7-2010

Remote Estimation of Gross Primary Production in Maize

Yi Peng
University of Nebraska - Lincoln

Anatoly A. Gitelson
University of Nebraska - Lincoln, agitelson2@unl.edu

Galina Keydan
University of Nebraska - Lincoln

Donald C. Rundquist
University of Nebraska - Lincoln, drundquist1@unl.edu

Bryan Leavitt
University of Nebraska - Lincoln

See next page for additional authors

Authors
Yi Peng, Anatoly A. Gitelson, Galina Keydan, Donald C. Rundquist, Bryan Leavitt, Shashi B. Verma, and Andrew B. Suyker

REMOTE ESTIMATION OF GROSS PRIMARY PRODUCTION IN MAIZE

Yi Peng, Anatoly A. Gitelson, Galina Keydan, Donald C. Rundquist, Bryan Leavitt, Shashi B. Verma, and Andrew E. Suyker

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

ABSTRACT

There is a growing interest in the estimation of gross primary productivity (GPP) in crops due to its importance in regional and global studies of carbon balance. We have found that crop GPP was closely related to its total chlorophyll content, and thus chlorophyll can be used as a proxy of GPP in crops. In this study, we tested the performance of various vegetation indices for estimating GPP. The indices were derived from spectral data collected remotely but at close-range over a period of eight years, from 2001 through 2008. The results show that chlorophyll indices, based on near infrared and either the green or red-edge regions of the spectrum, are capable of accurately predicting widely variable GPP in maize under both rainfed and irrigated conditions.

Keywords: GPP, Remote Sensing, Vegetation Indices

INTRODUCTION

Cultivated systems occupy about 24% of the Earth's terrestrial surface and, in general, can have equal or greater gross primary production (GPP) than the natural ecosystems that were originally converted for crop production. The maize cropping systems, that dominate agricultural land use in the north-central USA, play an important role in the annual carbon exchange in this region. Crop hybrids and field management practices have changed over the last three decades, increasing crop yields, decreasing tillage, and increasing residue inputs to the soil. These changes have impacted the amount of atmospheric carbon fixed through photosynthesis, as well as on the release of carbon dioxide (CO_2) due to the decomposition of organic matter.

Field studies have used the tower eddy covariance systems to provide information on the seasonal and inter-annual dynamics of CO_2 fluxes in crops (e.g., Verma et al, 2005). These techniques provide an integrated measurement of CO_2 fluxes with high temporal resolution over limited footprints. Therefore, up-scaling beyond these small footprints is needed for regional carbon budget assessments as well as for estimating crop yield. Since vegetation productivity is directly related to the interaction of solar radiation with the plant canopy, remote sensing techniques have been increasingly used for such up-scaling. The procedures developed, so far, can be grouped into two broad categories according to the way the absorption of solar radiation and its conversion into dry matter is modeled (e.g., Ruimy et al., 1999): canopy photosynthesis models (CPM) and production efficiency models (PEM). While CPMs compute the amount of leaves (i.e., leaf area index, LAI) used to absorb solar radiation, PEMs directly compute the absorbed solar radiation based on the original logic of Monteith (1972), which suggests that the gross primary production (GPP) is linearly related to the amount of absorbed photosynthetically active radiation:

$$GPP \propto \varepsilon \times \sum (fAPAR \times PAR_{in}) \quad (1)$$

where PAR_{in} is the incident photosynthetically active radiation, fAPAR is the fraction of PAR_{in} absorbed by the canopy, and ε is light use efficiency (LUE). Note: GPP = NEP + R_e, where NEP is net ecosystem production and R_e is ecosystem respiration.

Most PEMs are based on the assumption of a close linear relationship between the fAPAR and the Normalized Difference Vegetation Index (NDVI), as well as on a constant, though biome-specific, LUE (e.g., Ruimy et al., 1999). It has been shown that these assumptions do not hold in many circumstances. On the one hand, a significant decrease in the sensitivity of NDVI is observed for moderate-to-high vegetation density when fAPAR exceeds 0.7 (e.g., Kanemasu, 1974, Asrar et al., 1984, Vina and Gitelson, 2005). On the other hand, although LUE is a relatively conservative value among plants of the same metabolic type (e.g., Ruimy et al., 1999), its variability is species-specific rather than biome-specific (e.g., Ahl et al., 2004), and it varies considerably among vegetation types, with phenological stage, and in response to varying environmental conditions such as drought and diffuse radiation.

Many remote sensing models for GPP estimate LUE using look-up tables of maximum LUE for given vegetation type and then adjust those values downward on the basis of environmental stress factors (e.g., Running et al., 2004; Xiao et al., 2005). Several studies have attempted to assess LUE directly using the photochemical reflectance index, (PRI, Gamon et al., 1992), to estimate LUE at different scales, from leaf level to entire regions (e.g., Gamon et al., 1992, Rahman et al., 2004). The PRI vs. LUE relationship, however, varies considerably among vegetation types (Nichol et al., 2002; Sims et al., 2006a), and among different years at the same site (Sims et al., 2006b). In the case of agricultural crops, the use of PRI as a proxy of LUE did not show a major improvement over the GPP estimated with a constant LUE (Gitelson et al., 2006).

A more direct approach may be to devise GPP models based entirely on remotely sensed data, with continuous output at the spatial resolution of Earth-orbiting satellite sensors. Thus, attempts have been made to estimate GPP directly from the vegetation indices, such as the NDVI or Simple Ratio, without depending on an estimation of LUE. These indices were used as proxy of fraction of radiation absorbed by photosynthetically active "green" vegetation, $fAPAR_{green}$ (Hall et al., 1992). Since NDVI tends to saturate at moderate-to-high vegetation densities, alternative vegetation indices, such as the enhanced vegetation index, (EVI, Huete et al., 1997) have been suggested for use in the remote estimation of GPP (e.g., Xiao et al., 2005, Sims et al., 2006a). Sims et al., (2006a) have shown that a model based solely on EVI provided as good or better estimates of GPP for most of the sites than did the much more complex NASA-MODIS product.

Another approach is based on the assumption of a close relationship between GPP and total canopy chlorophyll (Chl) content (Gitelson et al., 2003b, 2006). This approach has solid biophysical background. Because long- or medium-term changes in canopy Chl are related to crop phenology, canopy stresses, and photosynthetic capacity of the vegetation, Chl is also related to GPP. It was found that canopy level Chl may appear to be the community property most relevant for the prediction of productivity (e.g., Whittaker and Marks, 1975). Low frequency (day-to-day) variation in GPP is associated with crop phenological stage and physiological status. Following Monteith's logic, GPP is a function of the amount of PAR absorbed by the canopy (APAR) and the capacity of the leaves to export or utilize the product of photosynthesis (i.e., LUE). The product of $fAPAR_{green}$ and LUE depends on the amount and distribution of photosynthetic biomass; thus it depends upon chlorophyll content and leaf physiology with Chl as a driver of $fAPAR_{green}$ and an indicator of LUE.

As a result, Gitelson et al., (2003a; 2006) suggested estimating crop GPP remotely by exploiting the consistent and not species-specific relationship between total crop chlorophyll content and the low frequency variation of GPP. They showed that the product of total Chl and PAR explained more than 98% of GPP variation in both irrigated and rainfed maize and soybean crops. Therefore, a procedure for assessing remotely the GPP of crops may be implemented through the estimation of total crop chlorophyll content.

Changes in leaf Chl content induce large differences in canopy reflectance. However, these changes are masked and/or confounded by other factors (e.g., canopy architecture, Chl distribution within the canopy, LAI, leaf water content, soil background) that also affect canopy reflectance. Therefore, remote Chl retrieval at canopy level is complicated and challenging. Recently, a Chlorophyll Index (CI) in the form $CI = [R(\lambda_1)^{-1} - R(\lambda_2)^{-1}] \times R(\lambda_3)$, where $R(\lambda)$ is reflectance in spectral bands λ_1, λ_2 and λ_3, has been developed for Chl retrieval from reflectance spectra (Gitelson et al., 2003b, 2005). To assess Chl content at canopy level, this model was spectrally tuned to find the optimal positions of $\lambda 1$, λ_2 and λ_3, in accord with the optical properties of vegetation. Optimal positions of spectral bands for the remote estimation of total Chl content in maize and soybean canopies for λ_1 were found in either the green (540-560 nm) or the red edge (700-730 nm) ranges, and for $\lambda_2 = \lambda_3$ was found in the near infrared range (beyond 750 nm) (Gitelson et al., 2005). Thus, chlorophyll indices $CI_{green} = (R_{NIR} / R_{green} - 1)$ and $CI_{red\ edge} = (R_{NIR} / R_{red\ edge} - 1)$ were used for remote Chl retrieval. Using this finding, it was suggested to estimate GPP using CIs as follows (Gitelson et al., 2006):

$$GPP \propto PAR_{in} \times CI_{green} \quad (2)$$
$$GPP \propto PAR_{in} \times CI_{red\ edge} \quad (3)$$

In this study, we investigated the potential of a model, $GPP \propto VI \times PAR_{in}$, based entirely on remotely sensed data. We tested the performance of widely used vegetation indices Simple Ratio (SR), NDVI, EVI2, Wide Dynamic Range Vegetation Index (WDRVI), CI_{green} and $CI_{red\ edge}$ in estimating GPP in maize using data taken at close range in rainfed and irrigated sites over a period of 8 years.

METHODS

Three study sites are located at the University of Nebraska-Lincoln Agricultural Research and Development Center near Mead, NE, US. 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 under continuous maize, while site 2 and site 3 are under a maize-soybean rotation (Table 1).

CO_2 Fluxes and Incoming Photosynthetically Active Radiation

The micrometeorological eddy covariance data used in this study were collected each year from 2001 through 2008. To have sufficient upwind fetch (in all directions), eddy covariance sensors were mounted 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 (details are given in Suyker et al., 2004). 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 by the eddy covariance tower during a day. Daytime estimates of ecosystem respiration (R_e) were obtained from the night CO_2 exchange and temperature relationship (e.g., Falge et al., 2002). The daytime GPP (in grams of carbon per meter square per day, $gC/m^2/d$) was then obtained by subtracting daytime respiration 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.

Incoming Photosynthetically Active Radiation (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.

Maize reflectance

Spectral 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 400-1100 nm with a spectral resolution of about 1.5 nm. Radiometer 1, equipped with a 25°

field-of-view optical fiber was pointed downward to measure the upwelling radiance of the crop (L_λ^{maize}). The position of the radiometer above the canopy was kept constant throughout the growing season (i.e. around 5.4 m), yielding a sampling area with a diameter of around 5 m. Radiometer 2, equipped with an optical fiber and cosine diffuser (yielding a hemispherical field of view), was pointed upward to simultaneously measure incident irradiance (E_λ^{inc}). The inter-calibration of the radiometers was accomplished, in order to match their transfer functions, by measuring the upwelling radiance (L_λ^{cal}) of a white Spectralon (Labshere, Inc., North Sutton, NH) reflectance standard simultaneously with incident irradiance (E_λ^{cal}). To mitigate the impact of solar elevation on radiometer intercalibration, the anisotropic reflectance from the calibration target was corrected in accord with Jackson et al (1992). Percent reflectance (R_λ) was computed as:

$$R_\lambda = (L_\lambda^{maize} / E_\lambda^{inc}) \times (E_\lambda^{cal} / L_\lambda^{cal}) * 100 * R_\lambda^{cal} \quad (4)$$

where R_λ^{cal} is the reflectance of the Spectralon panel linearly interpolated to match the band centers of each radiometer.

Spectral reflectance measurements at canopy level were carried out from May until October each year over the eight-year period 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). Radiometric data were collected close to solar noon (between 11:00 and 13:00 local time), when changes in solar zenith angle were minimal. For each measurement site, 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 data acquisition and site, and the median was calculated as the site reflectance. Measurements took about 5 minutes per plot and about 30 minutes per field. The two radiometers were inter-calibrated immediately before and immediately after measurement in each field.

Table 1. Crop management details for the three maize sites during 2001–2008.

	Site1	Site2	Site3
	Irrigated Maize	Irrigated Maize	Rainfed Maize
2001	Pioneer 33P67	Pioneer 33P67	Pioneer 33B51
2002	Pioneer 33P67		
2003	Pioneer 33B51	Pioneer 33B51	Pioneer 33B51
2004	Pioneer 33B51		
2005	DeKalb 63-75	Pioneer 33B51	Pioneer 33G68
2006	Pioneer 33B53		
2007	Pioneer 31N30	Pioneer 31N28	Pioneer 33H26
2008	Pioneer 31N30		

Calibration and validation of the models

Vegetation indices (VI) tested in this paper are following:
Simple Ratio (Jordan, 1969):

$$SR = R_{NIR} / R_{red} \quad (5)$$

Normalized Difference Vegetation Index (Rouse et al, 1974):

$$NDVI = (R_{NIR} - R_{red}) / (R_{NIR} + R_{red}) \quad (6)$$

Enhanced Vegetation Index (EVI2, Jiang et al., 2009)

$$EVI2 = 2.5 \times (R_{NIR} - R_{red}) / (R_{NIR} + 2.4 \times R_{red}) \quad (7)$$

Wide Dynamic Range Vegetation Index (Gitelson, 2004):

$$WDRVI = (\alpha \times R_{NIR} - R_{red}) / (\alpha \times R_{NIR} + R_{red}),\ \alpha = 0.2 \quad (8)$$

Green and red edge chlorophyll indices (Gitelson, 2003b & 2005):

$$CI_{green} = R_{NIR} / R_{green} - 1 \quad (9)$$

$$CI_{red\ edge} = R_{NIR} / R_{red\ edge} - 1 \quad (10)$$

Where R_{red}, R_{green}, $R_{red\ edge}$ and R_{NIR} are reflectances in the red (630-690nm), green (520-600nm), red edge (703-712nm) and NIR (760-900nm) spectral ranges.

VIs calculated from spectral reflectance data were used to establish and validate relationships between GPP and the product of VI and incoming PAR (PAR_{in}): GPP vs. VI × PAR_{in}. The approach to estimate GPP was tested by means of regression analysis. The dataset includes all spectral reflectance data taken in 2001 through 2008 for three sites and daytime GPP for the same days as spectral measurements (332 samples total). The samples were sorted in ascending order of GPP. Data with odd numbers (166 samples) were used for model calibration; i.e., the establishment of the relationship GPP vs. VI × PAR_{in}. Then, these relationships were validated using samples with even numbers (166 samples). Measured reflectances in the validation data set were used to estimate GPP values (GPP_{est}), and then GPP_{est} were compared with GPP as measured by the eddy covariance technique (GPP_{meas}). The root mean squire error (RMSE) of GPP estimation by the vegetation indices (Eq. 5-10) was calculated to evaluate the model accuracy.

RESULTS AND DISCUSSION

Firstly, we examined the relationship between GPP and total canopy chlorophyll content. Total canopy Chl was estimated as Chl = Chl_{leaf} × green LAI, where Chl_{leaf} is Chl content of collar or ear leaves (Gitelson et al., 2005, Ciganda et al., 2009) and green LAI was determined destructively (details in Gitelson et al., 2003c). Daytime GPP was normalized by PAR_{in} in order to remove modulation of GPP by a change in radiation conditions (PAR_{in}). It can be seen that the temporal behavior of canopy Chl was almost the same as that GPP/PAR_{in} during a growing season (Figure 1).

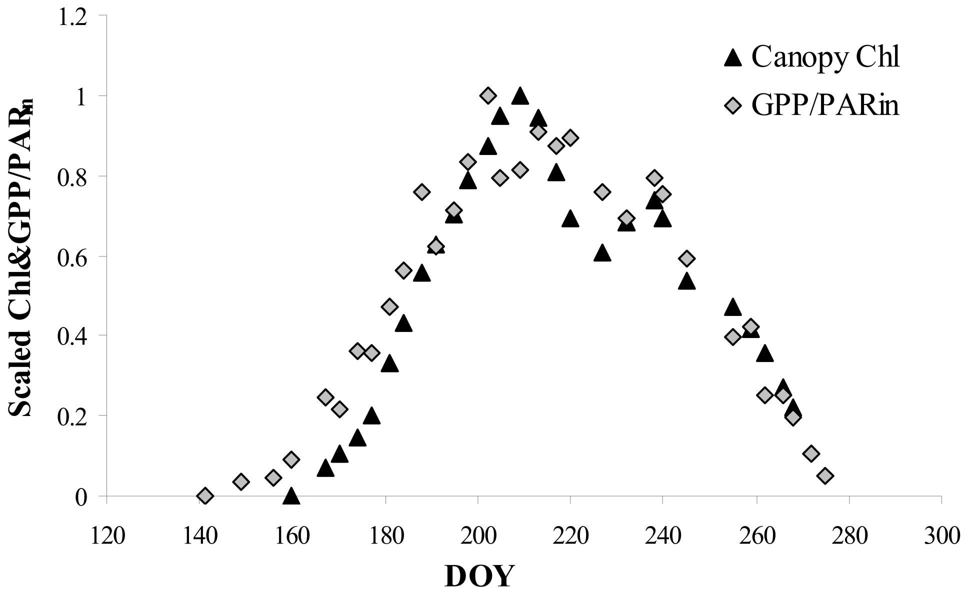

Fig. 1. Canopy chlorophyll content (Chl) and the ratio GPP/PAR_{in} plotted versus day of year for site 1 in 2003. Both chlorophyll and the ratio were scaled between 0 and 1.

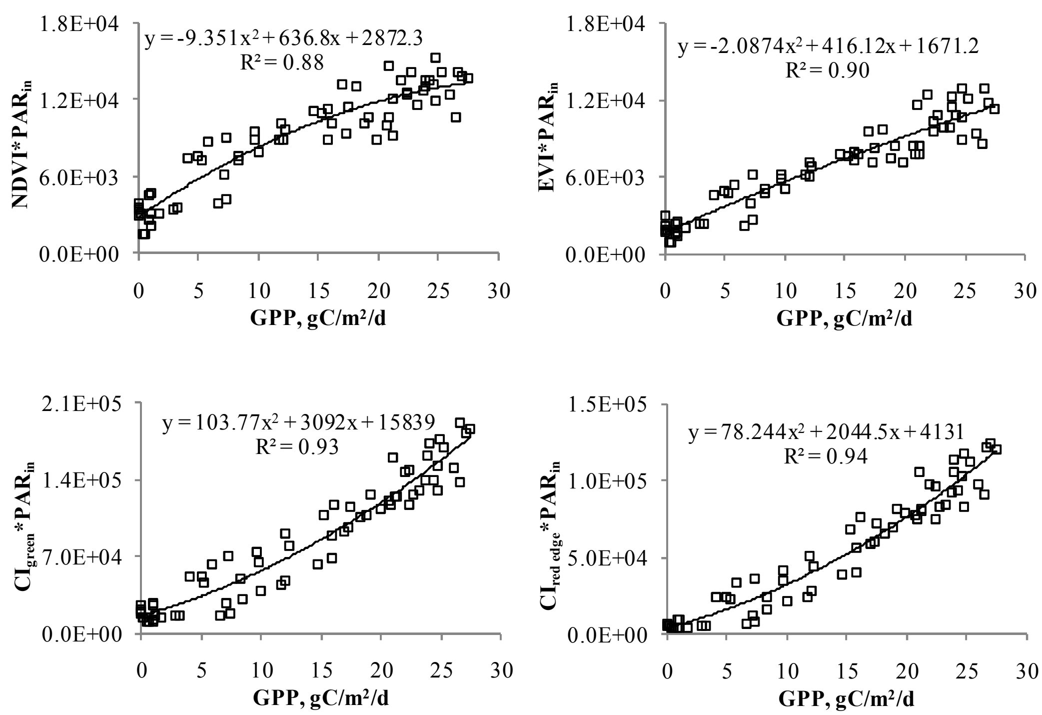

Fig. 2. Relationships between daytime gross primary production in irrigated sites in 2003 and the product of vegetation index and incident PAR for four vegetation indices: NDVI, EVI2, CI_{green}, and $CI_{red\ edge}$.

Based upon the close relationship between GPP and total canopy Chl, we compared the performance of NDVI, EVI2, CI_{green} and $CI_{red\ edge}$ in GPP estimation (Figure 2). NDVI increased quite sharply with an increase in GPP up to 7gC/m^2/d, but tended to saturate when GPP exceeded 10gC/m^2/d. EVI2 was sensitive to GPP in the whole range of GPP variation, while CI_{green} and $CI_{red\ edge}$ showed more sensitivity to moderate to high GPP values than to low GPP.

Table 2 summarizes the RMSE and coefficients of variation (CV = RMSE / mean GPP) of the quadratic polynomial relationships between daytime GPP and the product of vegetation indices and incident PAR (VI × PAR_{in}) for five vegetation indices (NDVI, EVI2, SR, CI_{green} and $CI_{red\ edge}$). For each site in 2001 through 2008, NDVI was consistently less accurate as a GPP predictor with the mean CV > 23%, while the chlorophyll indices ($CI_{red\ edge}$ and CI_{green}) were the best except for site 3 in 2001 and site 1 in 2002, when EVI2 performed better than the others. The last row in Table 2 is quite informative showing mean values of RMSE and the CV for each index. Ratio indices (SR and CIs) were the most accurate in GPP estimation.

Table 2. Root mean square error (RMSE) and coefficients of variation (CV = RMSE/mean GPP) of quadratic polynomial relationships between daytime GPP and the product of vegetation index (VI) and incident PAR (VI × PAR_{in}) for five vegetation indices: NDVI, EVI2, SR, CI_{green}, and $CI_{red\ edge}$. Maize hybrids and crop management practices in each site are shown in Table 1.

			Root Mean Square Error (gC/m^2/d)					CV (%)				
Year	Site	GPP Mean	NDVI	EVI2	SR	CI_{green}	$CI_{red\ edge}$	NDVI	EVI2	SR	CI_{green}	$CI_{red\ edge}$
2001	1	19.22	4.74	4.00	2.23	2.10	2.03	24.7	20.8	11.6	10.9	10.6
2001	2	16.71	4.57	3.93	2.02	2.11	1.92	27.4	23.5	12.1	12.6	11.5
2001	3	16.58	4.16	1.73	2.79	2.73	2.44	25.1	10.5	16.8	16.5	14.7
2002	1	15.24	2.85	1.97	2.81	2.46	2.38	18.7	12.9	18.4	16.1	15.6
2003	1	12.45	3.35	2.69	2.54	2.66	2.38	26.9	21.6	20.4	21.3	19.1
2003	2	14.22	3.60	2.99	2.23	2.48	2.04	25.3	21.0	15.7	17.4	14.4
2003	3	12.96	2.65	2.29	2.30	2.10	2.42	20.5	17.7	17.8	16.2	18.7
2004	1	13.37	3.67	2.30	2.30	2.43	2.06	27.4	17.2	17.2	18.1	15.4
2005	1	12.55	2.82	1.90	2.08	1.88	1.82	22.5	15.2	16.6	15.0	14.5
2005	2	13.05	3.42	2.29	2.38	2.13	1.96	26.2	17.5	18.2	16.3	15.1
2005	3	11.62	3.19	2.53	1.77	1.65	1.41	27.4	21.7	15.2	14.2	12.1
2006	1	14.44	2.67	2.39	1.15	1.18	0.97	18.5	16.6	8.0	8.2	6.7
2007	1	16.97	3.50	2.51	1.57	1.76	1.25	20.6	14.8	9.3	10.4	7.4
2007	2	16.95	3.25	2.31	1.20	1.28	1.19	19.2	13.6	7.1	7.5	7.0
2007	3	16.42	2.32	1.85	1.60	1.68	1.39	14.1	11.2	9.8	10.2	8.5
2008	1	19.25	4.72	1.76	1.89	1.01	1.04	24.5	9.1	9.8	5.2	5.4

Mean	3.5	2.5	2.1	2.0	1.8	23.1	16.6	14.0	13.5	12.3

Although the relationships between GPP and CIs for each site were very close with a mean CV < 13.5% and $r^2 > 0.9$, these relationships were specific for different sites and years. The coefficients of equations VI × PAR_{in} vs. GPP were different between years and between sites in the same year. For irrigated sites, the relationships for eight different years deviated especially for the years 2002 and 2006 (Fig. 3). This deviation became more pronounced at high GPP values. In rainfed sites, there was also variation in coefficients of the relationships between the years (Fig. 4).

The coefficients of the relationships also varied among the sites with different management practices. The slope of the best fit function of the relationship between GPP and PAR_{in} × CI for all rainfed sites was little lower than slope of best fit function for irrigated sites (Figures 5 and 6). Thus, the RMSE of GPP estimation in both irrigated and rainfed sites combined was slightly higher (2.69 vs. 2.56gC/m^2/d for CI_{green} and 2.54 vs. 2.41 gC/m^2/d for $CI_{red\ edge}$) than RMSE of GPP estimation of irrigated and rainfed sites when treated separately.

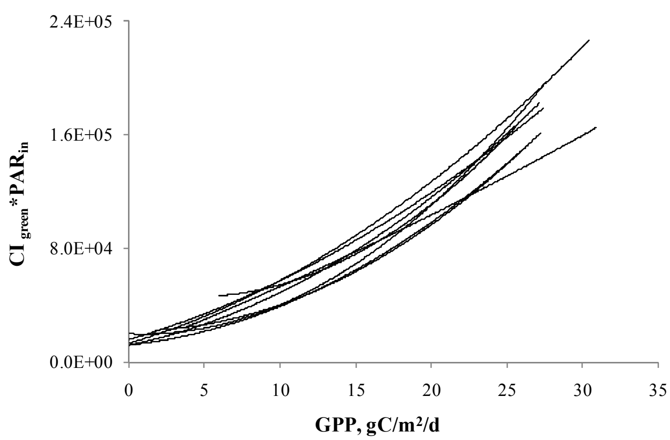

Fig. 3. Best fit functions of the relationships between daytime gross primary production and the products of CI_{green}×PAR for each irrigated site from 2001 through 2008 (see Table 1).

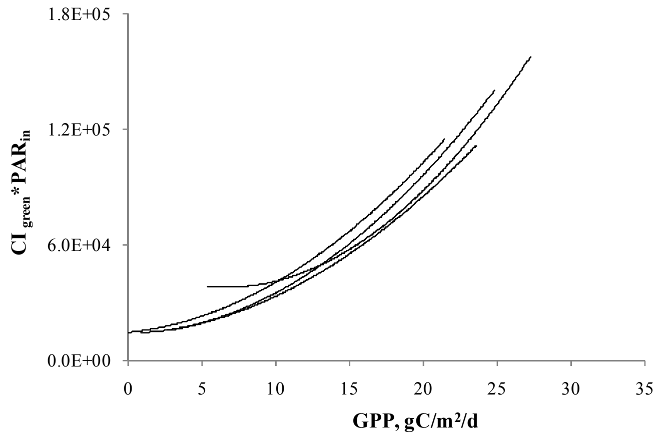

Fig. 4. Best fit functions of the relationships between daytime gross primary production and the products of CI_{green}×PAR for each rainfed site from 2001 through 2008 (see Table 1).

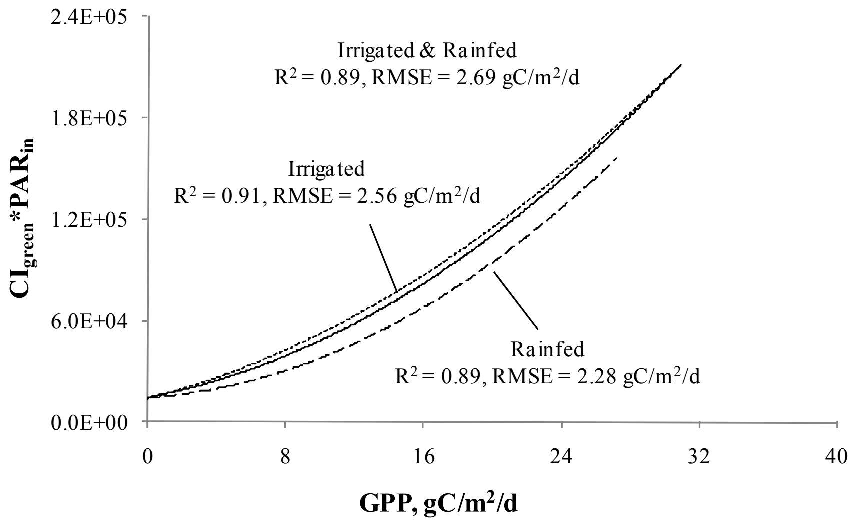

Fig. 5. Best fit functions of the relationships between daily gross primary production and the products of CI_{green}×PAR. Dotted line: 12 irrigated sites in 2001 through 2008, dashed line: 4 rainfed sites in 2002, 2004, 2006, and 2008, solid line: 16 irrigated and rainfed sites taken together.

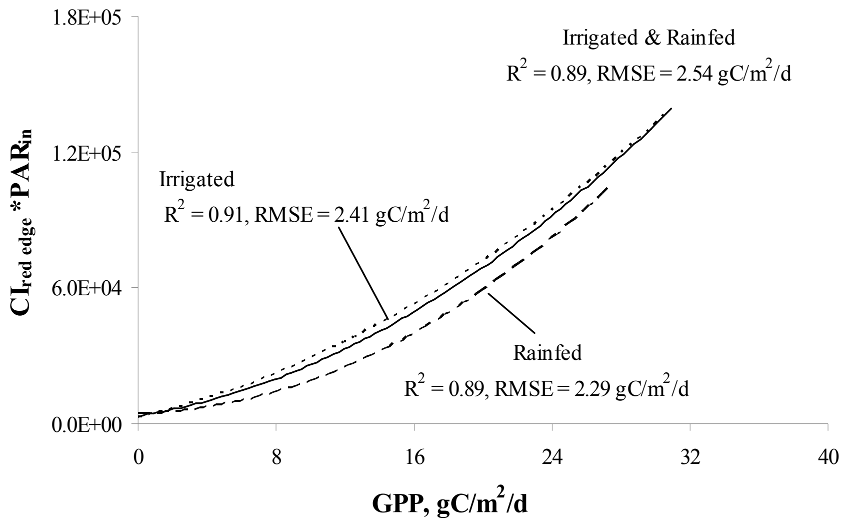

Fig. 6. Best fit functions of the relationships between daily gross primary production and the products of $CI_{red\ edge}$×PAR. Dotted line: 12 irrigated sites in 2001 through 2008, dashed line: 4 rainfed sites in 2002, 2004, 2006, and 2008, solid line: 16 irrigated and rainfed sites taken together.

The reason for the variable relationships among the years and sites is complicated. The different maize hybrids and field management practices (as shown in Table 1) over the eight years may have caused differences in crop physiological status, such as canopy architecture and density. In addition, other factors, such as water stress, temperatures, and soil moisture, may also contribute to the variation. However, this variation among the years and sites is within one standard error of GPP estimation, which is below 2.7gC/m^2/d for both CIs.

In Figure 7 and Table 3, the results of validation are shown. SR, CI_{green} and $CI_{red\ edge}$ were the best among vegetation indices tested in GPP estimation, while NDVI was much less accurate. Chlorophyll indices were also superior in estimating GPP in wheat (Wu et al., 2008). The first results of GPP estimating in crops using Landsat and Hyperion satellite data were also very promising (Gitelson et al., 2008; Wu et al., 2010). Thus, it confirms the validity of GPP estimating via vegetation indices related to chlorophyll content.

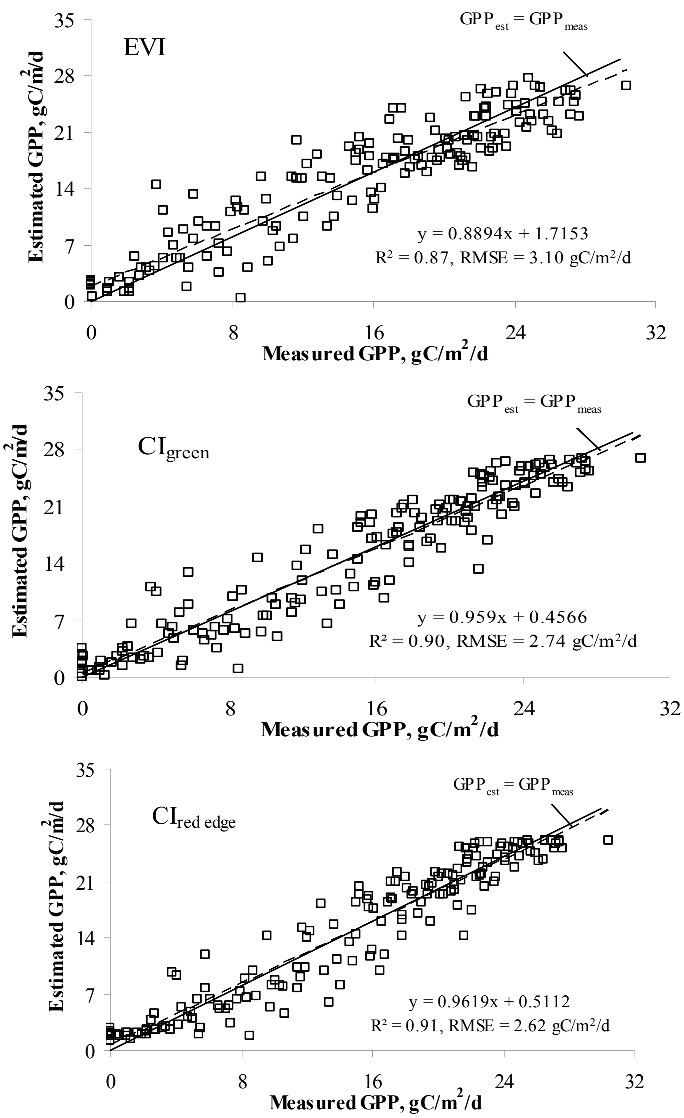

Fig 7. Validation of vegetation indices in estimating daytime gross primary production in 16 irrigated and rainfed maize sites in 2001 through 2008: enhanced vegetation index (EVI2), green chlorophyll index (CI_{green}) and red edge chlorophyll index ($CI_{red\ edge}$).

Table 3. The results of validation of vegetation indices in estimating daytime gross primary production in 16 irrigated and rainfed maize sites in 2001 through 2008. Offset, root mean square error (RMSE) and determination coefficient (R^2) of linear relationships between estimated and measured daily GPP are given for six vegetation indices.

	NDVI	WDRVI	EVI2	SR	CI_{green}	$CI_{red\ edge}$
Slope	0.86	0.92	0.89	0.95	0.96	0.96
Offset	1.9	1.16	1.72	0.69	0.46	0.51

RMSE, $gC/m^2/d$	3.62	3.5	3.10	2.88	2.74	2.62
R^2	0.82	0.84	0.87	0.89	0.90	0.91

However, it is still not clear how short term variation in GPP can be detected using vegetation indices (e.g., SR, NDVI, EVI2 or CIs) alone. GPP is affected by short-term (minutes to hours) environmental stresses (e.g., temperature, humidity, and soil moisture, among others). If these short-term stresses do not affect the "greenness" of the crop (i.e., $fAPAR_{green}$, canopy chlorophyll content, green LAI), the model will fail to detect a decrease in GPP related to the types of stressors mentioned.

CONCLUSION

GPP in crops is closely related to their total chlorophyll content. We presented the model that relates GPP with a product of chlorophyll and incident PAR that is based entirely on remotely sensed data. The model is capable of accurately predicting widely variable GPP in maize under both irrigated and rainfed conditions. The chlorophyll indices appear to be the best predicators of daytime GPP in maize, among the vegetation indices tested. The model was tested using vegetation indices calculated with reflectances that were simulated in the spectral bands of the Landsat-TM, MODIS, and MERIS sensors. The next step is to test the model and to assess its accuracy using real satellite data.

REFERENCES

Ahl, D. E., S. T. Gower, D. S. Mackay, S. N. Burrows, J. M. Norman, and G. R. Diak. (2004). Heterogeneity of light use efficiency in a northern Wisconsin forest: implications for modeling net primary production with remote sensing. Remote Sens. Environ., 93: 168-178.

Asrar, G., M. Fuchs, E.T. Kanemasu, and J.H. Hatfield. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agron. J., 76: 300-306.

Ciganda, V., A.A. Gitelson, and J. Schepers. 2009. Non-destructive determination of maize leaf and canopy chlorophyll content. Journal of Plant Physiology, 166:157-167.

Falge, E., et al. (2002), Seasonality of ecosystem respiration and gross primary production as derived from FLUXNET measurements, Agric. For. Meteorol., 113:53– 74.

Gamon, J. A., J. Penuelas and C. B. Field. (1992). A narrow waveband spectral index that tracks diurnal changes in photosynthetic efficiency. Remote Sens. Environ., 4: 35-44.

Gitelson, A. A., S. B. Verma, A. Viña, D. C. Rundquist, G. Keydan, B. Leavitt, T. J. Arkebauer, G. G. Burba, and A. E. Suyker. (2003a). Novel technique for remote estimation of CO2 flux in maize, Geophys. Res. Lett., 30(9), 1486, doi:10.1029/2002GL016543.

Gitelson, A. A., U. Gritz, M. N. and Merzlyak. (2003b). 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.

Gitelson, A. A., A. Viña, T. J. Arkebauer, D. C. Rundquist, G. Keydan, and B. Leavitt. (2003c). 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. (2004). Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. J. Plant Phys., vol. 161, no. 2: pp. 165-173.

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, L08403, doi:10.1029/2005GL022688.

Gitelson, A. A., A. Viña, S. B. Verma, D. C. Rundquist, T. J. Arkebauer, G. Keydan, B. Leavitt, V. Ciganda, G. G. Burba, and A. E. Suyker. (2006). 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., Viña, A., Masek J.G., Verma, S. B., and A. E. Suyker. (2008). Synoptic Monitoring of Gross Primary Productivity of Maize Using Landsat Data, IEEE Geoscience and Remote Sensing Letters, Vol. 5, No. 2, April 2008, 10.1109/LGRS.2008.915598.

Hall, F. G., K. F. Huemmrich, S. J. Goetz, P. J. Sellers, and J. E. Nickeson. (1992). Satellite remote sensing of surface energy balance: Success, failures and unresolved issues in FIFE. J. Geophys. Res., 97, 19,061-19,089.

Huete, A. R., H. Q. Liu, K. Batchily, and W. van Leeuwen. (1997). A comparison of vegetation indices global set of TM images for EOS-MODIS. Remote Sens. Environ., 59: 440-451.

Jackson, R. D., T. R. Clarke, and M. S. Moran. (1992). Bidirectional calibration results for 11 Spectralon and 16 BaSO4 reference reflectance panels. Remote Sens. Environ., 40: 231-239.

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

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.

Kanemasu, E.T.. (1974). Seasonal canopy reflectance patterns of wheat, sorghum, and soybean. Remote Sens. Environ., 3: 43-47.

Monteith, J. L.. (1972). Solar radiation and productivity in tropical ecosystems. J. Appl. Ecol., 9: 744-766.

Nichol, C. J., J. Lloyd, O. Shibistova, A. Arneth, C. Roser, A. Knohl, S. Matsubara, and J. Grace. (2002). Remote sensing of photosynthetic-light-use efficiency of a Siberian boreal forest. Tellus, Ser. B, 54, 677-687.

Rahman, A. F., V. D. Cordova, J. A. Gamon, H. P. Schmid, and D. A. Sims. (2004). Potential of MODIS ocean bands for estimating CO2 flux from terrestrial vegetation: A novel approach. Geophys. Res. Lett., 31, L10503, doi:10.1029/2004GL019778.

Rouse JW, Haas RH Jr, Schell JA, Deering DW. (1974). Monitoring vegetation systems in the Great Plains with ERTS. NASA SP-351, Third ERTS-1 Symposium NASA Washington DC. Vol 1: p. 309-317

Ruimy, A., L. Kergoat, and A. Bondeau. (1999). Comparing global models of terrestrial net primary productivity (NPP): Analysis of differences in light absorption and light-use efficiency. Global Change Biol., 5: 56-64.

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. Computers and Electronics in Agriculture, 43: 173-178.

Running, S. W., R. R. Nemani, F. A. Heinsch, M. S. Zhao, M. Reeves, and H. Hashimoto. (2004). A continuous satellite-derived measure of global terrestrial primary production. Bioscience, 54: 547-560.

Sims, D. A., A. F. Rahman, V. D. Cordova, B. Z. El-Masri, D. D. Baldocchi, L. B. Flanagan, A. H. Goldstein, D. Y. Hollinger, L. Mission, R. K. Monson, W. C. Oechel, H. P. Schmid, S. C. Wofsy, and L. Xu. (2006a). On the use of MODIS EVI to assess gross primary productivity of North American ecosystems. J. Geophys. Research, 111, G04015, doi:10.1029/2006JG000162.

Sims, D. A., H. Luo, S. Hastings, W. C. Oechel, A. F. Rahman, and J. A. Gamon. (2006b). Parallel adjustments in vegetation greenness and ecosystem CO2 exchange in response to drought in a southern California chaparral ecosystem. Remote Sens. Environ., 103: 289-303.

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

Suyker, A. E., S. B. Verma, G. 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.

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

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, L17403, doi:10.1029/2005GL023647.

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

Wu, C., Niu, Z., Tang, Q., Huang, W., Rivard, B., Feng, J. (2008). Remote estimation of gross primary production in wheat using chlorophyll-related vegetation indices. Agric. For. Meteorol., 149: 1015-1021.

Wu, C., Wang, L., Niu, Z., Gao, S., and Wu, M. (2010). Nondestructive estimation of canopy chlorophyll content using Hyperion and Landsat/TM images. Int. J. Remote Sensing, 31: 2159-2167.

Xiao, X., Q. Zhang, S. Saleska, L. Hutyra, P. De Camargo, S. Wofsy, S. Frolking, S. Boles, M. Keller, and B. Moore III. (2005). Satellite-based modeling of gross primary production in a seasonally moist tropical evergreen forest. Remote Sens. Environ., 94: 105-122.