAPAR_{green}$) and efficiency of converting absorbed radiation to biomass, light use efficiency (LUE):

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

Chlorophyll is a very important leaf pigment for absorbing radiation for photosynthesis. Total canopy chlorophyll (Chl) content was defined as the product of leaf chlorophyll content and total leaf area index, LAI (Ciganda et al., 2009; Gitelson et al., 2005), which seems the most relevant community property of vegetation productivity (e.g., Whittaker and Marks, 1975). The recent studies have

* Corresponding author. Tel.: +1 402 4728386.
E-mail address: agitelson2@unl.edu (A.A. Gitelson).

0168-1923/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.agrformet.2011.05.005

shown that the two key physiological properties of photosynthesis process in Eq. (1), $fAPAR_{green}$ and LUE, relate to total Chl content (Gitelson et al., 2006a; Hilker et al., 2011; Houborg et al., 2011; Peng et al., 2011). Thus, total Chl content relates to GPP, which, in turn, relates directly to photosynthesis. The close relationship between GPP and total Chl content in crops has been observed and this relationship seems non-species-specific (Gitelson et al., 2006a; Wu et al., 2009). The model that relies on the total Chl content and PAR_{in} for GPP estimation was suggested in the form (Gitelson et al., 2003a, 2006a):

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

There are two different approaches to the remote estimation of Chl content in crops. One of them is to assess the *leaf Chl content* by such vegetation indices (VI) as MCARI, TCARI, TCARI/OSAVI (Table 1). The other approach is to assess the *total Chl content* by such VIs as Chlorophyll Indices (CI_{green} and $CI_{red\ edge}$) and MTCI (Table 1), or to estimate *green LAI*, which closely relates to total crop canopy Chl content (Ciganda et al., 2008), by Simple Ratio, NDVI, EVI (Huete et al., 1997), WDRVI, and TVI-like VIs (Table 1).

While monitoring *leaf Chl content* is a crucial component of farm management (Daughtry et al., 2000; Haboudane et al., 2002), *canopy Chl content* or *total Chl content* relates closely to primary production (e.g., Lieth and Whittaker, 1975; Gitelson et al., 2006a; Wu et al., 2009; Hilker et al., 2011) and crop yield (Walters, 2003; Solari et al., 2008). Thus, the VIs, which closely relate to total canopy Chl content, can be employed to estimate crop GPP. So the model of Eq. (2) can be presented as:

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

The paradigm of the model (Eq. (3)) is based on the assumption that the total canopy Chl in crops is the main driver of GPP. This methodology was justified in detail by Gitelson et al. (2006a) and Peng et al. (2011), and the VIs used for total Chl content retrieval were successfully applied for GPP estimation in crops.

The objectives of this paper are (1) to test the performances of several widely used VIs for GPP estimation in maize; (2) to assess the accuracy of the model (Eq. (3)) in estimating irrigated and rainfed maize GPP; (3) to explore the possibility of using a unified algorithm for GPP estimation in both irrigated and rainfed maize; (4) to assess the accuracy and uncertainties of a unified algorithm for GPP estimation in fields that are different in crop management, filed history and climatic conditions.

2. Materials and methods

2.1. Study sites and field management practice

Three AmeriFlux sites were studied from 2001 through 2008. They are located within 1.6 km of each other at the University of Nebraska-Lincoln Agricultural Research and Development Center near Mead, Nebraska, USA. Site 1 and site 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 maize was planted in odd years (2001, 2003, 2005, and 2007). Prior to 2001, site 1 and site 2 had a 10-year history of maize–soybean rotation under no-till, while site 3 had a variable cropping history of primarily wheat, soybean, oats and maize with tillage (http://public.ornal.gov/ameriflux/site-select.cfm, 2011). Table 2 shows the maize hybrid, field management, maize productivity and yield in each field from 2001 through 2008.

2.2. CO_2 fluxes and PAR_{in}

Each site is equipped with an eddy covariance tower and meteorological sensors to obtain continuous measurements of CO_2 fluxes, water vapor and energy fluxes since 2001. To have sufficient upwind fetch in all directions, eddy covariance sensors were mounted in these three study sites at 3 m above the ground while the canopy was shorter than 1 m, and later moved to a height of 6.2 m until harvest to collect hourly data of CO_2 fluxes from 2001 through 2008 (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 night-time (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} exceeding 1 mmol/g/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). The daytime GPP was then acquired by subtracting Re from NEE. This approach has been widely used in the context of tower flux measurements and is considered to provide reasonable estimates at the landscape level (Verma et al., 2005; Suyker 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} exceeding 1 mmol/g/m^2/d.

2.3. Canopy reflectance measurement and vegetation indices used

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 was pointed downward to measure the upwelling radiance of the crop, while the other 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., 2006a). Spectral reflectance measurements at canopy level were carried out during the growing season each year from 2001 through 2008. This resulted in 173 measurement campaigns (18 in 2001, 31 in 2002, 34 in 2003, 31 in 2004, 21 in 2005, 15 in 2006, 14 in 2007 and 9 in 2008).

In this study, we tested several widely used VIs for GPP estimation presented in Table 1. We also used the ratio TCARI/OSAVI (Haboudane et al., 2002) and the product TVI × MCARI, where TVI is assumed to be a proxy for green LAI (Broge and Leblanc, 2000) and MCARI is a proxy for leaf Chl (Daughtry et al., 2000). The collected reflectance spectra were resampled to spectral bands of 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 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, MCARI, TCARI, MTCI, TCARI/OSAVI, TVI × MCARI and $CI_{red\ edge}$ were calculated.

Photochemical Reflectance Index, PRI (Gamon et al., 1992) was calculated in the form: $PRI = (\rho_{531} - \rho_{570})/(\rho_{531} + \rho_{570})$, where ρ_{531} and ρ_{570} are reflectances at 530 nm and 570 nm, respectively. It was used as a surrogate of LUE in a model $GPP = VI \times PAR_{in} \times LUE$.

Table 1
Summary of vegetation indices used in this paper.

Vegetation index	Formula	Reference
SR	ρ_{NIR}/ρ_{red}	Jordan (1969)
NDVI	$(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red})$	Rouse et al. (1974)
OSAVI	$(1+1.16)\times(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red}+0.16)$	Rondeaux et al. (1996)
EVI2	$2.5\times(\rho_{NIR}-\rho_{red})/(1+\rho_{NIR}+2.4\times\rho_{red})$	Jiang et al. (2008)
TVI	$0.5\times[120\times(\rho_{750}-\rho_{550})-200\times(\rho_{670}-\rho_{550})]$	Broge and Leblanc (2000)
MTVI1	$1.2\times[1.2\times(\rho_{800}-\rho_{550})-2.5\times(\rho_{670}-\rho_{550})]$	Haboudane et al. (2004)
MTVI2	$1.5\times[1.2(\rho_{800}-\rho_{550})-2.5\times(\rho_{670}-\rho_{550})]/\mathrm{sqrt}((2\rho_{800}+1)^2-(6\rho_{800}-5\mathrm{sqrt}(\rho_{670}))-0.5)$	Haboudane et al. (2004)
VARI	$(\rho_{green}-\rho_{red})/(\rho_{green}+\rho_{red})$	Gitelson et al. (2002)
WDRVI*	$(\alpha\times\rho_{NIR}-\rho_{red})/(\alpha\times\rho_{NIR}+\rho_{red}),\ 0<\alpha<1$	Gitelson (2004)
	$(\alpha\times\rho_{NIR}-\rho_{red})/(\alpha\times\rho_{NIR}+\rho_{red})+(1-\alpha)/(1+\alpha),\ \alpha=0.2$	This paper*
MCARI	$[(\rho_{700}-\rho_{670})-0.2(\rho_{700}-\rho_{550})]\times(\rho_{700}/\rho_{670})$	Daughtry et al. (2000)
TCARI	$3[(\rho_{700}-\rho_{670})-0.2(\rho_{700}-\rho_{550})\times(\rho_{700}/\rho_{670})]$	Haboudane et al. (2002)
MTCI	$(\rho_{NIR}-\rho_{red\ edge})/(\rho_{red\ edge}-\rho_{red})$	Dash and Curran (2004)
CI_{green}	$\rho_{NIR}/\rho_{green}-1$	Gitelson et al. (2003b) and Gitelson et al. (2005)
$CI_{red\ edge}$	$\rho_{NIR}/\rho_{red\ edge}-1$	Gitelson et al. (2003b) and Gitelson et al. (2005)

* In original formulation (Gitelson, 2004), WDRVI 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.

3. Results and discussion

The temporal behavior of GPP during growing season includes two types of variation. Low frequency variation of GPP mainly follows changes of crop growing cycles, which closely relates to Chl content, thus, to chlorophyll-related VIs. Fig. 1 shows several examples of temporal behavior of VIs and GPP, illustrating their similar temporal pattern during eight-year growing seasons.

Another type of GPP variation occurs at much higher frequency, which correspond to high frequency variations of PAR_{in} due to change in weather conditions. In addition, there is a significant decline of PAR_{in} (beginning in August in Mead, NE) as a result of the Earth's orbital eccentricity variation, which causes lower productivity in crops of the late season (Fig. 7 in Peng et al., 2011). The variations of GPP caused by variations of PAR_{in} either due to weather or seasonal changes would not be explained by chlorophyll-related VI alone, because variations of PAR_{in} would not result in the immediate changes of crop Chl content. When considering this, the model for GPP estimation in crops has to be based on the product of VI and PAR_{in} as Eq. (3).

Based on this model, we then tested several widely used chlorophyll-related indices for GPP estimation from the data collected over a period of eight years from 2001 through 2008.

3.1. GPP estimating in rainfed and irrigated maize

Maize grown in site 1 and site 2 was under scheduled irrigation management, while maize in site 3 relied entirely on rainfall. Irrigation provided about 40–50% of the total water received by maize in irrigated sites, while the rainfall is the only provision of water for the rainfed cropland use. Therefore, the precipitation mostly impacted the soil moisture in the rainfed site, which was very different from irrigated sites especially in drought years. Water stress occurred under low soil moisture condition, which would severely affect grain yield. For example, during dry periods in 2003, soil moisture at 10 cm depth in the rainfed site dropped more than 40% compared to that in irrigated sites. As a result, the ratio of grain yield in the irrigated site to that in rainfed site was above 1.8 in 2003, while in a "normal" year with higher precipitation (e.g., 2007), it was below 1.3 (Suyker and Verma, 2010). Our 8-year study period represents wet years as well as "normal" and dry years, in which the maize in the rainfed site might suffer from water stress at different degree, while the maize in irrigated sites was relatively stress-free. In addition, the density of planting in the rainfed site was much lower than in irrigated sites in order to account for differences in water-limited attainable yield (Fig. 2, Table 2). Thus, the maximal values of LAI, biomass and GPP were different between irrigated and rainfed maize. Having concurrent observations in the irrigated and rainfed sites, we address following questions: (1) how accurate

Table 2
Maize management details, yield and maximum GPP for the three study sites during 2001–2008.

Site/year	Maize hybrid	Density (plants/ha)	Tillage operation	Applied N (kg N/ha)	Max GPP ($gC/m^2/d$)	Yield (Mg/ha)
Site 1: Irrigated continuous maize						
2001	Pioneer 33P67	82,000	Intensive tillage	196	31.1	13.51
2002	Pioneer 33P67	81,000	No-till	214	28.8	12.97
2003	Pioneer 33B51	77,000	No-till	233	27.3	12.12
2004	Pioneer 33B51	84,012	No-till	293	30.4	12.24
2005	DeKalb 63–75	82,374	No-till	246	26.7	12.02
2006	Pioneer 33B53	84,012	Conservation-plow	210	26.2	10.46
2007	Pioneer 31N30	74,000	Conservation-plow	272	30.6	12.79
2008	Pioneer 31N30	84,000	Conservation-plow	123	26.9	11.99
Site 2: Irrigated maize–soybean rotation						
2001	Pioneer 33P67	81,000	Intensive tillage	196	33.5	13.41
2003	Pioneer 33B51	78,000	No-till	169	28.2	14.00
2005	Pioneer 33B51	81,000	No-till	170	27.2	13.24
2007	Pioneer 31N28	75,000	No-till	183	27.6	13.21
Site 3: Rainfed maize–soybean rotation						
2001	Pioneer 33B51	52,600	Intensive tillage	128	28.9	8.72
2003	Pioneer 33B51	57,600	No-till	90	25.2	7.72
2005	Pioneer 33G68	56,300	No-till	118	22.5	9.10
2007	Pioneer 33H26	52,000	No-till	125	24.3	10.23

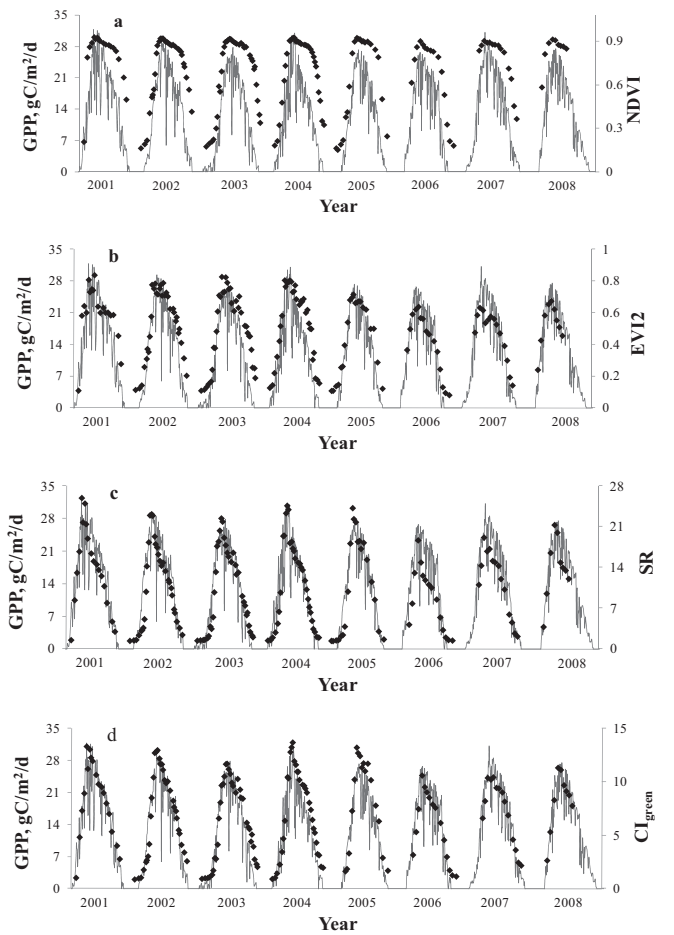

Fig. 1. Temporal behavior of GPP and (a) NDVI, (b) EVI2, (c) SR, (d) CI_{green} in maize during the growing seasons 2001 through 2008. The solid lines are the daily GPP; the diamonds represent the VIs at selected dates.

is the model (Eq. (3)) in estimating GPP for rainfed and irrigated maize? (2) Are the algorithms developed for irrigated and rainfed maize different?

We established the relationships of GPP vs. VI × PAR_{in} for irrigated maize (12 fields: site 1 from 2001 through 2008; site 2 in 2001, 2003, 2005 and 2007) and for rainfed maize (4 fields: site 3 in 2001, 2003, 2005 and 2007) separately, and then compared the determination coefficients (R^2), root mean square errors (RMSE)

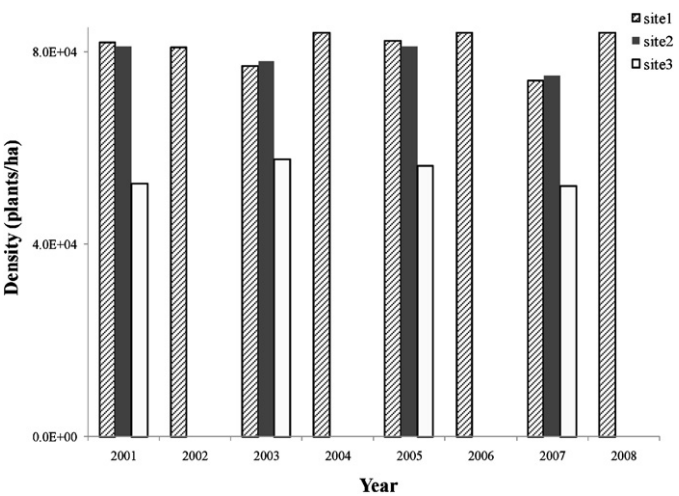

Fig. 2. Density of maize planting in the three sites from 2001 through 2008.

and coefficients of variation (CV) of the two relationships for fifteen VIs; twelve of them presented in Table 3. R^2 of the relationships GPP vs. TCARI × PAR_{in} was 0.40 for irrigated maize and 0.62 for rainfed maize; R^2 was even lower for TCARI/OSAVI (0.11 for irrigated maize and 0.22 for rainfed maize). These VIs were suggested for leaf Chl estimation and, not surprisingly, they do not track total crop Chl content and GPP. The relationship TVI × MCARI × PAR_{in} vs. GPP was weaker than that of TVI × PAR_{in} vs. GPP. TVI is a surrogate of *green LAI*, while MCARI is a surrogate of leaf Chl. Total crop Chl is a product of leaf Chl and *total LAI*; this explains weaker relation of TVI×MCARI×PAR_{in} with GPP.

For all VIs, presented in Table 3, the relationships with GPP for both irrigated and rainfed maize were quite close with CV below 25% except MCARI with CV above 30% for GPP estimation in irrigated sites and 23% in rainfed sites. NDVI was a good indicator of low-to-moderate GPP but was insensitive to GPP above 14 gC/m^2/d. At intermediate to high Chl content (a) the red reflectance tends to saturate and becomes insensitive to Chl content, and (b) NIR reflectance is much higher than the red reflectance ($\rho_{NIR} \gg \rho_{red}$), which results in very low sensitivity of NDVI to red reflectance, and, thus, to Chl content (Asrar et al., 1984; Goward and Huemmerich, 1992; Gitelson, 2004; Gitelson et al., 2006b; Vina and Gitelson, 2005). VARI, EVI2 and WDRVI were more sensitive than NDVI to moderate-to-high GPP, but such NDVI-like indices were still less sensitive to high Chl content. The SR, CIs and MTCI remain sensitive to the wide range of Chl content as well as GPP (Gitelson et al., 2003a; Gitelson et al., 2006b; Dash and Curran, 2004; Peng et al., 2011).

The maximum GPP produced by irrigated maize were approximately 15% higher than that of rainfed maize. So the model based on NDVI- and TVI-like indices for GPP estimation is more accurate for rainfed than irrigated maize, because they are more capable of estimating low-to-moderate GPP, but less sensitive to high GPP, which is more often in irrigated sites. The SR and CIs, which are sensitive to the wide range of Chl content and GPP, are able to estimate GPP in rainfed maize as accurately as in irrigated maize. As shown in Table 3, the different water supply, plant densities, dynamic ranges of LAI, biomass and GPP did not result in significant difference in R^2, RMSE and CV of the relationships based on SR and CIs in irrigated and rainfed fields. It shows that the model that relies on total crop Chl content and PAR_{in} can be applied to estimate GPP accurately not only in maize under best management practices (irrigated maize) but also the maize grown in water-limited conditions (rainfed maize).

While the model (Eq. (3)) was accurate in estimating GPP in both rainfed and irrigated maize, the algorithms, developed for irrigated and rainfed maize, were statistically significantly different for all the VIs except NDVI (p-value was 0.84 for NDVI, less than 0.01 for EVI2, VARI, MTCI and WDRVI, and less than 0.0001 for CI_{green}, $CI_{red\ edge}$ and SR). Scattering of the relationship of NDVI × PAR_{in} vs. GPP was rather wide, which made it impossible to distinguish the difference between rainfed and irrigated sites. For other VIs tested, the slope of the relationship of GPP vs. VI × PAR_{in} for the rainfed sites was consistently larger than for irrigated sites. The main reason for such difference might be that the density of planting in the rainfed site was at least 25% lower than in irrigated sites (Fig. 2, Table 2). In crops with the same total Chl content, maize in the rainfed site had higher GPP than that in more densely planted irrigated sites. In other words, maize planted at a lower density can produce more GPP per Chl content. The plant density affects the light climate inside the canopy, so fAPAR value. Thus, light penetrates deeply into the sparsely distributed plants and can be absorbed for photosynthesis more efficiently. In more densely planted fields, light absorption by leaves underneath the top layer would be somewhat limited by the shadow of nearby plants. This is accord with Borras et al. (2003) findings that increased maize plant population

Table 3
Determination coefficients (R^2), root mean square errors (RMSE) and coefficients of variation (CV) of quadratic polynomial relationships between daytime GPP and the product of vegetation index and incident PAR (VI × PAR_{in}) for 12 vegetation indices in irrigated maize (12 fields) and rainfed maize (4 fields). Maximum GPP produced by maize was 34.17 gC/m^2/d in irrigated sites, while 29.47 gC/m^2/d in the rainfed sites.

		MCARI	NDVI	MTVI1	TVI	VARI	EVI2	MTVI2	WDRVI	MTCI	SR	CI_{green}	$CI_{red\ edge}$
R^2	Irrigated	0.63	0.78	0.80	0.80	0.81	0.81	0.85	0.87	0.92	0.88	0.91	0.91
	Rainfed	0.82	0.84	0.90	0.90	0.88	0.87	0.92	0.91	0.80	0.88	0.89	0.89
RMSE,gC/m^2/d	Irrigated	4.94	3.85	3.64	3.60	3.57	3.48	3.17	2.98	2.25	2.59	2.56	2.41
	Rainfed	3.23	3.14	2.43	2.45	2.68	2.60	2.14	2.27	3.39	2.33	2.28	2.26
CV, %	Irrigated	31.3	24.4	23.1	22.8	22.6	22.0	20.1	18.8	14.2	16.4	16.2	15.2
	Rainfed	23.6	22.9	17.7	17.9	19.6	19.0	15.7	16.5	24.8	17.0	16.6	16.5

decreases the light penetration within the canopy, and also affects light composition perceived by leaves and the vertical profile of leaf N content of crops, thus decreasing grain protein concentrations.

3.2. A unified algorithm for GPP estimation in rainfed and irrigated maize

Although the algorithms for GPP estimation in irrigated and rainfed maize were found to be different, there is a need for a unified algorithm that is able to estimate GPP in maize grown in both irrigated and rainfed fields. It is an especially important issue when using remote sensing techniques with coarse spatial resolution that do not able to separate the signals from sites with different irrigation practices. In order to assess the accuracy of a unified algorithm for GPP estimation in both rainfed and irrigated maize, we established one relationship between GPP and VI × PAR_{in} based on data collected over16 fields containing rainfed and irrigated maize from 2001 through 2008. Table 4a summarizes the statistical characteristics (R^2, RMSE and CV) of such unified algorithms for twelve VIs and the relationships are presented in Fig. 3.

By comparing Table 4a with Table 3, one can see that the accuracy of the unified algorithms for GPP estimation using NDVI- and TVI-like indices (NDVI, VARI, EVI2, WDRVI, TVI, MTVI1 and MTVI2) were almost the same as the accuracy of the algorithms developed for irrigated sites; however, it was lower than the accuracy of the algorithms developed for rainfed sites. For these indices, most errors came from less accurate estimation of moderate-to-high GPP values due to their decrease in sensitivity to the moderate-to-high total chlorophyll/green biomass. The NDVI- and TVI-like indices were more accurate for GPP estimation in rainfed maize, since much less number of samples with high GPP was available in rainfed fields than irrigated fields.

The unified algorithms based on MTCI, SR and CIs, which are sensitive to wide range of GPP, were able to accurately estimate GPP in both irrigated and rainfed sites. CV of GPP estimation by SR and CIs, in irrigated and rainfed sites combined were only slightly higher (17.65% vs. 17.01% for SR, 17.52% vs. 16.64% for CI_{green} and 16.60% vs. 16.50% for $CI_{red\ edge}$) than that of irrigated and rainfed sites when treated separately. MTCI also was able to estimate GPP with CV below 18%.

Overall, all relationships established for irrigated and rainfed data combined, except MCARI, were quite close (Fig. 3), showing that it is possible to use a unified algorithm to accurately estimate maize GPP in both rainfed and irrigated sites. Among the twelve VIs tested, SR, CIs and MTCI seems to be most accurate for GPP estimation. Importantly to note that the products of PAR_{in} and EVI2, VARI and WDRVI have linear relations with GPP while the sensitivity of other NDVI- and TVI-like indices decreased as GPP exceeded 14 gC/m^2/d. In contrast, the sensitivity of the products of PAR_{in} and SR, MTCI, CI_{green} and $CI_{red\ edge}$ to moderate-to-high GPP was higher than their sensitivity to low GPP.

To show the role of PAR_{in} in the model (Eq. (3)), we established relationships GPP vs. VI and calculated statistics of these relationships (Table 4b). The accuracy of GPP estimation by VIs alone was much lower than using Eq. (3).

We compared the performances of the product VI × PRI × PAR_{in} and VI × PAR_{in} for GPP estimation and found no improvement by using PRI as an approximation of LUE for GPP estimation for both irrigated and rainfed maize. While relationship PRI vs. total canopy Chl was significant (R^2 = 0.60, p-value < 0.01), the relationship of PRI with LUE = GPP/$APAR_{green}$, where $APAR_{green}$ is the radiation absorbed by green elements of plants (Hall et al., 1992), was very weak (R^2 = 0.07, p-value = 19.35). Thus, PRI may not be effective as a surrogate of LUE in ecosystems where Chl content closely follows the seasonal dynamic of CO_2 exchange such as croplands, deciduous forests and grasslands (Garbulsky et al., 2011; Peng et al., 2011).

The maize hybrid, field history and crop management in studied 16 maize fields differed from field to field (Table 2). Eight different cultivars of maize were grown in the 16 fields, density of planting ranged from 52,000 to 84,012 plants/ha, and nitrogen applied ranged from 90 to 293 kg N/ha among the fields. Site 1 is irrigated continuous maize system, site 2 is irrigated maize–soybean rotation system, and site 3 is rainfed maize–soybean rotation system. In addition, site 1 was under tillage operation since 2006, while site 2 and site 3 under no-till management. Because the residue reflectance was much higher than bare soil reflectance, from 2006 through 2008 soil reflectance in site 1 was significantly lower than that in sites 2 and 3. Furthermore, the climatic conditions were also quite different among 8 years. For example, the growing seasons of 2001 and 2002 were slightly warmer than 2003. There were obvious dry periods during reproductive stages in 2001 and 2003 and during vegetative stages in 2005. However, 2006, 2007 and 2008 were relatively wet years with no significant dry period (Suyker and Verma, 2010). In accord with that, the dynamic ranges of LAI, GPP and yield produced by maize were different in the 16 fields. For example, the maximum LAI was 6.2 m^2/m^2 in the "good" year (site 1 in 2001), while only 4.3 m^2/m^2 in the dry year (site 3 in 2003). All these differences existing among years and fields might affect relationships between GPP and VI × PAR_{in}. In Fig. 4, relationships between GPP and VI × PAR_{in} in 16 fields are presented together with the best-fit functions for all 16 fields combined. Table 5 summarized how the unified algorithms work in estimating GPP in each of these 16 fields. Overall, the unified algorithms based on CIs, MTCI, SR and WDRVI were found to be most accurate for GPP estimation with the mean CV of 16 fields less than 23%, while the algorithms based on NDVI, VARI, EVI2, TVI and MTVI1were less accurate (CV was between 26% and 29%). MCARI had the highest CV exceeding 35% (Fig. 5).

3.2.1. Model calibration and validation

To calibrate and validate the algorithms for GPP estimation, we created a dataset including all data taken from 2001 through 2008 in three sites (332 samples in total), and sorted all samples in ascending order of GPP. Data with odd numbers were used for establishing the relationships GPP vs. VI × PAR_{in} and, thus, calibrating the algorithms. The established relationships are presented in Table 6. In addition to such statistical characteristic of the established relationships as determination coefficient R^2, it is important to assess sensitivity of each algorithm to GPP. To estimate how sen-

Table 4a
Determination coefficients (R^2), root mean square error (RMSE), coefficients of variation (CV) of quadratic polynomial relationships between daytime GPP and VI × PAR_{in} established using data collected in 16 irrigated and rainfed fields from 2001 through 2008. GPP ranged from 0 to 35 $gC/m^2/d$.

	MCARI	NDVI	MTVI1	TVI	VARI	EVI2	MTVI2	WDRVI	SR	CI_{green}	MTCI	$CI_{red\ edge}$
R^2	0.67	0.80	0.82	0.82	0.82	0.82	0.86	0.87	0.86	0.88	0.89	0.88
RMSE, $gC/m^2/d$	4.61	3.71	3.44	3.41	3.40	3.34	3.01	2.88	2.70	2.68	2.66	2.54
CV (%)	30.0	24.1	22.3	22.1	22.1	21.7	19.6	18.7	17.5	17.4	17.3	16.5

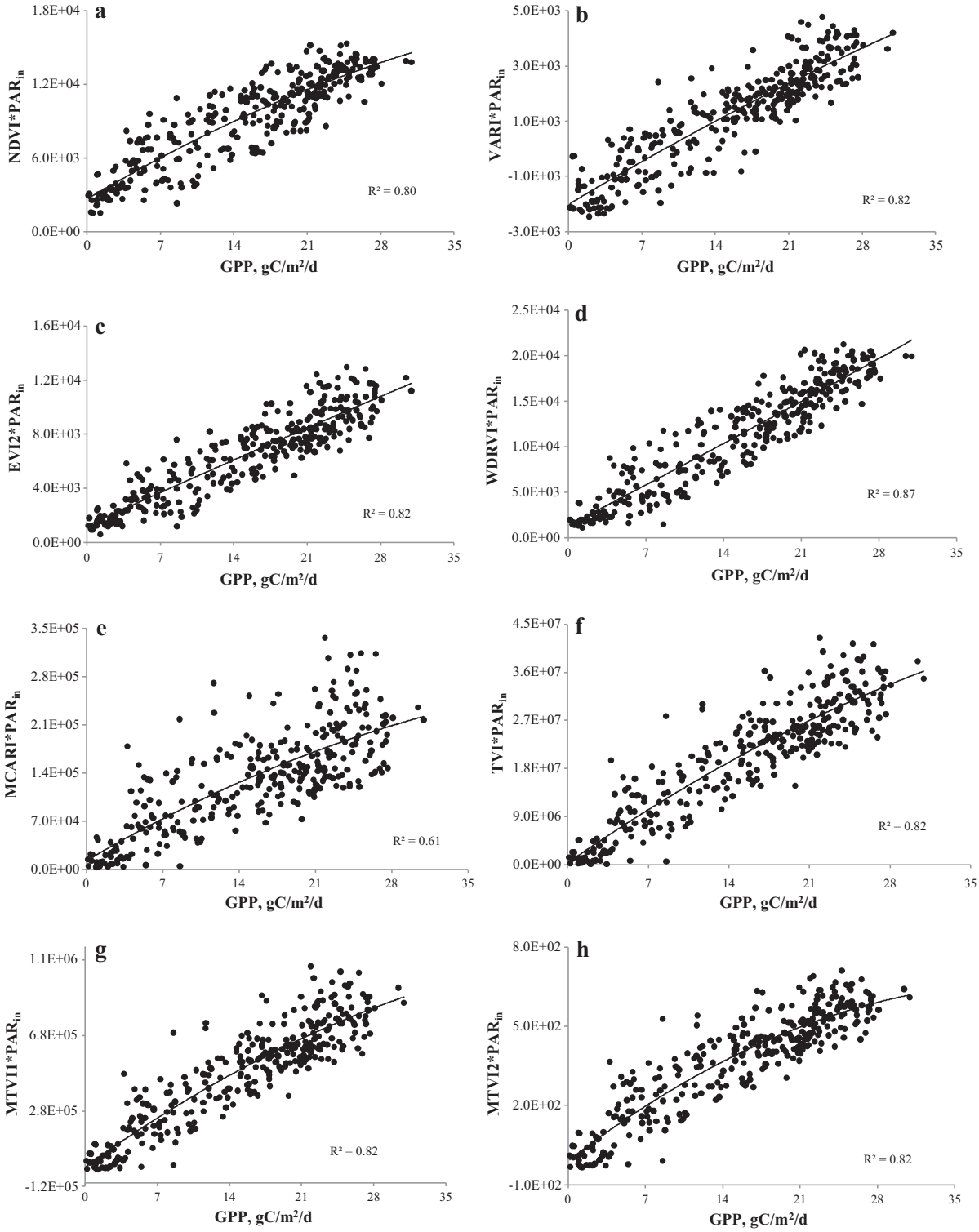

Fig. 3. Relationship between GPP and (a) NDVI × PAR_{in}, (b) VARI × PAR_{in}, (c) EVI2 × PAR_{in}, (d) WDRVI × PAR_{in}, (e) MCARI × PAR_{in}, (f) TVI × PAR_{in}, (g) MTVI1 × PAR_{in}, (h) MTVI2 × PAR_{in}, (i) SR × PAR_{in}, (j) MTCI × PAR_{in}, (k) CI_{green} × PAR_{in}, (l) $CI_{red\ edge}$ × PAR_{in} for maize data collected in 16 irrigated and rainfed fields from 2001 through 2008.

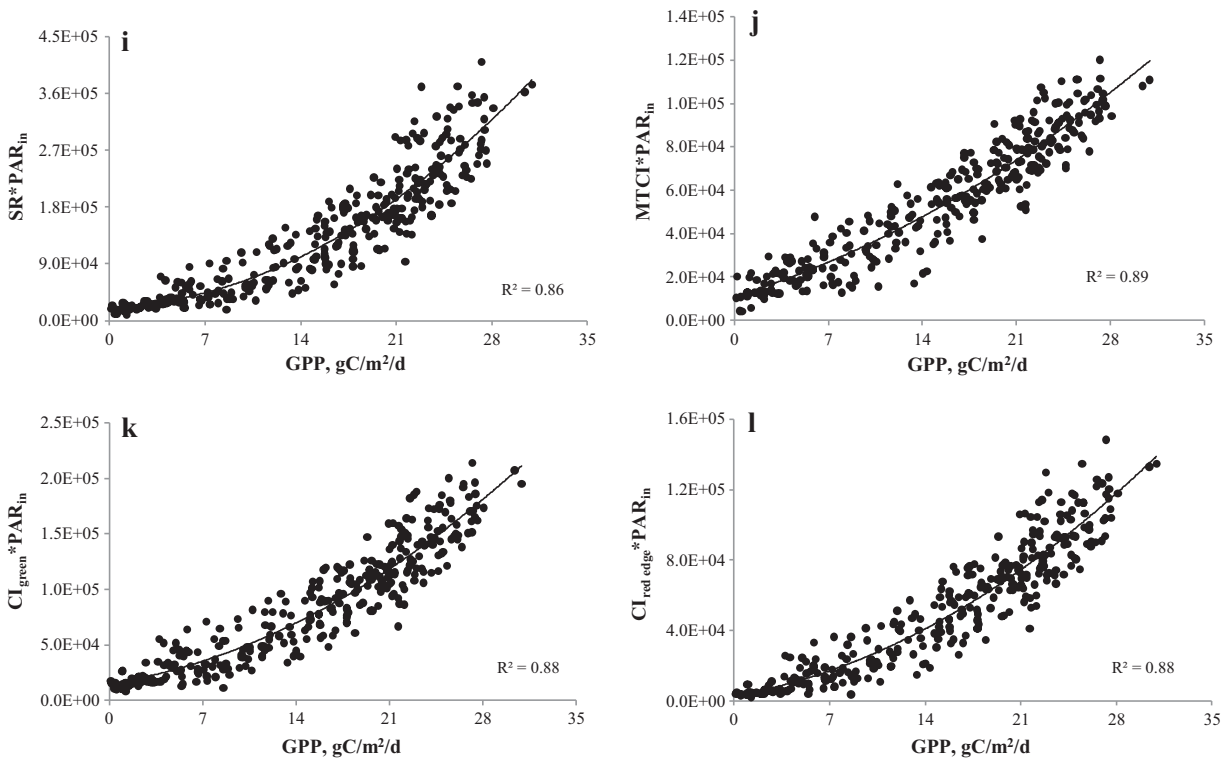

Fig. 3. (*Continued*).

Table 4b
Determination coefficients (R^2), root mean square error (RMSE), coefficients of variation (CV) of quadratic polynomial relationships between daytime GPP and VI established using data collected in 16 irrigated and rainfed fields from 2001 through 2008. GPP ranged from 0 to 35 gC/m^2/d.

	MCARI	MTVI1	TVI	EVI2	CI_{green}	MTVI2	NDVI	SR	WDRVI	VARI	$CI_{red\ edge}$	MTCI
R^2	0.52	0.70	0.70	0.71	0.75	0.75	0.77	0.78	0.78	0.78	0.79	0.81
RMSE, gC/m^2/d	5.58	4.40	4.39	4.32	4.03	4.01	3.87	3.77	3.76	3.74	3.67	3.53
CV (%)	36.3	28.6	28.5	28.0	26.2	26.0	25.1	24.5	24.4	24.3	23.8	22.9

sitive of VIs to GPP, we compared the noise equivalent (NE) of each VI tested in this paper (Fig. 6). It was calculated as:

$$NE = \frac{RMSE\{VI \times PAR_{in}\ vs.\ GPP\}}{d(VI \times PAR_{in})/d(GPP)}$$

where RMSE{VI × PAR_{in} vs. GPP} is root mean square error of the relationship VI × PAR_{in} vs. GPP, d(VI × PAR_{in})/d(GPP) is first derivative of VI × PAR_{in} with respect to GPP (Vina and Gitelson, 2005). The NE of MCARI was the highest among the VIs tested. It can be seen that NDVI- and TVI-like indices had smaller noise equivalent

Table 5
Coefficients of variation (CV) of the relationship between measured GPP and GPP estimated in each of 16 different fields using relationships GPP vs. VI × PAR_{in}, established using data taken from 2001 through 2008 (Fig. 3). Details about crop management practices in each field are shown in Table 2.

Site #	Year	GPP, gC/m^2/d		CV (%)											
		Max	Mean	MCARI	NDVI	VARI	EVI2	MTVI1	TVI	MTVI2	WDRVI	SR	CI_{green}	MTCI	$CI_{red\ edge}$
1	2001	31.1	14.8	47.2	34.0	27.3	31.0	36.3	36.1	31.1	26.5	19.3	18.9	18.6	18.5
2	2001	33.5	13.7	54.1	37.4	36.2	38.2	45.1	44.6	40.4	32.1	24.9	24.3	21.6	24.3
3	2001	28.9	12.8	47.1	32.8	30.4	24.5	27.4	27.1	26.5	26.3	29.1	27.9	22.5	24.5
1	2002	28.8	14.3	26.7	22.5	26.3	14.6	16.3	15.9	15.7	17.8	19.9	17.5	17.0	16.8
1	2003	27.3	12.6	38.6	30.4	32.0	28.6	29.0	28.5	26.3	26.5	24.4	24.4	18.9	23.2
2	2003	28.2	13.4	35.9	28.7	25.1	26.0	27.1	26.7	23.5	22.7	18.8	20.2	18.6	18.0
3	2003	25.2	10.1	20.8	28.5	26.1	23.9	23.6	24.1	22.6	23.6	29.5	28.8	44.8	30.3
1	2004	30.4	12.9	32.9	29.0	20.7	23.6	22.9	22.7	20.5	22.5	21.4	23.5	14.0	20.2
1	2005	26.7	13.7	22.4	24.3	20.4	16.8	18.0	18.1	12.1	14.7	14.6	14.7	15.0	13.7
2	2005	27.2	14.2	26.8	25.9	22.1	18.0	18.2	18.1	15.8	18.1	16.8	15.8	16.5	14.3
3	2005	22.5	12.5	25.6	27.8	19.6	21.6	20.5	21.0	16.9	17.1	18.8	18.0	27.9	15.9
1	2006	26.2	14.4	35.5	20.7	25.0	25.8	25.3	25.3	21.2	14.4	17.7	14.7	13.0	15.0
1	2007	30.6	13.5	39.3	31.2	22.7	36.7	31.4	31.3	25.1	22.3	16.4	19.3	15.1	18.1
2	2007	27.6	12.8	49.8	29.6	31.1	31.7	29.7	29.1	24.1	20.6	17.8	17.6	11.6	17.2
3	2007	24.3	11.4	20.5	25.9	24.2	32.2	20.1	20.7	18.2	22.0	28.5	31.7	23.0	29.1
1	2008	26.9	13.4	37.3	36.9	33.9	24.6	25.5	24.9	23.3	25.7	17.5	11.9	25.1	12.9
Mean		27.8	13.2	35.0	29.1	26.5	26.1	26.0	25.9	22.7	22.5	21.0	20.6	20.2	19.5

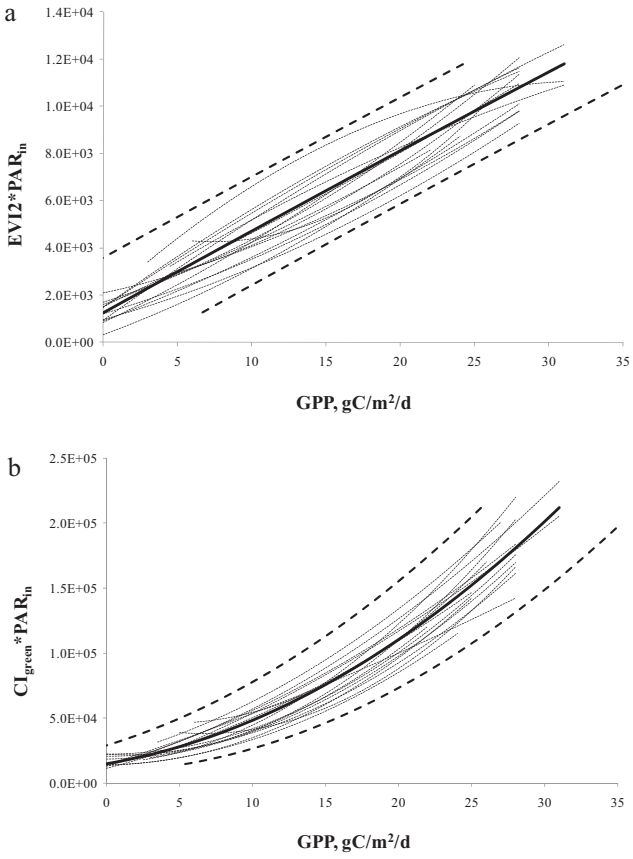

Fig. 4. Best fit functions of the relationships between GPP and the products of (a) EVI2 × PAR$_{in}$ and (b) CI$_{green}$ × PAR$_{in}$ for each of 16 fields from 2001 through 2008 (dash lines). The solid lines are the best fit functions for all data in 16 irrigated and rainfed fields combined from 2001 through 2008. The bold dash lines represent the 95% confidential interval (i.e., two standard error of GPP estimation).

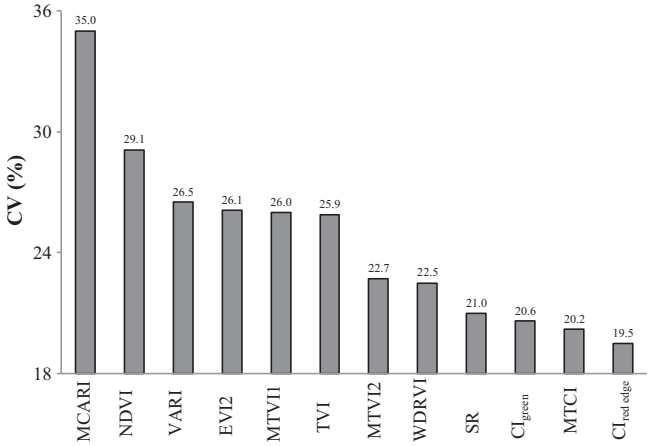

Fig. 5. Mean coefficients of variation (CV) of relationships between measured daytime GPP and GPP estimated by a unified algorithm established using maize data taken over 16 different fields from 2001 through 2008 (Table 5).

Table 6
The results of calibration of the algorithms for estimating daytime GPP in 16 irrigated and rainfed maize sites from 2001 through 2008: GPP = $f(x)$, x = VI × PAR$_{in}$. Best fit functions and determination coefficients (R^2) are given for twelve vegetation indices.

VI	Best fit function	R^2
MCARI	GPP = −2.91E−10 * x^2 + 1.7 E−4 * x − 0.35	0.71
NDVI	GPP = 1.94E−3 * x − 2.59	0.79
VARI	GPP = −1.03E−7 * x^2 + 4.1E−3 * x + 10.83	0.80
MTVI1	GPP = −8.47E−12 * x^2 + 3.5E−5 * x + 1.12	0.84
TVI	GPP = −6.35E−15 * x^2 + 9.2E−7 * x + 0.23	0.84
EVI2	GPP = −9.26E−8 * x^2 + 0.0035 * x − 3.08	0.88
MTVI2	GPP = −6.75E−8 * x^2 + 2.92 E−3 * x + 1.66	0.87
WDRVI	GPP = −1.93E−8 * x^2 + 1.70E−3 * x − 0.76	0.87
SR	GPP = 28.8 * $(1 - e^{-6.78e-6*x})$	0.92
MTCI	GPP = −1.16E−9 * x^2 + 3.85E−4 * x − 1.60	0.89
CI$_{green}$	GPP = −154 + 14.7 * ln (x + 27900.61)	0.92
CI$_{red\ edge}$	GPP = −121 + 12.42 * ln (x + 16082.91)	0.93

(i.e., were more sensitive to GPP) for GPP below 14 gC/m^2/d than NE for higher GPP. Among these indices, WDRVI had the lowest noise equivalent independent of GPP. The SR, MTCI, CI$_{green}$ and CI$_{red\ edge}$ had much lower noise equivalent (i.e., more sensitivity) when GPP exceeded 14gC/m^2/d. Thus, they are more appropriate for estimating moderate-to-high GPP, while NDVI- and TVI-like indices were more sensitive to low GPP values.

The algorithms presented in Table 6 were then validated using validation data set (samples with even numbers). Measured reflectances in the validation dataset were used to calculate VIs and predict GPP values, and then predicted GPP values were compared with GPP measured by the eddy covariance technique. Table 7 and Fig. 7 show the accuracy of GPP prediction by the established (Table 6) algorithms. Among the twelve indices, CIs, MTCI and SR were the most precise estimates of GPP with CV < 18%, followed by WDRVI and MTVI2 with CV around 20%. NDVI, VARI, EVI2, TVI and

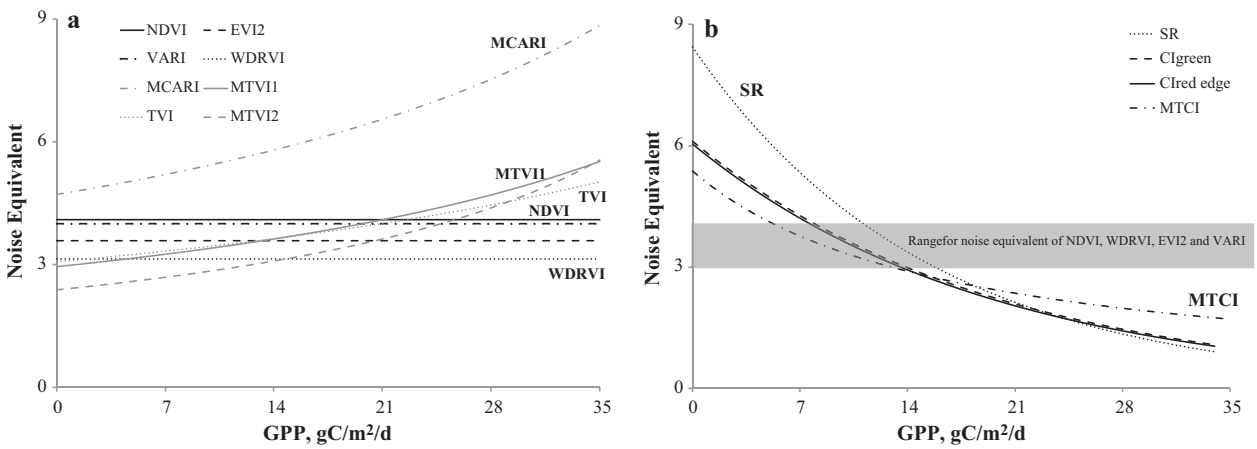

Fig. 6. Noise equivalent of GPP estimation by the product of VI × PAR$_{in}$ for (a) NDVI, WDRVI, EVI2, VARI, MCARI, TVI, MTVI1and MTVI2; (b) SR, CI$_{green}$, CI$_{red\ edge}$ and MTCI. When GPP was above 14 gC/m^2/d, the SR, CI$_{green}$, CI$_{red\ edge}$ and MTCI had lower noise equivalent (i.e., more sensitivity to GPP) than indices in Fig. 6a.

Table 7
The results of validation of algorithms for estimating daytime GPP in 16 irrigated and rainfed maize sites from 2001 through 2008. Slopes and offsets of the relationships between GPP predicted by algorithms (Table 6) and measured daytime GPP, root mean square errors (RMSE) are given for twelve vegetation indices.

	MCARI	NDVI	MTVI1	TVI	VARI	EVI2	MTVI2	WDRVI	CI_{green}	MTCI	SR	$CI_{red\ edge}$
Slope	0.66	0.74	0.79	0.79	0.80	0.81	0.82	0.82	0.83	0.86	0.84	0.85
Offset	5.13	4.12	3.22	3.13	3.03	3.01	2.76	2.78	2.67	2.14	2.29	2.29
RMSE, $gC/m^2/d$	4.92	3.80	3.60	3.58	3.57	3.55	3.11	2.92	2.75	2.65	2.62	2.56

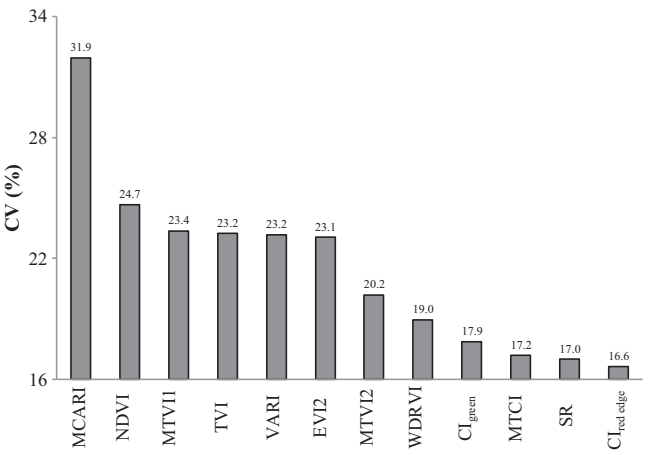

Fig. 7. Coefficients of variation (CV) of relationships between measured daytime GPP and GPP predicted by established algorithms presented in Table 6.

MTVI1 appeared to estimate GPP less precisely with CV more than 23%, and MCARI was the worst with CV more than 31%(Fig. 7).

This study gives clear understanding the role of crop Chl content plays in GPP estimation. We are well aware that the presented model does not take into account GPP decline that does not relate to a decrease in Chl content. It is a case when GPP is affected by short-term (minutes to hours) environmental stresses (e.g., temperature, humidity, and soil moisture, among others), that do not affect the Chl content (i.e., crop greenness), thus, do not affect chlorophyll-related indices. The model presented here will fail to detect a decrease in GPP related to the types of stressors mentioned. Next step in this direction should be including other biophysical characteristics (i.e., temperature) and assess efficiency of modified model.

The choice of the VI depends on the spectral characteristics of the radiometers or the specific satellite sensors used. If red edge band is available (as in MERIS), MTCI and $CI_{red\ edge}$ are recommended to use. If green, red and NIR bands are available, as in 500 m resolution MODIS data and in MERIS data, CI_{green}, VARI and TVI-like indices can be used. SR, WDRVI and EVI2 are recommended for estimating GPP using 250 m MODIS data.

4. Conclusions

The model that relied on total Chl content and PAR_{in} can be applied to accurately estimate GPP in both irrigated and rainfed maize. Unified algorithms, based on this model, can be used without re-parameterization for GPP estimation in the fields that are different in irrigation, crop management, field history and climatic conditions. The VIs that closely relate to total Chl content and green LAI were capable of estimating maize GPP accurately with CV less than 30%. Among indices tested, Chlorophyll Indices, MTCI and SR were consistently the most accurate for GPP estimation in maize. The VIs used in this study was calculated with reflectance simulated in the spectral bands of the MODIS and MERIS satellite sensors, which provides a theoretical framework for using real satellite data to estimate GPP at regional and global scales.

Acknowledgements

This research was supported by NASA NACP grant No. NNX08AI75G and partially by the U.S. Department of Energy: (a) EPSCoR program, Grant No. DE-FG-02-00ER45827 and (b) Office of Science (BER), Grant No. DE-FG03-00ER62996. We gratefully acknowledge the support and the use of facilities and equipment provided by the Center for Advanced Land Management Information Technologies (CALMIT) and Carbon Sequestration Program, University of Nebraska-Lincoln. We are sincerely grateful to Donald. C. Rundquist, Shashi B. Verma and Andy E. Suyker for their help and support, and Anthony Lawrence Nguy-Robertson for fruitful discussion and suggestions. We also thank two anonymous reviewers for providing valuable comments to the manuscript.

References

Asrar, G., Fuchs, M., Kanemasu, E.T., Hatfield, J.L., 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agron. J. 76, 300–306.
Borras, L., Maddonni, G.A., Otegui, M.E., 2003. Leaf senescence in maize hybrids: plant population, row spacing and kernel set effects. Field Crops Res. 82, 13–26.
Broge, N.H., Leblanc, E., 2000. 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.
Cassman, K.G., Wood, S., 2005. Cultivated systems. In: Millennium Ecosystem Assessment: Global Ecosystem Assessment Report on Conditions and Trends ,. Island Press, Washington, DC, pp. 741–789.
Ciganda, V., Gitelson, A.A., Schepers, J., 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.
Ciganda, V., Gitelson, A.A., Schepers, J., 2009. Non-destructive determination of maize leaf and canopy chlorophyll content. J. Plant Physiol. 166, 157–167.
Dash, J., Curran, P.J., 2004. The MERIS terrestrial chlorophyll index. Int. J. Remote Sens. 25, 5003–5013.
Daughtry, C.S.T., Walthall, C.L., Kim, M.S., Brown de Colstoun, E., McMurtrey III, J.E., 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sens. Environ. 74 (229 239), 141–152.
Falge, E., et al., 2002. Seasonality of ecosystem respiration and gross primary production as derived from FLUXNET measurements. Agric. Forest Meteorol. 113, 53–74.
Gamon, J.A., Penuelas, J., Field, C.B., 1992. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. Remote Sens. Environ. 41, 35–44.
Garbulsky, M.F., Penuelas, J., Gamon, J., Inoue, Y., Filella, I., 2011. The photochemical reflectance index (PRI) and the remote sensing of leaf, canopy and ecosystem radiation use efficiencies: a review and meta-analysis. Remote Sens. Environ. 115, 281–297.
Gitelson, A.A., Kaufman, Y.J., Stark, R., Rundquist, D., 2002. Novel algorithms for remote estimation of vegetation fraction. Remote Sens. Environ. 80, 76–87.
Gitelson, A.A., Verma, S.B., Viña, A., Rundquist, D.C., Keydan, G., Leavitt, B., Arkebauer, T.J., Burba, G.G., Suyker, A.E., 2003a. Novel technique for remote estimation of CO_2 flux in maize. Geophys. Res. Lett. 30 (9), 1486, doi:10.1029/2002GL016543.
Gitelson, A.A., Gritz, U., Merzlyak, M.N., 2003b. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. J. Plant Physiol. 160 (3), 271–282.
Gitelson, A.A., 2004. Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. J. Plant Physiol. 161 (2), 165–173.
Gitelson, A.A., Viña, A., Ciganda, V., Rundquist, D.C., Arkebauer, T.J., 2005. Remote estimation of canopy chlorophyll content in crops. Geophys. Res. Lett. 32, L08403, doi:10.1029/2005GL022688.
Gitelson, A.A., Viña, A., Verma, S.B., Rundquist, D.C., Arkebauer, T.J., Keydan, G., Leavitt, B., Ciganda, V., Burba, G.G., Suyker, A.E., 2006a. Relationship between gross primary production and chlorophyll content in crops: implications for the synoptic monitoring of vegetation productivity. J. Geophys. Res. 111, D08S11, doi:10.1029/2005JD006017.
Gitelson, A.A., Keydan, G.P., Merzlyak, M.N., 2006b. Three-band model for noninvasive estimation of chlorophyll, carotenoids, and anthocyanin contents in higher plant leaves. Geophys. Res. Lett. 33, L11402, doi:10.1029/2006GL026457.

Goward, S.M., Huemmerich, K.E., 1992. Vegetation canopy PAR absorptance and the normalized difference vegetation index: an assessment using SAIL model. Remote Sens. Environ. 39, 119–140.

Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J., Dextraze, L., 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sens. Environ. 81, 416–426.

Haboudane, D., Miller, J.R., Pattey, E., Zarco-Tejada, P.J., Strachan, I.B., 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.

Hall, F.G., Huemmrich, K.F., Goetz, S.J., Sellers, P.J., Nickeson, J.E., 1992. Satellite remote-sensing of surface-energy balance – success, failures, and unresolved issues in fife. J. Geophys. Res. Atmos. 97, 19061–19089.

Hilker, T., Gitelson, A., Coops, N.C., Hall, F.G., Black, T.A., 2011. Tracking plant physiological properties from multi-angular tower-based remote sensing. Oecologia, doi:10.1007/s00442-010-1901-0.

Houborg, R., Anderson, M.C., Daughtry, C.S.T., Kustas, W.P., Rodell, M., 2011. Using leaf chlorophyll to parameterize light-use-efficiency within a thermal-based carbon, water and energy exchange model. Remote Sens. Environ. 115, 1694–1705.

Huete, A.R., Liu, H.Q., Batchily, K., van Leeuwen, W.J.D., 1997. A comparison of vegetation indices over a global set of TM images for EOS-MODIS. Remote Sens. Environ. 59, 440–451.

Jiang, Z., Huete, A.R., Didan, K., Miura, T., 2008. Development of a two-band enhanced vegetation index without a blue band. Remote Sens. Environ. 112, 3833–3845.

Jordan, C.F., 1969. Derivation of leaf area index from quality of light in the forest floor. Ecology 50, 663–666.

Lieth, H., Whittaker, R.H., 1975. Primary productivity of the biosphere. In: Ecological Studies, vol. 14. Springer-Verlag, pp. 7–16.

Malmstrom, C.M., Thompson, M.V., Juday, G.P., Los, S.O., Randerson, J.T., Field, C.B., 1997. Interannual variation in global-scale net primary production: testing model estimates. Global Biogeochem. Cycles 11, 367–392.

Monteith, J.L., 1972. Solar radiation and productivity in tropical ecosystems. J. Appl. Ecol. 9, 744–766.

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

Rondeaux, G., Steven, M., Baret, F., 1996. Optimization of soil-adjusted vegetation indices. Remote Sens. Environ. 55, 95–107.

Rouse, J.W., Haas Jr., R.H., Schell, J.A., Deering, D.W., 1974. Monitoring vegetation systems in the Great Plains with ERTS. In: NASA SP-351. Third ERTS-1 Symposium NASA, vol. 1 , Washington, DC, pp. 309–317.

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

Schuepp, P.H., Leclerc, M.Y., Macpherson, J.I., Desjardins, R.L., 1990. Footprint prediction of scalar fluxes from analytical solutions of the diffusion equation. Boundary Layer Meteorol. 50, 355–373.

Solari, F., Shanahan, J., Ferguson, R., Schepers, J., Gitelson, A.A., 2008. Active sensor reflectance measurements of corn nitrogen status and yield potential. Agron. J. 100, 571–579.

Suyker, A.E., Verma, S.B., Burba, G.G., Arkebauer, T.J., 2005. Gross primary production and ecosystem respiration of irrigated maize and irrigated soybean during a growing season. Agric. Forest Meteorol. 131, 180–190.

Suyker, A.E., Verma, S.B., 2010. Coupling of carbon dioxide and water vapor exchanges of irrigated and rainfed maize–soybean cropping systems and water productivity. Agric. Forest Meteorol. 150, 553–563.

Verma, S.B., Dobermann, A., Cassman, K.G., Walters, D.T., Knops, J.M., Arkebauer, T.J., Suyker, A.E., Burba, G.G., Amos, B., Yang, H., Ginting, D., Hubbard, K.G., Gitelson, A.A., Walter-Shea, E.A., 2005. Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. Agric. Forest Meteorol. 131, 77–96.

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

Walters, D.T., 2003. Diagnosis of nitrogen deficiency in maize and the influence of hybrid and plant density. In: North Central Extension-industry Soil Fertility Conference, vol. 19 , Des Moines, IA.

Whittaker, R.H., Marks, P.L., 1975. Methods of assessing terrestrial productivity. In: Lieth, H., Whittaker, R.H. (Eds.), Primary Productivity of the Biosphere. Ecological Studies, vol. 14. Springer-Verlag, pp. 55–118.

Wu, C., Niu, Z., Tang, Q., Huang, W., Rivard, B., Feng, J., 2009. Remote estimation of gross primary production in wheat using chlorophyll-related vegetation indices. Agric. Forest Meteorol. 149, 1015–1021.