

Gross primary production estimation from MODIS data with vegetation index and photosynthetically active radiation in maize

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Received 16 August 2009; revised 29 November 2009; accepted 28 January 2010; published 30 June 2010.

[1] Gross primary production (GPP) is a significant important parameter for carbon cycle and climate change research. Remote sensing combined with other climate and meteorological data offers a convenient tool for large-scale GPP estimation. GPP was estimated as a product of vegetation indices (VIs) and photosynthetically active radiation (PAR). Four kinds of vegetation indices [the normalized difference vegetation index (NDVI), the weighted difference vegetation index, the soil-adjusted vegetation index, and the enhanced vegetation index (EVI)] derived from the Moderate Resolution Imaging Spectroradiometer daily surface reflectance product were selected to test our method. The in situ GPP was calculated using the eddy covariance technique and the PAR data were acquired from meteorological measurements. Because VIs were found to be a reliable proxy of both light use efficiency (LUE) and the fraction of absorbed PAR (f_{APAR} ; R^2 of 0.63–0.87 for LUE and 0.69–0.76 for f_{APAR}), the product $\text{VI} \times \text{VI} \times \text{PAR}$ is used as a measure of GPP according to Monteith logic. Moderate determination coefficients R^2 from 0.65 for NDVI to 0.71 for EVI were obtained when GPP was estimated from a single index in maize. When testing our method, calculating GPP as a product of $\text{VI} \times \text{VI} \times \text{PAR}$, the determination coefficients R^2 largely improved, fluctuating from 0.81 to 0.91. $\text{EVI} \times \text{EVI} \times \text{PAR}$ provided the best estimation of GPP with the highest R^2 of 0.91 because EVI was found to be the best indicator of both LUE and f_{APAR} (R^2 of 0.87 and 0.76, respectively). These results will be helpful for the development of future GPP estimation models.

Citation: Wu, C., Z. Niu, and S. Gao (2010), Gross primary production estimation from MODIS data with vegetation index and photosynthetically active radiation in maize, *J. Geophys. Res.*, 115, D12127, doi:10.1029/2009JD013023.

1. Introduction

[2] Gross primary production (GPP) is defined as the overall rate of fixation of carbon through the process of vegetation photosynthesis. It is used to quantify the amount of biomass produced within an ecosystem over a unit of time, regardless of the amount of respiration [Monteith, 1972]. The seasonal difference of GPP and ecosystem respiration (R_e) determines the net ecosystem exchange (NEE) of CO_2 between the atmosphere and forest ecosystems and is important for understanding global carbon cycle climate change research [Xiao *et al.*, 2004; Yan *et al.*, 2009]. Quantitative estimates of the spatial and temporal distribution of GPP at regional to global scales are essential for understanding ecosystem response to increased atmospheric

CO_2 level and are thus critical to political decisions [Metz *et al.*, 2006]. Many current GPP models are somewhat based on the light use efficiency (LUE) model proposed by Monteith [1972] in which carbon flux is a function of the photosynthetically active radiation absorbed by green vegetation (APAR) and the efficiency of light absorption is used as the reference for carbon fixation.

[3] The eddy covariance (EC) technique is one of the best micrometeorological methods for the estimation of CO_2 , water, and energy exchange between the atmosphere and terrestrial ecosystems [Li *et al.*, 2007]. Gas exchanges from EC measurements are affected by changes in atmospheric gas composition and climate, which makes it of great importance in research of both short- and long-term perturbations and implications for climate and global biogeochemical cycles [Gamon *et al.*, 2006]. However, besides the difficulty of partitioning the respiration of ecosystems into autotrophic respiration and heterotrophic respiration, the EC only provides integrated CO_2 flux measurements over footprints with sizes and shapes that vary with the tower height, canopy physical characteristics, and wind velocity [Osmond *et al.*, 2004].

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[4] Satellite remote sensing provides consistent and systematic land surface observations and has played an increasing role in characterizing vegetation structure and estimating GPP. It can overcome the lack of extensive flux tower observations over large areas [Running *et al.*, 2000; Behrenfeld *et al.*, 2001]. The fundamental methodology of GPP estimation is based on Monteith's [1972] equation:

$$\text{GPP} = \text{LUE} \times f_{\text{APAR}} \times \text{PAR}, \quad (1)$$

where LUE is the light use efficiency, often in units of mol CO_2 per mol photosynthetic photon flux density ($\text{mol CO}_2 \text{ mol}^{-1} \text{PPFD}$), and f_{APAR} represents the fraction of absorbed photosynthetically active radiation (PAR).

[5] Many models and methods using the LUE basis have been proposed for GPP estimation from ground measurements and satellite remote sensing data. For example, the vegetation photosynthesis model (VPM) proposed by Xiao *et al.* [2004] assumes that the leaf and forest canopies are composed of photosynthetically active vegetation and non-photosynthetic vegetation. The VPM was successfully validated for GPP estimation in different ecosystems, including tropical evergreen forest and alpine and evergreen needle leaf forest. Recently, research by Yan *et al.* [2009] derived a satellite-based VPM using multiyear satellite images and crop (wheat-maize double cropping) phenological parameters. This work demonstrates the potential of the satellite-driven VPM for scaling up GPP estimation of intensified agricultural ecosystems. The limitation of LUE models, however, is that they require meteorological inputs that are often not available at sufficiently detailed temporal and spatial scales, resulting in substantial errors in the outputs [Yuan *et al.*, 2007; Coops *et al.*, 2007]. Consequently, it is worthwhile to consider ways in which models might be simplified by basing them entirely on remote sensing data. Sims *et al.* [2008] proposed a temperature and greenness (TG) model of GPP estimation based solely on the enhanced vegetation index (EVI) and the Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST). Gitelson *et al.* [2006] demonstrated the feasibility of using crop chlorophyll content to assess midday GPP with a root-mean-square error of less than $0.3 \text{ mg CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ in rainfed and irrigated crops. This method of GPP estimation from chlorophyll content was further validated by Wu *et al.* [2009] in the growth cycle of wheat, and they found a moderate correlation between the product of canopy vegetation indices (VIs) and in situ GPP data.

[6] In this study, the daily MODIS surface reflectance product was selected for midday GPP estimation because MODIS can provide daily coverage of the study sites with an acceptable ground resolution and the required spectral characteristics. On the basis of previous research, we selected some VIs that were proved to have the potential to estimate LUE ($\text{mol CO}_2 \text{ mol}^{-1} \text{PPFD}$) and f_{APAR} and proposed a method to estimate GPP ($\text{mg CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) with the MODIS data.

[7] The paper is organized as follows. First, we selected four kinds of VIs as potential candidates for the estimation of LUE and f_{APAR} . Then we tested these VIs in the estimation of GPP with MODIS daily reflectance data in a relatively homogenous agricultural ecosystem (maize) using the EC measured in situ GPP and meteorological measure-

ments of PAR. The study should be helpful for future GPP models driven by all remote-sensing inputs.

2. Materials and Method

2.1. Methodology

[8] For large-scale GPP estimation, the most important task is to find a convenient way to evaluate the input parameters (i.e., LUE, f_{APAR} , and PAR). VIs were applied to determine the leaf and canopy biophysical characteristics that could be further used for LUE and f_{APAR} estimation [Xiao *et al.*, 2004; Gitelson *et al.*, 2005; Inoue *et al.*, 2008; Wu *et al.*, 2009].

[9] Continuous research has focused on LUE with remote-sensing observations. Results indicated that the LUE could be estimated by spectral VIs [e.g., photochemical reflectance index, normalized difference spectral index in bands 710 and 410 nm ($\text{NDSI}_{[710,410]}$), and Medium Resolution Imaging Spectrometer terrestrial chlorophyll index] derived from in situ measurements [Gamon *et al.*, 1997; Nakaji *et al.*, 2006; Inoue *et al.*, 2008; Wu *et al.*, 2009], airborne optical remote-sensing systems [Nichol *et al.*, 2000], and spaceborne satellite observations [Drolet *et al.*, 2005]. These results demonstrated that certain indices could be reliable proxies of LUE. It is well recognized from previous research that f_{APAR} can be expressed as a function of leaf area index (LAI , $\text{m}^2 \text{ m}^{-2}$), which has been used in a radiation use efficiency model. Furthermore, VIs have been incorporated into such models to avoid using LAI because f_{APAR} is more direct and logical than using LAI in the estimation of GPP, and VIs have a linear and robust relationship with f_{APAR} [Viña and Gitelson, 2005; Bacour *et al.*, 2006]. However, the GPP estimation from LUE, f_{APAR} , and PAR may be mostly affected by the uncertainty of the $\text{VI}/f_{\text{APAR}}$ relationship, which in most cases is assumed to be linear [Running *et al.*, 2000; Gitelson *et al.*, 2006]. Therefore, LUE and f_{APAR} are both estimated both VIs, and the GPP is a product of VIs and PAR:

$$\text{GPP} \propto \text{VI} \times \text{VI} \times \text{PAR}. \quad (2)$$

[10] Inoue *et al.* [2008] successfully estimated LUE and f_{APAR} from VIs derived from ground canopy measurements for rice. However, the possibility of using satellite observations to estimate LUE and f_{APAR} is still not very clear and needs further investigation in the use of GPP estimation.

2.2. Study Sites

[11] The study sites were located outside the city of Zhangye, Gansu Province, in western China (Figure 1). All measurements were taken from 10 June to 13 July 2008. The maize was planted in early May 2008 in the typical solonchic soil of western China with relatively sufficient nutrition and water supplies. The experiment lasted from the beginning (three to four leaves, 5 cm in height) to the middle (about 1.8 m in height) of the plant's life cycle.

[12] There were two reasons for this selection. First, the vegetation cover is maize and is a simple and homogenous ecosystem with few confounding factors (e.g., drought) [Inoue *et al.*, 2008]. Second, maize is an important vegetation type for regional and global studies of carbon balance.

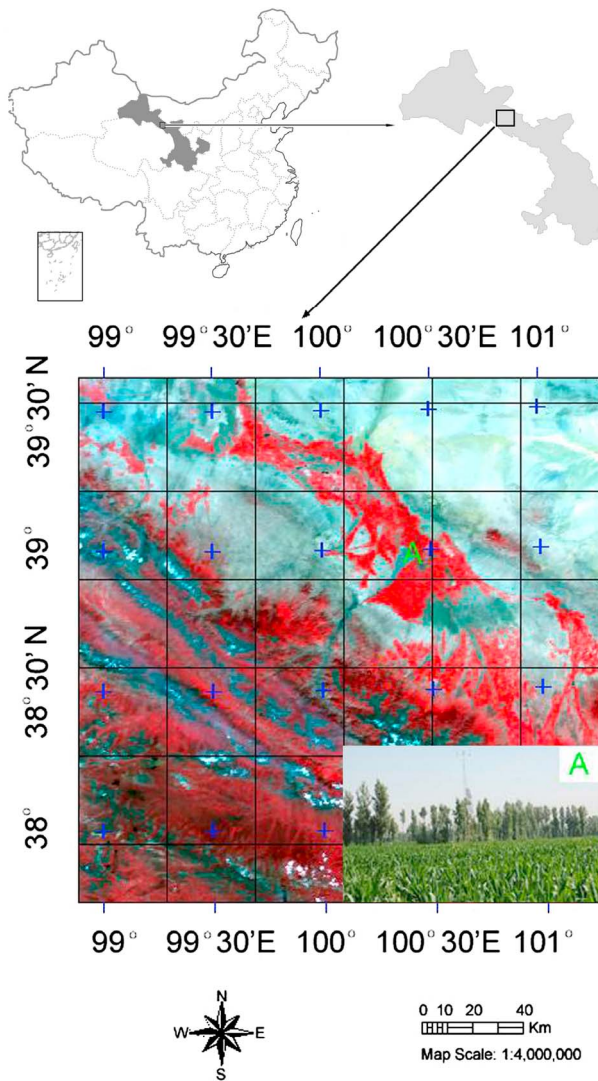


Figure 1. Description of the study site with MODIS data.

2.3. LAI Acquisitions

[13] The maize LAI was measured every day on the basis of gap fraction measurements with a widely used plant canopy analyzer (LAI-2000, LI-COR, Inc., Lincoln, Nebraska). During the LAI acquisition, we selected an area of about $20 \times 20 \text{ m}^2$ near the flux tower. Ten evenly distributed sample points were selected inside this area. The LAI value for each point is an average of three readings taken with the LAI-2000 instrument and calculated using the LAI-2000 software; all the data were averaged for later analysis.

2.4. Eddy Covariance and Meteorological Measurements

[14] At the experimental site, a three-dimensional ultrasonic anemometer (CR5000, Campbell Scientific) is used in the eddy covariance applications to measure the turbulent fluctuations of horizontal and vertical wind. Momentum flux and friction velocity were calculated from the turbulent wind fluctuations. CO_2 and H_2O fluctuations were measured with a closed-path infrared gas analyzer (LI-6262, LI-COR) and

an open-path infrared $\text{CO}_2/\text{H}_2\text{O}$ gas analyzing system (model LI7500, LI-COR Inc., Lincoln, Nebraska). The tower height at the site is about 20 m and provided half-hourly readings of these parameters (e.g., NEE, temperature). Besides the flux measurement, some meteorological variables, especially the PAR, soil and air temperature, and soil heat flux, were also measured and averaged every 10 min. To control the data quality, we checked the half-hourly averaged flux data and removed those values associated with periods when the sensors were repaired or calibrated and the outliers attributed to other causes. A detailed description of data processing and quality control (including gap filling) is given by *Li et al.* [2009].

[15] To compare the EC and meteorological measurements with the satellite observations, we selected and averaged 10 PAR readings and 5 NEE/temperature (T) readings during the MODIS image overpass time [Sims *et al.*, 2005]. For example, if the MODIS image overpass time is 1145, 5 readings of NEE/ T are at times 1030, 1100, 1130, 1200, and 1230; 10 readings of PAR are at times 1100, 1110, 1120, 1130, 1140, 1150, 1200, 1210, 1220, and 1220. This was due to different time intervals (10 min for PAR and 30 min for NEE/ T) for these two measurements. The specific time of the MODIS image overpass was acquired from the corresponding head file.

2.5. MODIS Data Acquisition

[16] The MODIS is a key instrument on board the Terra and Aqua satellites with 36 spectral bands ranging from 450 to 2100 nm. These data provide important insights for global dynamics research.

[17] To form a suite of data, the product (MOD 09, 500 m) of the Terra MODIS surface-reflectance atmospheric correction algorithm from 13 June to 10 July 2008 was downloaded (https://lpdaac.usgs.gov/lpdaac/get_data/wist) to estimate the midday GPP at the satellite overpass time. The cloud-contaminated images were eliminated by using the MODIS cloud-detecting algorithm [Platnick *et al.*, 2003]. After selection, 16 cloud-free days of data were used to develop our method for GPP estimation. The location of the study site was georegistered with the in situ GPS measurements and average values of nine pixels (3×3) was used to represent the tower footprint. This was acceptable because the flux footprint for this site extended for at least 1.5 km in all directions from the flux tower.

2.6. LUE and f_{APAR} Calculation

[18] We used an indirect method to derive LUE and f_{APAR} for cross validation. Close correlation was found between the LAI and f_{APAR} for different vegetation types [Xiao *et al.*, 2004]. For this reason, f_{APAR} was calculated using the mean in situ LAI values, light extinction coefficient ($k = 0.5$), and the following equation [Ruimy *et al.*, 1999]:

$$f_{\text{APAR}} = 0.95(1 - e^{-k\text{LAI}}). \quad (3)$$

[19] Because $\text{GPP}_{\text{EC}} = \text{LUE} \times f_{\text{APAR}} \times \text{PAR}$, we generated the LUE values using GPP_{EC} (measured by the EC method), f_{APAR} (calculated from in situ measurements of LAI), and PAR (meteorological measurements of PAR). Therefore,

Table 1. Vegetation Indices^a

Indices	Bands (nm)	Formula	Reference
NDVI	B1, B2	$(B2 - B1)/(B2 + B1)$	<i>Rouse et al.</i> [1974]
WDVI	B1, B2	$B2 - 1.06 \times B1$	<i>Clevers</i> [1989]
SAVI	B1, B2	$(1 + 0.5) \times (B2 - B1)/(B1 + B2 + 0.5)$	<i>Huete</i> [1988]
EVI	B1, B2, B3	$2 \times (B2 - B1)/(1 + B2 + 6 \times B1 - 7.5 \times B3)$	<i>Huete et al.</i> [1997]

^aSpectral bands used in calculating the VIs correspond to MODIS bands B1 (620–670 nm), B2 (841–876 nm), and B3 (459–479 nm). EVI, enhanced vegetation index; NDVI, normalized difference vegetation index; SAVI, soil-adjusted vegetation index; VI, vegetation index; WDVI, weighted difference vegetation index.

both LUE and f_{APAR} for this study site were calculated using the tower-based GPP, in situ LAI, and PAR measurements.

2.7. Vegetation Indices Selection

[20] Because GPP in this study is estimated as the product of LUE, f_{APAR} , and PAR, those vegetation indices that proved to be good proxies of LUE and f_{APAR} are of the most interest. *Inoue et al.* [2008] tested several VIs (e.g., $\text{NDSI}_{[710,410]}$, $\text{NDSI}_{[710,520]}$, and $\text{NDSI}_{[530,550]}$) for LUE and f_{APAR} estimation in rice and their results indicated that certain VIs derived from narrowband reflectance were good candidates for LUE and f_{APAR} estimation with R^2 around 0.50 and 0.75, respectively. On the basis of this study, four indices were selected to test our method in GPP estimation and are shown in Table 1.

2.7.1. Index of Normalized Difference

[21] The most well known and widely used vegetation index is the normalized difference vegetation index (NDVI) developed by *Rouse et al.* [1974]. It is based on the contrast between the maximum absorption in the red wavelength from chlorophyll pigments and the maximum reflection in the infrared wavelength caused by leaf cellular structure. Using hyperspectral narrow wave bands, this index is quantified by equation (4):

$$\text{NDVI} = (R_{\text{NIR}} - R_{\text{red}})/(R_{\text{NIR}} + R_{\text{red}}), \quad (4)$$

where R_x is the reflectance at the given wavelength (nm), and NIR stands for near-infrared. However, it is well known that NDVI has several limitations, including saturation in a multilayer closed canopy and sensitivity to both atmospheric aerosols and the soil background [*Huete et al.*, 2002].

2.7.2. Soil-Adjusted Vegetation Index

[22] The soil-adjusted vegetation index (SAVI) was developed to account for changes in the background optical to align the VI isolines with the greenness isolines over the entire dynamic range of the greenness measure [*Broge and Leblanc*, 2001]. *Huete* [1988] used the first SAVI, which included a soil-adjustment factor (L) to account for first-order soil background variations:

$$\text{SAVI} = (1 + L)(R_{\text{NIR}} - R_{\text{red}})/(R_{\text{NIR}} + R_{\text{red}} + L). \quad (5)$$

Huete [1988] found the optimal value of L to vary with vegetation density, so he used a constant of 0.5 because the optimization of L would require prior knowledge of vegetation amounts.

2.7.3. Wide Dynamic Range Vegetation Index

[23] The weighted difference vegetation index (WDVI) is different from the ratio indices in that the greenness isolines

in the red-NIR space do not converge in the origin, but remain parallel to the principal axis of soil spectral variation. *Clevers* [1989] defined WDVI as:

$$\text{WDVI} = R_{\text{NIR}} - 1.06R_{\text{red}} \quad (6)$$

where R_{NIR} and R_{red} are reflectance at near infrared and red ranges.

2.7.4. Enhanced Vegetation Index

[24] *Huete et al.* [1997] proposed the EVI using the blue wave band to primarily account for atmospheric correction and variable soil and canopy background reflectance. EVI directly normalizes the reflectance in the red wave band as a function of the reflectance in the blue wave band:

$$\text{EVI} = 2.5 \times \frac{R_{\text{NIR}} - R_{\text{red}}}{1 + R_{\text{NIR}} + 6 \times R_{\text{red}} - 7.5 \times R_{\text{blue}}}. \quad (7)$$

[25] EVI was successfully used for the study of temperate forests [*Zhang et al.*, 2003] and is much less sensitive to aerosols than NDVI [*Xiao et al.*, 2003]. A recent study by *Sims et al.* [2008] validated the use of EVI for GPP estimation.

3. Results

3.1. Respiration (Re) Estimation from NEE and T

[26] An ecosystem assimilates atmospheric CO_2 via photosynthesis and releases CO_2 via respiration. The balance between photosynthesis and respiration determines whether an ecosystem is sequestering or releasing CO_2 [*Wang et al.*, 2004]. Temperature is an important environmental factor that affects respiration. An exponential relationship between NEE_{CO_2} and T is often expected and this relationship can be used for daytime Re assessment, since the nocturnal NEE is generally considered equal to the ecosystem respiration [*Baldocchi et al.*, 1997; *Chen et al.*, 1999].

[27] In this nighttime NEE- T relationship exploration, we selected the data (NEE and T) from 2200 LT to the next day before 0300 LT from 10 June to 13 July 2008 (data of maize sites). Because of uncertainties between NEE and T in the weak wind conditions, NEE data from periods of high friction velocity ($u^* > 0.2 \text{ m s}^{-1}$) are selected [*Law et al.*, 1999; *Inoue et al.*, 2008].

[28] As shown in Figure 2, a good correlation was observed between nighttime NEE and the corresponding temperature with R^2 of 0.80 ($n = 82$). This finding is consistent with other studies [*Wang et al.*, 2004; *Inoue et al.*, 2008].

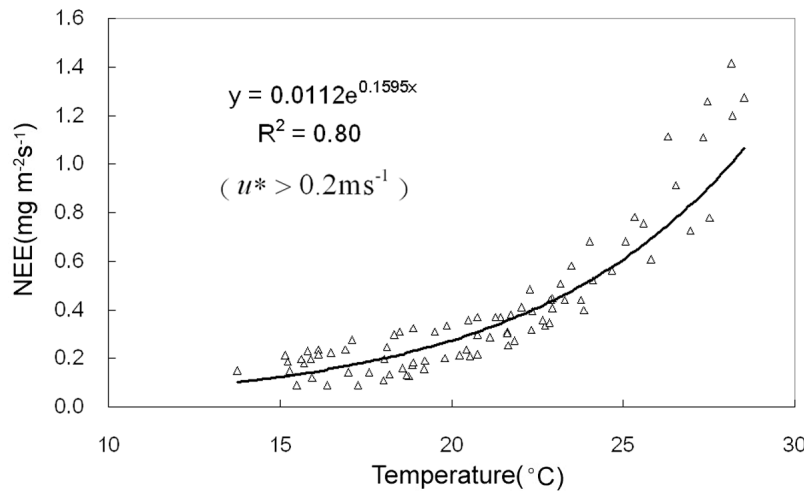


Figure 2. Relationship between nighttime net ecosystem exchange (NEE; $\text{mg m}^{-2} \text{s}^{-1}$) and temperature with R^2 of 0.80 at the maize site ($u^* > 0.2 \text{ m s}^{-1}$). Significance level of the relationships is indicated by an asterisk: $*P < 0.01$.

3.2. GPP and PAR

[29] Figure 3 shows NEE and T in the daytime when the MODIS data were acquired. The in situ measurements of GPP are usually acquired from EC measured NEE and Re with the following equation:

$$\text{GPP} = Re - \text{NEE}. \quad (8)$$

[30] First, we should find the relationship between nighttime Re (equals to nighttime NEE) and nighttime T . Then, the coefficients were used to calculate the daytime Re using daytime T . Then the in situ GPP was determined by daytime Re and daytime NEE. Figure 4 describes the in situ GPP and PAR distribution at the time of the MODIS acquisition. Estimates of daytime Re from the nighttime Re - T relation are associated with considerable uncertainties such as the

overestimation of daytime respiration due to the extrapolation of nighttime respiration fluxes [Brooks and Farquhar, 1985].

3.3. LUE and f_{APAR}

[31] The results of LUE and f_{APAR} calculated are shown in Figure 5. Both LUE and f_{APAR} increased gradually as the maize grew, because the biophysical characteristics (e.g., leaf and canopy chlorophyll content, LAI) increased with the growth of the maize and enhanced the capability of photosynthesis, which led to the increase of both LUE and f_{APAR} [Gitelson *et al.*, 2008; Wu *et al.*, 2009].

[32] However, when these two variables are compared, LUE exhibited a larger variation, from 0.006 to 0.027 $\text{mol CO}_2 \text{ mol}^{-1} \text{PPFD}$, while f_{APAR} varied from 0.55 to 0.78. This is because LUE was affected by numerous factors, such as water deficit, temperature, and wind speed, whereas f_{APAR}

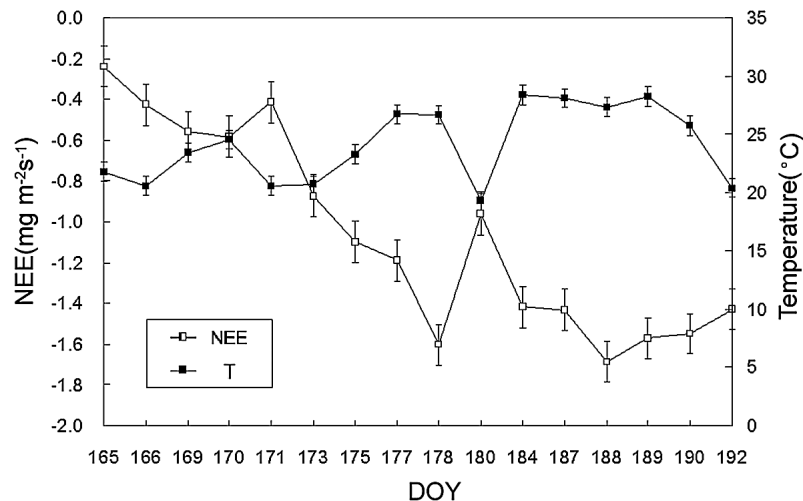


Figure 3. Tower-based measurements of daytime net ecosystem exchange (NEE; $\text{mg m}^{-2} \text{s}^{-1}$) and temperature T ($^{\circ}\text{C}$) distribution for maize at the same time of the MODIS acquisition. Points represent data (\pm standard error) for each day.

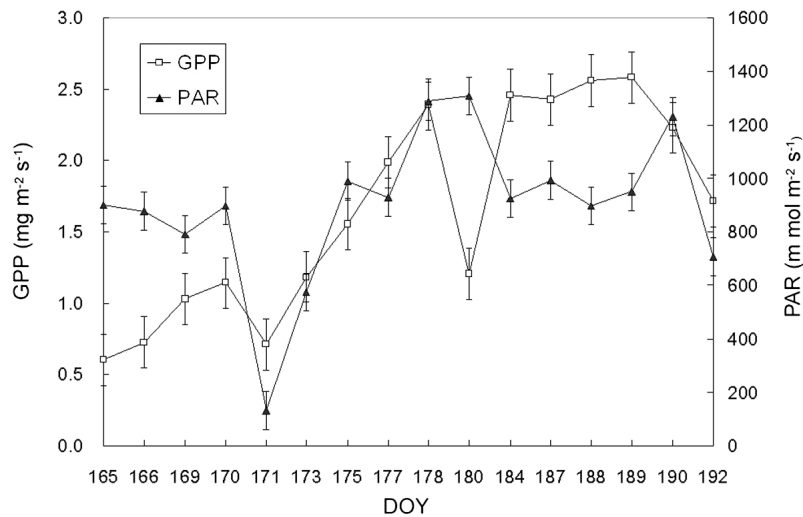


Figure 4. Tower-based measurements of GPP ($\text{mg m}^{-2} \text{s}^{-1}$) and PAR ($\text{m mol m}^{-2} \text{s}^{-1}$) distribution for maize at the same time of the MODIS acquisition. Points represent data (\pm standard error) for each day.

was mainly controlled by the canopy greenness, typically LAI.

3.4. GPP Estimation

3.4.1. Relationship Between VIs and LUE, f_{APAR}

[33] In this study, we evaluated the broadband MODIS VIs for the LUE and f_{APAR} estimation and tried to understand the mechanism of our GPP estimation methodology. As shown in Figure 6a, good determination coefficients R^2 were acquired for the relationship between the selected VIs and LUE. The EVI seemed to be the best estimator of LUE with the highest R^2 value of 0.87. The other two indices, WDI and SAVI, were also reliable, with R^2 of 0.85 and 0.74, respectively.

[34] The selected VIs were also investigated for f_{APAR} estimation (Figure 6b). The strong relationship between maize VIs and f_{APAR} indicated that f_{APAR} can also be con-

veniently estimated from MODIS VIs. Among the selected VIs, NDVI and EVI had the best relation with f_{APAR} , with the highest R^2 of 0.76. The other two indices, WDI and SAVI, had a comparable precision for f_{APAR} evaluation with R^2 of 0.71 and 0.69, respectively. Interestingly, the linear regression model seemed to perform best for f_{APAR} estimation; this conclusion was consistent with that of *Viña and Gitelson* [2005], who indicated that VIs were found to be a good linear proxy of f_{APAR} .

3.4.2. Relationship Between GPP and $\text{VI} \times \text{VI} \times \text{PAR}$

[35] GPP can be estimated by correlating in situ GPP with a single index and this method worked well in some studies. *Gitelson et al.* [2008] estimated GPP in maize from Landsat data with R^2 higher than 0.90. In this study, we were more concerned with using GPP as a product of LUE, f_{APAR} , and PAR. Therefore, we also plotted GPP as a function of a single index mainly to compare with our method.

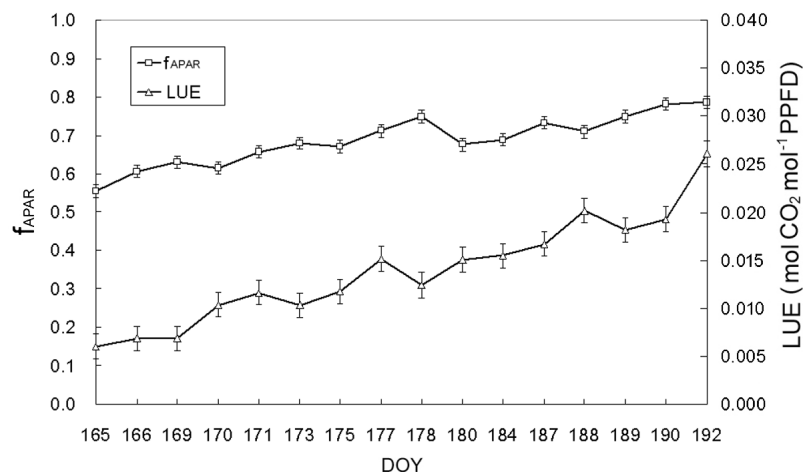


Figure 5. LUE ($\text{mol CO}_2 \text{mol}^{-1}$ photosynthetic photon flux density) and f_{APAR} calculated from in situ measurements of maize at the same time of the MODIS acquisition. Points represent data (\pm standard error) for each day.

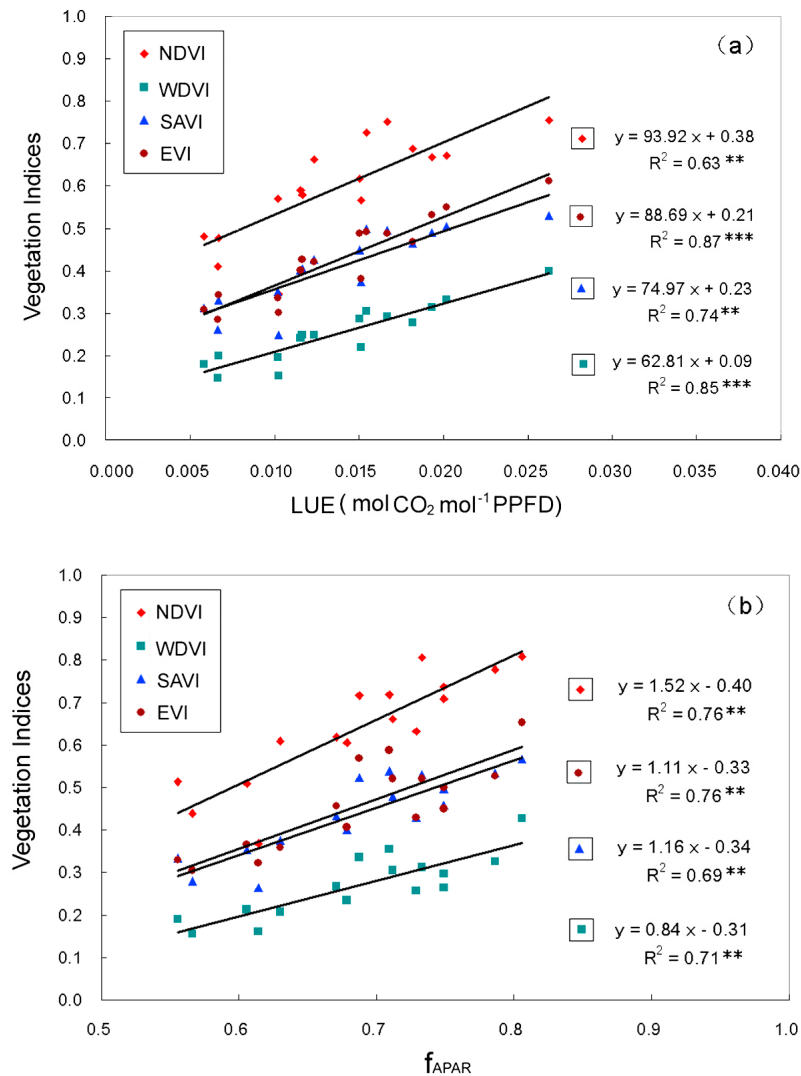


Figure 6. Relationship between the VIs calculated from the MODIS reflectance product and (a) light use efficiency (LUE; mol CO₂ mol⁻¹ photosynthetic photon flux density) and (b) f_{APAR} of in situ measurements in maize. For LUE estimation, $R^2 = 0.63, 0.85, 0.74$, and 0.87 for NDVI, SAVI, WdVI, and EVI, respectively; for f_{APAR} estimation, $R^2 = 0.76, 0.71, 0.69$, and 0.76 for NDVI, SAVI, WdVI, and EVI, respectively. Significance level of the relationships is indicated by asterisks: ** $P < 0.01$, *** $P < 0.001$. EVI, enhanced vegetation index; NDVI, normalized difference vegetation index; SAVI, soil-adjusted vegetation index; WdVI, wide dynamic range vegetation index.

[36] GPP has a moderate correlation with NDVI ($R^2 = 0.65$) and EVI ($R^2 = 0.71$; Figure 7). Among all the VIs, EVI was found to be the most appropriate candidate for GPP estimation. Two reasons may explain this phenomenon. First, EVI is an index that better overcomes the background disturbances and sky condition. For example, Nakaji *et al.* [2007] demonstrated that sky condition had little effect on the relationship between EVI and f_{APAR} . The second reason may be because EVI can better interpret the seasonal growth condition of maize. Waring *et al.* [2006] indicated that MODIS-derived EVI was not only independent of climatic drivers but also appeared to be a good surrogate to estimate seasonal patterns in GPP. The results of GPP estimation from VIs were consistent with other studies. The correlations

between LUE and VIs made an independent estimate of LUE unnecessary and the use of VIs also eliminated short-term fluctuations in solar radiation and other environmental parameters [Gitelson *et al.*, 2006; Sims *et al.*, 2008].

[37] When we estimated GPP using the expression $VI \times VI \times PAR$, the determination coefficients R^2 largely improved ($R^2 = 0.81$ to 0.91), indicating that GPP can be well estimated with MODIS (Figure 8). Besides GPP versus $NDVI \times NDVI \times PAR$ (R^2 of 0.81), all determination coefficients of GPP estimation were greater than 0.86 with the highest value of 0.91 from $EVI \times EVI \times PAR$. Another important meaning of this model lies in its linear regression. Monteith [1972] demonstrated that the efficiency epsilon with which crops or natural communities produce dry matter

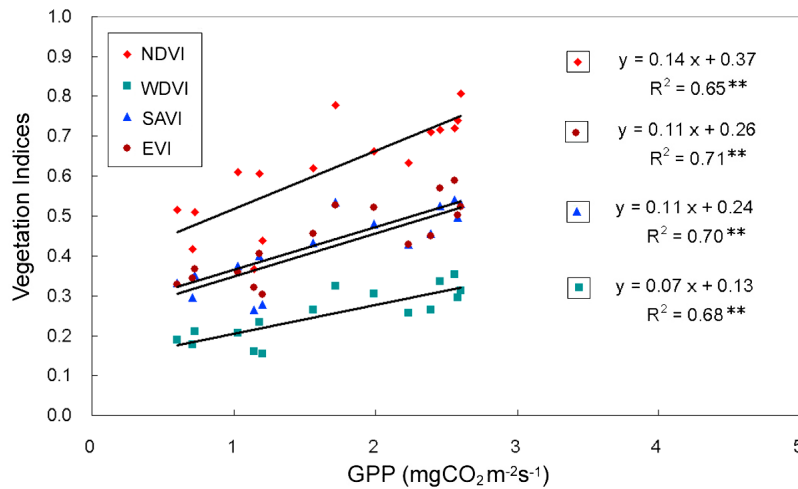


Figure 7. Relationship between the VIs calculated from the MODIS reflectance product and tower-based GPP (mg CO₂ m⁻² s⁻¹) in maize with $R^2 = 0.65$, 0.68 , 0.70 , and 0.71 for NDVI, SAVI, WdVI, and EVI, respectively. Significance level of the relationships is indicated by asterisks: $^{**}P < 0.01$.

is defined as the net amount of solar energy stored by photosynthesis in any period divided by the solar constant integrated over the same period. That means GPP over a period can be calculated as the efficiency multiplied by the

integrated solar radiation. This was validated in our results and the linear regression model was confirmed the best fit for GPP estimation, strongly implying that this method can maintain sensitivity and overcome the saturation problem in

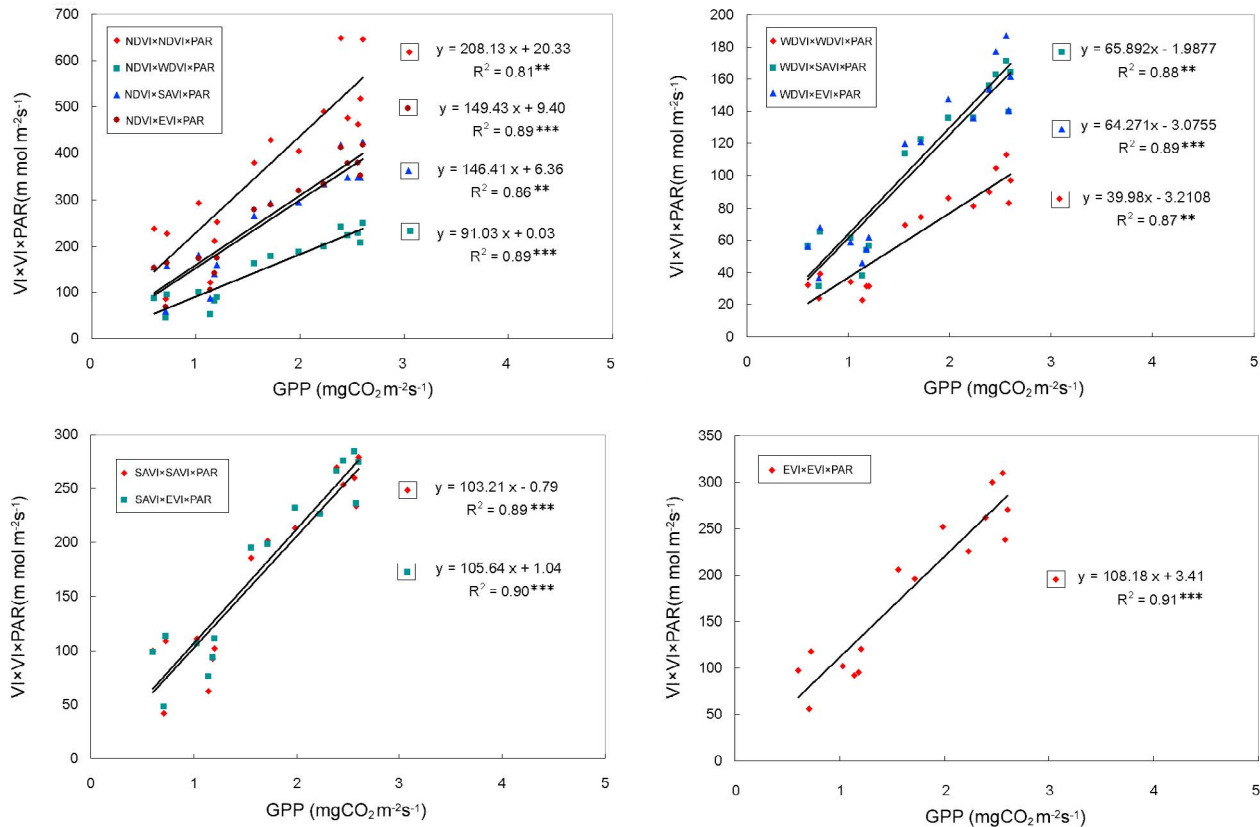


Figure 8. Relationship between the product VI × VI × PAR (VIs calculated from MODIS reflectance product and PAR from tower-based measurements) and tower-based GPP (mg CO₂ m⁻² s⁻¹) for maize. Ten combinations were used for all VIs selected and are indicated in the figure legends. Significance level of the relationships is indicated by asterisks: $^{**}P < 0.01$, $^{***}P < 0.001$.

areas with high vegetation coverage and, thus, is more robust in global GPP estimation.

4. Discussions

4.1. LUE Estimation From VIs

[38] The LUE model is attractive because of the close relationship between APAR of green tissues and a widely available spectral reflectance index [Sims *et al.*, 2006a]. However, it is also the most challenging variable to be determined at a global scale because LUE is often expressed as a biome-specific constant, adjusted through a few globally measurable meteorological variables representing canopy stresses [Running *et al.*, 2004]. Before testing the relationship between LUE and VIs, one should realize the wide range of definitions of LUE.

[39] In this paper, LUE was calculated on the basis of incident light rather than absorbed light. As the result, a strong correlation between LUE and most “greenness” vegetation indices was expected in crops with no significant stress (i.e., maize). In comparison among the VIs, NDVI had the least potential for LUE assessment, maybe because NDVI was largely affected by background information (e.g., soil reflectance). EVI, on the other hand, was proposed to account for atmospheric correction and variable soil and canopy background reflectance by incorporation of a blue band and, therefore, is better for the interpretation of LUE. This conclusion also agrees with the research of Sims *et al.* [2006b], indicating that the GPP-EVI relationship was best for sites with large seasonal EVI variations. The relationship between LUE and VIs from MODIS images had an important implication in that MODIS VIs could be proxies of LUE. Consequently, in GPP estimation an independent LUE is not necessary.

4.2. Evaluation of the VI \times VI Approach

[40] In many cases a single VI can provide reasonable estimates of GPP for both forest [Sims *et al.*, 2006a] and crops [Gitelson *et al.*, 2006]. As demonstrated by Sims *et al.* [2008], GPP estimated from the simple model had limitations in that it provided no means for either estimating the timing of the photosynthetic inactive period or tracing the seasonal GPP fluctuations subject to drought conditions. Besides, short-term (minutes to hours) GPP variations caused by short-term environmental stresses (e.g., temperature, humidity, or soil moisture) cannot be estimated from VIs alone, because these short-term stresses do not affect crop greenness [Gitelson *et al.*, 2008]. Therefore, a single index cannot address all the factors that can influence GPP estimation. From the founding of other studies [Inoue *et al.*, 2008; Sims *et al.*, 2008; Wu *et al.*, 2009], we incorporated spectral indices (suggested as a reliable proxy of LUE and f_{APAR}) and PAR for GPP estimation following Monteith’s theory.

[41] The VI \times VI approach proposed in this paper was mainly focused on Monteith logic because the input variables of both LUE and f_{APAR} could be estimated by the VIs. On the other hand, this approach could be explained by the TG model described by Sims *et al.* [2008] for GPP estimation. In the TG model, a combination of EVI \times LST correlated well with GPP because EVI could be a good

indicator of greenness and LST was found to be a proxy of PAR. In our method, we used the in situ measured PAR; the VI \times VI constituted a nonlinear stretch of a single VI, increasing its sensitivity for high-vegetation green biomass.

[42] From a biochemical and environmental view, GPP is largely affected by leaf and canopy biochemical components (for photosynthesis and intercept of energy) and radiation conditions (PAR). Zhang *et al.* [2009] demonstrated that only the PAR absorbed by photosynthetic pigments, especially chlorophyll content, enables photosynthetic processes, whereas PAR absorbed by nonphotosynthetic components such as branches, stems, and litter contributed little to CO₂ fixation. Therefore, a single index may be insufficient to address all the parameters in GPP estimation, which may partly explain the better performance by each index replacing LUE and f_{APAR} for GPP assessment. Another important aspect of this method was the elimination of the uncertainties in PAR (in situ measurements of PAR were used) for GPP estimation because PAR can vary substantially over space and time [Xiao *et al.*, 2004], especially when the GPP is determined over a short time scale [Sims *et al.*, 2008].

[43] We proposed our method on the basis of previous work at much higher spatial scales (e.g., Landsat [Gitelson *et al.*, 2008]) or bandwidth (e.g., hyperspectral [Inoue *et al.*, 2008]); thus, there is a need to discuss the issues that might arise from applying fine-scale analyses to the broader scale. First, the application areas must be large enough to ensure relative homogeneity because different ecosystems may have different reactions and it seems unlikely that there is a universal relationship of f_{APAR} or LUE with a VI. Second, the hyperspectral data have fine spectral resolution and, therefore, can potentially detect subtle changes of vegetation from its specific characteristics of reflectance. However, hyperspectral data are also very sensitive to disturbances such as aerosol, branches, and stems [Kucharik *et al.*, 1998]. This sensitivity may partly explain why some researchers have reported no difference between the ability to estimate crop agronomic variables using broadband- and narrowband-based vegetation indices [Broge and Mortensen, 2002]. Gitelson *et al.* [2008] demonstrated that the Landsat data, with broader bandwidth than MODIS, could provide reliable estimates of GPP. In our paper, VIs derived from the MODIS data were validated for both LUE and f_{APAR} estimation in maize. Therefore, it is possible to use MODIS data for GPP estimation in future model development.

4.3. Limitations of the Study

[44] Previous research that evaluated MODIS GPP estimates indicated that it was difficult to apply these estimates in the mixed forest biome or the open scrublands [Gebremichael and Barross, 2006]. In this paper, our method worked well in a relatively simple ecosystem, and this result may have positive implications for the application of this model in shrubs and needle forests, both of which are challenges in remote-sensing application. However, some limitations must still be addressed for better use of the empirical relationships.

[45] First, we used VIs as proxies of both LUE and f_{APAR} in the GPP estimation. The results indicated that all these indices were responsive to both variables at different degrees. Therefore, it is difficult to state if one index can be

attributed to LUE or f_{APAR} alone. The $\text{VI} \times \text{VI}$ approach constitutes a nonlinear stretch of a single VI, increasing its sensitivity for high-vegetation green biomass and noise. Therefore, further research on more rigorous evaluation of the convincing logic or theoretical foundation of the $\text{VI} \times \text{VI}$ approach would have been preferable and more worthy.

[46] Second, the validation of VIs derived from MODIS for LUE and f_{APAR} estimation was only conducted in the maize site, which has an “ideal” condition that may not represent the conditions occurring in many other ecosystems limited by drought, temperature, or nutrients. The $\text{VI} \times \text{VI}$ approach of GPP estimation in other extreme conditions may be problematic because VIs are not good indicators of LUE in drought condition [Sims et al., 2006a]. Furthermore, in areas where radiation is variable, GPP may depend not only on vegetation greenness but also on meteorological variables. Therefore, in situ climate data (e.g., rainfall and soil moisture) would be helpful in future GPP models [Sims et al., 2006a, 2008].

[47] The third consideration to be addressed is that the observed relationships derived from the 1 month spent observing data may not represent the whole maize growth period across different phenological stages because some researchers had proved that leaf age affects the seasonal patterns of photosynthetic capacity and net ecosystem exchange of carbon [Wilson et al., 2001; Gitelson et al., 2005]. At the maize site, because the data were taken over a time period of 1 month (mainly covering the seeding and jointing stage of maize), it is uncertain if the results can be used to obtain daily estimates of GPP, but at least it validated this approach at the satellite overpass time.

5. Conclusions

[48] In this paper, the GPP of a maize ecosystem was successfully estimated with the daily MODIS surface reflectance product. On the basis of previous studies, we explored GPP as a product of VIs and PAR. This method worked well in the maize ecosystem; determination coefficients R^2 were all above 0.81 and the highest value was 0.91 for $\text{EVI} \times \text{EVI} \times \text{PAR}$. These results were much improved compared to those estimated from a single index (R^2 varied from 0.65 to 0.71).

[49] Although GPP can be well estimated in terms of VIs and PAR, this method still needs meteorological measurements of PAR. Therefore, for the model application, we require either a model using in situ measured PAR or we must find a reliable way to evaluate it using other measurements, such as land surface temperature [Sims et al., 2008] or from MODIS products that provide the aerosol type and atmospheric conditions [Liang et al., 2006; Liu et al., 2008]. This approach would substantially benefit such GPP models. Our research conducted on the maize ecosystem may include potential ecophysiological relationships that might be common for various types of vegetation. These results provide useful insights for the assessment of LUE and GPP in other ecosystems using a wide range of available spectral data. This information will also be useful for the full use of the MODIS observations for global GPP estimation and will provide a reference for sensor selections and future sensor designs for ecosystem studies.

[50] **Acknowledgments.** We offer our thanks to Anatoly Gitelson from University of Nebraska-Lincoln for important suggestions to the paper. We also thank Yu Fangfang of ERT, Inc. (NOAA/NESDIS/STAR), for language corrections. We also appreciate the constructive suggestions of all anonymous reviewers. This work was funded by China's Special Funds for Major State Basic Research Project (2007CB714406), the Knowledge Innovation Program of the Chinese Academy of Sciences (KZCX2-YW-313), and the State Key Laboratory of Remote Sensing Science (KQ060006).

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