Estimation of gross primary production in wheat from in situ measurements

Chaoyang Wu a,b,*, Xiuzhen Han c, Jinsheng Ni d, Zheng Niu a, Wenjiang Huang a,e

a The State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing Applications, Chinese Academy of Sciences, Beijing 100101, China
b Graduate University of Chinese Academy of Sciences, Beijing 100039, China
c National Engineering Research Center for Information Technology in Agriculture, Beijing 100089, China
d Beijing Oriental TITAN Technology Co., Ltd, Beijing 100083, China
e National Engineering Research Center for Information Technology in Agriculture, Beijing 100089, China

A R T I C L E   I N F O

Article history:
Received 28 September 2009
Accepted 17 February 2010

Keywords:
Gross primary production
Vegetation index
LAI
Wheat
PAR

A B S T R A C T

Gross primary production (GPP) is a parameter of significant importance 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. This paper presents a study of GPP estimation using three methods with in situ measurements of canopy reflectance, LAI, and the photosynthetically active radiation (PAR). First, because LAI is considered as an indicator of the factor of absorbed PAR (fAPAR), it provides reasonable estimates of GPP for all types of wheat with coefficient of determination $R^2$ of 0.7353. The second method uses four kinds of vegetation indices (VIs) to estimate GPP because these indices are suggested to be reliable candidates in the estimation of light use efficiency (LUE). Good determination coefficients were acquired in estimating GPP with $R^2$ ranging from the lowest of 0.7604 for NDVI to the highest of 0.8505 for EVI. A new method was proposed for the estimation of GPP following the Monteith logic, which considering GPP as a product of VI $\times$ VI $\times$ PAR. Results indicated that this method can provide the best estimates of GPP as determination coefficient $R^2$ increased largely compared to the other two methods. EVI $\times$ EVI $\times$ PAR was demonstrated to be the most suitable for the estimation of GPP with the highest $R^2$ of 0.9207, which was about 10% larger as compared to GPP estimated from the single EVI. These results will be helpful for the development of new models of GPP estimation with all remote sensing inputs.

© 2010 Elsevier B.V. All rights reserved.

1. Introduction

Quantification of the magnitude of net terrestrial carbon (C) uptake, and how it varies inter-annually, is an important question with future potential sequestration influenced by both increased atmospheric CO$_2$ and changing climate (Nemani et al., 2003). As the magnitude of this uptake remains uncertain, understanding the C cycle at local, regional and global scales requires Earth surface processes to be monitored at high spatial and temporal resolutions (Zhao et al., 2005). Estimates of the spatial and temporal distribution of gross primary production (GPP) at regional to global scales are critical for the understanding of ecosystem response to the increased atmospheric carbon dioxide (CO$_2$) level and are thus central to political decisions (Metz et al., 2006).

Remote sensing provides consistent and systematic observations of vegetation and ecosystems, and has played an increasing role in characterization of vegetation structure and estimating GPP for different kinds of vegetations, including crops, forests and grassland (Running et al., 2000; Xiao et al., 2004; Yuan et al., 2007; Sims et al., 2008; Gitelson et al., 2008; Wu et al., 2009). Numerous methods have been proposed to estimate GPP with remote sensing observations. The most convenient method is the regression method with in situ measurements of canopy reflectance, LAI, and the photosynthetically active radiation (APAR). For example, the normalized difference vegetation index (NDVI) derived by Rouse et al. (1974) is the most widely used for the estimation of terrestrial environmental parameters. One of the important models of GPP estimation is the Vegetation Photosynthesis Model (VPM) proposed by Xiao et al. (2004, 2005) that assumes the leaf and forest canopies are composed of photosynthetically active vegetation (PAV, mostly chloroplast) and non-photosynthetic vegetation (NPV, mostly senescent foliage, branches and stems). The VPM has been successfully validated for GPP estimation in different ecosystems, including tropical evergreen forest, alpine and evergreen needle leaf forest. To run VPM model, input parameters determination are necessary, such as temperature data used for Tscalar (downward-regulation scalars for the effects of temperature) calculation and some constants assigned for different ecosystems. Therefore, less dependent on input parameters becomes a moment-
tion for the development of new models in GPP estimation (Yuan et al., 2007). For example, Sims et al. (2008) proposed a model of GPP estimation based solely on enhanced vegetation index (EVI) and land surface temperature (LST). Gitelson et al. (2006) demonstrated the feasibility of a developed technique for the remote estimation of crop chlorophyll content to assess mid-day GPP in both crops under rainfed and irrigated conditions. This method of GPP estimation in consideration of chlorophyll content was further validated by Wu et al. (2009) in the growth cycle of wheat, in which a determination coefficient $R^2$ around 0.60 was observed between product of canopy VIs and the in situ GPP. Among all the predictive methods, the light use efficiency (LUE) model based on Monteith’s logic (1972) may have the most potential to adequately address the spatial and temporal dynamics of GPP. It proposes that biological production is directly proportional to the amount of photosynthetically active radiation absorbed by the vegetation canopy (Monteith, 1972, 1977; Goetz and Prince, 1999; Running et al., 2000). The fundamental methodology of GPP estimation is based on the Monteith (1972) equation as:

$$GPP = LUE \times f_{APAR} \times PAR$$

where $LUE$ is the light use efficiency and $f_{APAR}$ represents the fraction of absorbed PAR (photosynthetically active radiation). It has been demonstrated in previous research that the $f_{APAR}$ can be expressed as a function of LAI (e.g., $f_{APAR} = 0.95 (1 - e^{-0.5LAI})$), and this conclusion has been used in radiation-use-efficiency (RUE) model (Ruimy et al., 1999). Therefore, GPP estimation using Eq. (1) can be simplified as:

$$GPP \propto LUE \times LAI \times PAR$$

Besides, both LUE and LAI can be estimated by certain VIs (Huete et al., 2002; Inoue et al., 2008; Wu et al., 2009) and GPP in Eq. (2) can be written as:

$$GPP \propto VI \times VI \times PAR$$

The reason of skipping using LAI is because $f_{APAR}$ is more direct and logical than using LAI in the estimation of GPP, and that VIs have linear and robust relationship with $f_{APAR}$ (Viña and Gitelson, 2005; Bacour et al., 2006).

This paper presented a study using three methods for GPP estimation from the in situ measurements in the growth cycle of wheat. First, GPP can be estimated from the canopy LAI as the canopy LAI is a good proxy of $f_{APAR}$ (Ruimy et al., 1999; Xiao et al., 2004). The second method of estimating GPP uses four kinds of VIs that are demonstrated to be reliable proxies of LUE (Gitelson et al., 2005; Inoue et al., 2008; Wu et al., 2009). Besides, we propose a new method of GPP estimation following the Monteith logic (GPP as a product of LUE, $f_{APAR}$ and PAR) with Eq. (3). The model will be very useful for the development of new approaches of GPP estimation with all remote sensing inputs. Validation of these methods was conducted in the growth cycle of wheat (from 7 April to 29 May 2007) with the in situ measurements of canopy reflectance, GPP, LAI and PAR.

2. Material and method

2.1. Study area

The study area was located at the National Experimental Station for Precision Agriculture (40°10.6 N, 116°26.3 E), 20 kilometers northeast of Beijing, China. This experimental station has been in operation since 2001 and lies within the warm temperate zone characterized by a mean annual rainfall of 507.7 mm and a mean annual temperature of 13 °C. The crop material of this paper was wheat (*Triticum aestivum* L.), one of the most important crops in China.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Center wavebands (nm)</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>800, 670</td>
<td>$NDVI = (R_{800} - R_{670})/(R_{800} + R_{670})$</td>
</tr>
<tr>
<td>CI4555</td>
<td>800, 550</td>
<td>$CI4555 = (R_{455}/R_{555}) - 1$</td>
</tr>
<tr>
<td>WDVI</td>
<td>800, 670</td>
<td>$WDVI = R_{800} - 1.06 \times R_{670}$</td>
</tr>
<tr>
<td>EVI</td>
<td>800, 670, 450</td>
<td>$EVI = 2.5 \times \frac{R_{450}}{R_{670} + R_{800} - 2R_{670}}$</td>
</tr>
</tbody>
</table>

2.2. Description of the ground data

2.2.1. Description of the material

Six types of wheat encompassing three classes of canopy leaf orientation (9507, Linkang2: planophile; Chayou66, jing8: spherical; Laizhou3729, jing411: erectophile) were selected in this experiment (Fig. 1). Each type was cultivated in an area approximating 4000 m² (about 200 m x 20 m). Wheat was planted in a silt clay soil with a sufficient and regular water supply.

2.2.2. Acquisition of reflectance

Data were collected on four clear days (April 17th, April 28th, May 16th and May 29th) in 2007. Canopy radiance data were collected from 400 to 2400 nm using a portable spectroradiometer (FS-FR2500, ASD, USA) with field of view of 25° normal to the canopy located at a distance of approximately 1 m from the canopy surface. Reflectance measurements were taken by averaging 10 scans at optimized integration times. For each single type of wheat, ten subplots were selected for spectra measurements evenly distributed in the areas of 200 m x 20 m. Therefore, the 200 m x 20 m area was divided into ten 20 m x 10 m areas and each was taken as a subplot for spectra measurement. Reflectance spectra were derived through calibration relative to a 99% white reference panel (LabSphere, Inc., North Sutton, New Hampshire, USA). Calibration panel reflectance measurements were taken before and after the measurements.

2.2.3. Acquisition of GPP

Leaf photosynthesis (GPP) was measured using a Li-6400 portable gas analysis system (Li-COR, Inc., Lincoln, Nebraska, USA) with a quantum sensor in the measuring cell to obtain PAR (incident photosynthetically active radiation). Ten plots were selected for each type of wheat. In each plot, leaf photosynthesis was collected at three positions (top, middle and bottom) of the wheat canopy. The average values of these three measurements were used as a representative value for the selected plot. These measurements and radiance data collecting were conducted in the morning around 10:30 (local time) on each operational day.

2.2.4. Acquisition of canopy LAI

Canopy LAI was measured using a widely accepted method. All plants within a 0.6 m x 0.6 m area were collected immediately following spectral measurements. Leaves of all the sampled plants were collected to determine the LAI. A sub-sample of plant leaves was used to measure the leaf area in the lab with a Li-Cor 3100 area meter (Li-COR, Inc., Lincoln, Nebraska, USA). The leaf area of the sub-sample (LAIsub) was used to establish the LAI of the 0.6 m x 0.6 m sample area. A detailed description can be found in Gitelson et al. (2006).

2.3. Index selection

In this section we selected four kinds of vegetation indices (Table 1) that were demonstrated to be good indicators of LUE and
could be further used in our GPP estimation methodology (Gitelson et al., 2006; Inoue et al., 2008; Wu et al., 2009).

2.3.1. Index of normalized difference

The most well known and widely used vegetation index is the NDVI developed by Rouse et al. (1974). It is based on the contrast between the maximum absorption in the red due to chlorophyll pigments and the maximum reflection in the infrared caused by leaf cellular structure. Despite its intensive use, it is well known that NDVI has several limitations, including saturation in a multilayer closed canopy and sensitivity to both atmospheric aerosols (Huete et al., 2002). Using hyperspectral narrow wavebands, this index is quantified by the following equation, where \( R_x \) is the reflectance at the given wavelength (nm):

\[
\text{NDVI} = \frac{R_{\text{Nir}} - R_{\text{Red}}}{R_{\text{Nir}} - R_{\text{Red}}} \tag{4}
\]

2.3.2. Green chlorophyll index

Gitelson et al. (2005) proposed the green chlorophyll index (CI\text{green}) model using a stepwise technique based on linear regression of the model vs. total chlorophyll content in the canopy and found close relationships between CI\text{green} and canopy chlorophyll content in maize and soybean. A further application of CI\text{green} is for the remote estimation of GPP. Accurate estimates of mid-day GPP in both crops under rainfed and irrigated conditions have been observed with root mean square error of GPP estimation of less than 0.3 mg m\(^{-2}\) s\(^{-1}\) (Gitelson et al., 2006).

Gitelson et al. (2005) defined CI\text{green} as:

\[
\text{CI\text{green}} = \frac{R_{\text{Nir}}}{R_{\text{Green}}} - 1 \tag{5}
\]

2.3.3. Index of WDVI

WDVI (weighted difference vegetation index) is different from the ratio indices in that the greenness isolines in the Red-NIR space do not converge in the origin, but instead remain parallel to the principal axis of soil spectral variation.

Clevers (1989) defined WDVI as:

\[
\text{WDVI} = R_{\text{Nir}} - 1.06R_{\text{Red}} \tag{6}
\]

2.3.4. Index of EVI

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

\[
\text{EVI} = 2.5 \times \frac{R_{\text{Nir}} - R_{\text{Red}}}{1 + R_{\text{Nir}} + 6 \times R_{\text{Red}} - 7.5 \times R_{\text{Blue}}} \tag{7}
\]

EVI has been successfully used for the study of temperate forests (Zhang et al., 2003; Boles et al., 2004), and is less sensitive to aerosols than NDVI (Xiao et al., 2003). Recent validation of EVI for GPP estimation was also conducted by Sims et al. (2008) that indicated the usefulness of this index.

3. Results and discussions

3.1. Relationship between GPP and LAI

As GPP is related to canopy structure variables, such as LAI, it is reasonable if LAI can provide certain insight for the interpretation of canopy photosynthesis. This assumption is further validated by the observed correlation between LAI and \( f_{\text{PAR}} \), which is another important input parameter for GPP estimation (Weiss et al., 2004).

In the first method, we explored the potential of LAI as an indicator of GPP. Accurate estimates of mid-day GPP in both crops under rainfed and irrigated conditions have been observed with root mean square error of GPP estimation of less than 0.3 mg m\(^{-2}\) s\(^{-1}\) (Gitelson et al., 2006).

Gitelson et al. (2005) defined CI\text{green} as:

\[
\text{CI\text{green}} = \frac{R_{\text{Nir}}}{R_{\text{Green}}} - 1 \tag{5}
\]

2.3.3. Index of WDVI

WDVI (weighted difference vegetation index) is different from the ratio indices in that the greenness isolines in the Red-NIR space do not converge in the origin, but instead remain parallel to the principal axis of soil spectral variation.

Clevers (1989) defined WDVI as:

\[
\text{WDVI} = R_{\text{Nir}} - 1.06R_{\text{Red}} \tag{6}
\]

2.3.4. Index of EVI

Huete et al. (1997) proposed the EVI using the blue band to primarily account for atmospheric correction and variable soil and canopy background reflectance. EVI directly normalizes the...
cally, LAI is defined as the leaf area per unit of ground area and could be a measure for interception of the energy that can be transmitted into the canopy. Therefore, the PAR absorbed by the canopy will be affected by LAI. A validation of this conclusion is the widely acknowledged relationship between LAI and APAR (Ruimy et al., 1999).

Another aspect need to be addressed is the nonlinear relationship between GPP and LAI which indicates that GPP will not be interpreted appropriately based solely on LAI for dense canopies (such as LAI > 3). This can be attributed to the nonlinear relationship observed between LUE and LAI because LUE also tends to be saturated at high values of LAI (Wu et al., 2009).

The main source of error for GPP estimation from LAI may depend on the LAI acquisition and the relationship between LAI and APAR. First, an independent measurement of canopy LAI is needed to avoid uncertainties introduced by equipment measures (Arias et al., 2007). Second, APAR is an important factor for GPP calculation and the nonlinear relationship between LAI and APAR may introduce uncertainty in GPP interpretation at dense canopies. VIs have shown to be linear proxies of APAR, while LAI may not provide such linear relationship and thus further affect the GPP estimation methodology in which APAR needs to be correctly interpreted (Fensholt et al., 2004; Viña and Gitelson, 2005; Gitelson et al., 2008).

3.2. Relationship between GPP and VIs

GPP can be conveniently estimated by correlating in situ GPP with a single index and this method worked well in many cases. For example, Gitelson et al. (2008) estimated GPP in maize from VIs derived from Landsat/TM data with $R^2$ above 0.90. GPP estimation from a single index was also conducted as the second method mainly to explore the potential of VIs as proxies of GPP.

The basis of estimating GPP from VIs lies in the capability of VIs in characterizing the biomass of an ecosystem accumulated. Fig. 3 depicted the results of GPP estimation from the VIs selected in this paper (Fig. 3). Good coefficients of determination $R^2$ were acquired for all indices, fluctuating from the lowest of 0.7604 for NDVI to the highest of 0.8505 for EVI. $C_{\text{green}}$ and WDI were of comparable precision in the estimation of GPP with $R^2$ of 0.8013 and 0.7964, respectively. EVI derived by incorporating a blue band that can alleviate the background effects was demonstrated to be most suitable for GPP estimation, which is consistent with other study indicating EVI is more robust than other indices (Sims et al., 2008; Gitelson et al., 2008).

For all indices selected, $C_{\text{green}}$ showed a linear relationship between GPP while logarithmic regressions were found to be best fit for the other three indices (NDVI, WDI and EVI). This is because $C_{\text{green}}$ is derived using a stepwise technique based on linear regression (Gitelson et al., 2005) and the nonlinear relationships for the other three indices were also consistent with other research (Gitelson et al., 2008).

Results in this section demonstrated that a single index indicated the greenness of canopy can provide reasonable estimates of GPP. The underlying mechanism is that spectral indices were demonstrated to be good candidates for LUE estimation (Gamon et al., 2006; Li et al., 2007; Gitelson et al., 2008; Inoue et al., 2008). However, as demonstrated by Sims et al. (2008), GPP estimation from this simple model had limitations either in providing no means for estimating the timing of the photosynthetic inactive period or tracing the seasonal GPP fluctuations subject to drought conditions. Besides, short-term (minutes to hours) variations in GPP due to short-term environmental stresses (e.g., temperature, humidity, soil moisture) cannot be estimated from VIs alone, since these short-term stresses do not affect crop greenness (Gitelson et
al., 2008). Therefore, a single index cannot mechanically address all the factors that will influence the GPP estimation.

### 3.3. Relationship between GPP and VI × VI × PAR

In this part, we validate a new model that closely follows the Monteith logic. GPP is an indicator of ecosystem accumulating biomass and thus depends on the photosynthesis capability of green vegetation, the canopy structure, and the illumination conditions. Therefore, we used this new model that considering of GPP as a product of VI, VI and PAR.

Before validation, we explored the potential of VIs in LAI estimation which will be helpful in finding the most suitable combinations of VIs in the GPP estimation model. Fig. 4 showed the relationship between LAI and VIs selected (Fig. 4). NDVI was demonstrated to be a possible candidate for LAI estimation with a determination coefficient $R^2$ of 0.6554. EVI had the highest $R^2$ of 0.7216 in estimating LAI and both of the other two VIs, Clgreen and WDVI, showed moderated potential in LAI estimation with $R^2$ of 0.6812 and 0.6607, respectively. Based on these VI/LAI relationship and results in the first method, we can just validate the GPP estimation as:

$$GPP \propto VI \times EVI \times PAR \quad (8)$$

GPP was successfully estimated with this model and high coefficients of determination $R^2$ were observed for all the selected indices (Fig. 5). The $R^2$ of GPP estimation improved largely for all indices comparing to results in Fig. 3. EVI × EVI × PAR was demonstrated to be the most suitable for GPP estimation with the highest $R^2$ of 0.9207, which was about 10% larger as compared to GPP estimated from the single index EVI. The reason is that VIs can be reliable proxies of LUE and EVI is a good indicator of LAI (a proxy of $f_{APAR}$) (Gamon et al., 1997; Sims and Gamon, 2002; Gitelson et al., 2005; Inoue et al., 2008; Wu et al., 2009). Our method used EVI as a proxy of LAI, and the result agreed well with the relationship of VI/LAI. Furthermore, this conclusion was also consistent with the second method, in which EVI was also demonstrated to be the most suitable candidate for GPP estimation (Fig. 3).

Another merit of our method lies in the linear regression with GPP which can avoid the saturation limit for dense canopies. Monteith (1972) demonstrated that efficiency Epsilon with which crops or natural communities product dry matter 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 model and the linear regression was found to be the best fit for GPP estimation which means it may have the potential in keeping sensitive and overcoming the saturation limit when used in high coverage areas and are more robust in global estimation of GPP where a wide dynamic range of GPP values are expected.

From the biochemical and environmental view, GPP is largely affected by the leaf and canopy biochemical components (for photosynthesis and intercept of energy) and the radiation conditions (PAR). Zhang et al. (2009) demonstrated that only the PAR absorbed by photosynthetic pigments, especially chlorophyll content, enabled photosynthetic processes, whereas the PAR absorbed by non-photosynthetic components such as branches, stems, and litter will contribute little for CO2 fixation. Therefore, a single index may mechanically be insufficient for addressing all the parameters in GPP estimation. This may explain the “split” of process by each index replacing of LUE and EVI replacing of $f_{APAR}$ will work better for GPP assessment. Besides, another important aspect of this method is the elimination of the uncertainties in PAR for GPP estimation because PAR can vary substantially over space and time, especially when determination of GPP over a long timescale (Xiao et al., 2004).
However, our method still has limitations especially for the requirement of an independent measurement of PAR. Fortunately, research has already been carried out to estimate PAR from MODIS products that provide the aerosol type and atmospheric conditions (Liang et al., 2006; Liu et al., 2008). It is of very significant meaning if the PAR can be successfully estimated by the satellite data because it will be helpful to build a model using all remote sensing inputs and to better follow the Monteith logic in GPP estimation.

4. Conclusions

GPP of six types of wheat in the growth cycle were estimated from three methods with the in situ measurements of canopy reflectance, LAI and PAR. The canopy structure parameter LAI provided reasonable estimates of GPP with coefficient of determination $R^2$ of 0.7353. VIs, considered as proxies of LUE, were also good candidates for GPP estimation with $R^2$ fluctuating from the lowest of 0.7604 for NDVI to the highest of 0.8505 for EVI. We introduced a new method for the estimation of GPP following the Monteith logic considering GPP as a product of VIs and PAR because VIs can be proxy of both LUE and $f_{APAR}$. Results indicated that our method can provide reliable estimates of GPP as coefficient of determination $R^2$ improved largely compared to the other two methods, although it still has limitations, such as the need of an independent measure of PAR.

Our research conducted on wheat ecosystem may include potential ecophysiological relationships might be common for various types of vegetation. These results provide useful insights for the assessment of GPP in other ecosystems using a wide range of available spectral data. There are three main points of the model. First, better precision was observed compared to GPP estimation from LAI or VI ($R^2$ in our study in wheat ecosystem). Second, it better follows the Monteith logic of GPP estimation in an ecosystem (GPP = LUE $\times f_{APAR} \times$ PAR). The third aspect refers to the linear correlation with GPP, which will be very helpful for global GPP estimation with wide dynamical ranges. Further research is needed to evaluate the new model (GPP as a product of VI $\times$ PAR) in operational application of GPP estimation with satellite based observations and refine the models that can estimate PAR from the remotely sensed data.

Acknowledgements

We like to offer our thanks to Prof. Anatoly Gitelson from University of Nebraska-Lincoln for important suggestions and Dr. Fangfang Yu from ERT, Inc. @NOAA/NEDIS/STAR for language corrections. We also very appreciate the suggestions by the two anonymous reviewers which made the study more consistent. This work was funded by the China’s Special Funds for Major State Basic Research Project (2007CB714406), Open Research Fund of State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (09R04), and by WP9 Satellite based drought monitoring system of pilot areas, and by the National High Technology Research and Development Program of China (863 Program, No. 2006AA120107).

References


Fig. 5. GPP estimation as a product of VI, EVI and PAR (significance level of the relationships was indicated by asterisk: **$P<0.01$, ***$P<0.001$, the legend refers to the wheat types in Fig. 1).