Deriving a light use efficiency estimation algorithm using in situ hyperspectral and eddy covariance measurements for a maize canopy in Northeast China

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Abstract
We estimated the light use efficiency (LUE) via vegetation canopy chlorophyll content (CCC) based on in situ measurements of spectral reflectance, biophysical characteristics, ecosystem CO₂ fluxes and micrometeorological factors over a maize canopy in Northeast China. The results showed that among the common chlorophyll-related vegetation indices (VIs), CCC had the most obviously exponential relationships with the red edge position (REP) ($R^2 = .97$, $p < .001$) and normalized difference vegetation index (NDVI) ($R^2 = .91$, $p < .001$). In a comparison of the indicating performances of NDVI, ratio vegetation index (RVI), wide dynamic range vegetation index (WDRVI), and 2-band enhanced vegetation index (EVI2) when estimating CCC using all of the possible combinations of two separate wavelengths in the range 400–1300 nm, EVI2 [1214, 1259] and EVI2 [726, 1248] were better indicators, with $R^2$ values of .92 and .90 ($p < .001$). Remotely monitoring LUE through estimating CCC derived from field spectrometry data provided accurate prediction of midday gross primary productivity (GPP) in a rainfed maize agro-ecosystem ($R^2 = .95$, $p < .001$). This study provides a new paradigm for monitoring vegetation GPP based on the combination of LUE models with plant physiological properties.

KEYWORDS
Canopy chlorophyll content, eddy covariance, hyperspectral remote sensing, light use efficiency, spectral vegetation indices

1 | INTRODUCTION

The accurate assessment of vegetation gross primary productivity (GPP) is of great importance for regional and global studies of terrestrial ecosystem carbon budgets (Gitelson et al., 2006; Peng & Gitelson, 2011; Wu, Niu, & Gao, 2012), and it also plays a significant role in dynamic responses of terrestrial ecosystem carbon cycling to global climate change (Fang, Yu, & Qi, 2015; Fang & Zhang, 2013; Shen & Fang, 2014). The eddy covariance (EC) technique provides long-term continuous and frequent observations of CO₂ flux at the ecosystem level (e.g., Baldocchi, 2003). Remote sensing techniques conduct consistent and systematic monitoring of vegetation structure and function at the regional and site levels (Ide, Nakaji, & Oguma, 2010; Lawley et al., 2016; Running, Thornton, Nemani, & Glassy, 2000). How to effectively relate CO₂ flux observations with remote sensing techniques at the site level and ultimately to implement repetitive observations of CO₂ flux over extensive spatial areas are becoming critical challenges for assessing global carbon budgets and monitoring ecosystem dynamical processes. The key for addressing these questions lies in the development of remote sensing-based ecosystem process models at broad spatial scales that can be effectively and quantitatively parameterized and validated by CO₂ fluxes at site level.

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Currently, the accurate estimations of the fraction of absorbed photosynthetically active radiation (fAPAR) and the light use efficiency (LUE) are two large sources of model uncertainties for LUE models (Inoue, Peñuelas, Miyata, & Mano, 2008; Peng & Gitelson, 2011). On the one hand, studies showed that the sensitivity of the normalized difference vegetation index (NDVI) to variations in fAPAR usually decreases when fAPAR exceeds 0.7 for moderate-to-high vegetation density (Viña & Gitelson, 2005), moreover, the relationship of NDVI-fAPAR was also influenced by plant phenology (e.g., Jenkins et al., 2007; Running et al., 2000). On the other hand, studies have demonstrated that LUE was not a prescribed constant during the whole growing season (e.g., Jarvis & Leverenz, 1983) and was not only related to the absorbed photosynthetically active radiation (APAR) by green vegetation but also affected by the soil water content (SWC), nutrient conditions, ratio of direct to diffuse radiation, canopy age, and site history (Alton, North, & Los, 2007; DeLucia, Drake, Thomas, & Gonzalez-Meler, 2007). Thus, studies on how to effectively improve the accuracy of remote estimation models for fAPAR and LUE were especially essential. Involving remote estimation of fAPAR, corresponding research has been conducted (Zhang, Zhou, & Nilsson, 2015). So in this study, we will focus on the parameter LUE and its quantitative algorithms. Studies indicated that the variation in foliar chlorophyll content was well correlated with temporal changes in LUE (Dawson, North, Plummer, & Curran, 2003; Peng et al., 2011), and it was also found that foliar chlorophyll content was a good proxy for leaf photosynthetic capacity (Croft et al., 2017). In addition, studies have shown that spectral vegetation indices (Vis) closely related to chlorophyll were used to estimate GPP, such as the photochemical reflectance index (PRI), which is strongly related to the photosynthetic radiation use efficiency of plant leaves (Gamon, Serrano, & Surfus, 1997; Peñuelas, Filliela, & Gamon, 1995). However, its applicability at the canopy or ecosystem scales is still not well known (Ide et al., 2010; Nakaji et al., 2008; Rossini et al., 2010).

Therefore, to estimate the ecosystem LUE using remote sensing-based models, we made seasonal measurements of the spectral reflectance, ecosystem CO₂ fluxes, ecophysiological characteristics, and micrometeorological variables over a maize cropland. This study aims to estimate LUE for a maize canopy through exploring the relationships between the spectral Vis and photosynthetic-efficiency or capacity-variable canopy chlorophyll content (CCC_canopy). The specific objectives were to (1) construct quantitative algorithms for CCC_canopy considering the saturation of Vis with increasing green plants; and (2) test whether the estimation models for CCC_canopy derived from field spectrometry can be effectively validated by EC fluxes data; and (3) ultimately assess the performance of hyperspectral remote sensing information for assessing CCC_canopy. This study will provide theoretical bases for constructing ecosystem productivity models driven by full remote sensing information.

2 | MATERIALS AND METHODS

2.1 | Experimental site

The experimental site was located at Jinzhou Agricultural Ecosystem Research Station (41°8′53″N, 121°12′6″E, 23 m a.s.l.), the Institute of Atmospheric Environment, Chinese Meteorological Administration, Shenyang. It belongs to a temperate continental monsoon climate zone, with mean annual air temperature of 9°C and mean annual precipitation of 690 mm for the past 40 years. The rainfall maize is the main crop type in this area. The maize hybrid was Nong Hua 101, and it was sown in early May and harvested in late September. The maize was planted about 23 cm apart in rows and the distance of about 57 cm between rows at this experimental site. The fields are under till management and N fertilizer is around 300 kg N/ha (Han et al., 2007). The soil is a typical brown soil, which is composed of sand of 45%, silt of 40%, and clay of 15%. The pH value of the soil was 6.3, a soil organic matter content ranged from 0.6 to 0.9%, and total N was 0.069% (Han et al., 2007; Li, Zhou, & Wang, 2010; Zhang et al., 2015).

2.2 | Field measurements

An ASD (Analytical Spectral Devices, Boulder, CO, USA) FieldSpec3 spectroradiometer with a wavelength range of 350–2500 nm was used to collect canopy spectral reflectance data biweekly from late May to late September during the whole growing season in 2011 (nine measurement campaigns). The area-coefficient method (CMA, 1993) was used to measure leaf area index (LAI). A more detailed description of spectral reflectance and LAI measurements are given as Zhang et al. (2015).

Total CCC_canopy is an important biophysical characteristic parameter at the canopy level (Gitelson et al., 2005; Ustin et al., 1998) and is the product of LAI and the leaf chlorophyll content (LCC) (Gitelson et al., 2005). LCC was measured by a SPAD-502 meter (Minolta Corporation, NJ, USA) with the same observation dates as the spectral reflectance measurements in nine campaigns. Gitelson et al. (2005) has showed that upper canopy leaves chlorophyll could be representative of the entire canopy chlorophyll. In this study, the SPAD values (M, SPAD-502 Meter Value) at the middle-upper positions of all green leaves for the same five observed standard plants for LAI were measured on each sampling date. Here, we only used the data of the third leaf from the top down, which have the most notably seasonal variations compared with other leaves, and ultimately the mean values of the five standard plants were obtained to represent the SPAD value of each sampling date. The SPAD values reflect the relative quantity of LCC by measuring transmission at 650 nm in the red domain and 920 nm in the infrared region (Markwell, Osterman, & Mitchell, 1995). CCC_canopy was calculated by Eqs. (1)–(3) as follows (Gitelson et al., 2005; Markwell et al., 1995):

\[
\text{Chlorophyll content (Chl, μmol/m}^2) = 10^{(M-897.01)}
\]

(1)

\[
\text{Leaf chlorophyll content (LCC, mg/m}^2) = \text{Chl(μmol/m}^2) \times 897.01(\text{g/mol}) \times 10^{-3}(\text{mg/μg})
\]

(2)

\[
\text{Canopy chlorophyll content (CCC_canopy, g/m}^2) = \text{LAI} \times \text{LCC(mg/m}^2) \times 10^{-3}(\text{g/mg})
\]

(3)

CO₂ fluxes over the maize canopy at the experimental site were measured by EC instruments system including an open path infrared CO₂/H₂O gas analyzer (Li-7500; Campbell Scientific Inc., MS, USA), a 3-D...
sonic anemometer (CSAT3; Campbell Scientific Inc.) at a height of 3.5 m and an automatically stored data logger (CR5000; Campbell Scientific Inc.), as well as micrometeorological variables including air temperature and humidity (HMP45C; Vaisala, Helsinki, Finland) at heights of 2.4 m and 4.1 m, wind speed (014A/034B; Campbell Scientific Inc.), PAR (LI190SB; LI-COR Inc., Lincoln, NE, USA) at the height of 3.5 m, and SWC (EasyAG sensors; Campbell Scientific Inc.) at depths of 10, 20, 30, and 40 cm were also measured in the 2011 growing season (Zhang & Zhou, 2014). They were installed in an undisturbed rainfed maize field occupying 43 ha with adequate fetches in all directions and uniform enough to meet requirements for EC measurements of carbon fluxes (Li et al., 2010).

2.3 | Data analysis

The net ecosystem CO₂ exchange (NEE) data were determined by the EC method as the mean covariance between fluctuations in vertical wind speed (m/second) and the carbon dioxide concentration (ppm) on a half-hourly basis (Equation 4) (Baldocchi, 2008), and data processing and quality control procedures were conducted. To obtain complete time-series of half-hour CO₂ fluxes data, the gap-filling method of Reichstein et al. (2005) was used to fill NEE data. We used Equation (5) to estimate daytime ecosystem respiration (Rₑ°C) and Equation (6) to partition NEE into GPP (GPP = 0 during the night) and Rₑ°C. NEE is positive when CO₂ is emitted from the ecosystem into the atmosphere, where GPP and Rₑ°C are both positive (Reichstein et al., 2005).

\[
NEE = \frac{m}{C} \tag{4}
\]

\[
Rₑ°C = Rₑ°C_{ref} \times e^{(1/(T_{ref} - T_0) - 1/(T - T_0))} \tag{5}
\]

\[
GPP = -NEE + Rₑ°C \tag{6}
\]

TABLE 1 Spectral vegetation indices (VIs) used in the study

| Indices | Formula | References |
|---------|---------|------------|
| Normalized difference vegetation index (NDVI) | \(\frac{(\rho_{\text{red}} - \rho_{\text{nir}})}{(\rho_{\text{red}} + \rho_{\text{nir}})}\) | Tucker (1979) |
| Enhanced vegetation index (EVI) | \(2.5 \times \frac{(\rho_{\text{red}} - \rho_{\text{nir}})}{(\rho_{\text{red}} + 6 \times \rho_{\text{nir}} - 7.5 \times \rho_{\text{blue}} + 1)}\) | Huete et al. (2002) |
| Ratio vegetation index (RVI) | \(\rho_{\text{nir}}/\rho_{\text{red}}\) | Rouse et al. (1973) |
| Red edge NDVI | \(\frac{(\rho_{750} - \rho_{710})}{(\rho_{750} + \rho_{710})}\) | Gitelson and Merzlyak (1996) |
| Photochemical reflectance index (PRI) | \(\rho_{531} - \rho_{570}/\rho_{531} + \rho_{570}\) | Gitelson et al. (1997) |
| Modified chlorophyll absorption ratio index (MCARI) | \(\frac{(\rho_{705} - \rho_{710})}{(\rho_{705} + \rho_{750})}\) | Wu et al. (2009) |
| Chlorophyll index of green (CIGreen) | \(\frac{(\rho_{750} - \rho_{550})}{(\rho_{750} + \rho_{550})}\) | Gitelson et al. (2005) |
| Chlorophyll index of red edge (CIREdEdge) | \(\frac{(\rho_{750} - \rho_{710})}{(\rho_{750} + \rho_{710})}\) | Gitelson et al. (2005) |
| MERIS terrestrial chlorophyll index (MTCI) | \(\frac{(\rho_{753} - \rho_{681})}{(\rho_{708} - \rho_{681})}\) | Dash and Curran (2004) |
| Canopy chlorophyll index (CCI) | \(D_{720}/D_{700}\) | Sims et al. (2006) |
| Wide dynamic range vegetation index (WDRVI) | \((\alpha \rho_{\text{nir}} - \rho_{\text{red}})/(\alpha \rho_{\text{nir}} + \rho_{\text{red}})\) | Gitelson (2004) |

\(\rho_{\text{nir}}, \rho_{\text{red}}, \text{ and } \rho_{\text{red}}\) are the averaged reflectance among the waveband range to match MODIS data in the near-infrared (841–876 nm), red (620–670 nm), and shortwave infrared (SWIR1: 1628–1652 nm) wavelengths, respectively.

VIs with combinations of two separate wavelengths at the range of 400–1300 nm

\[
\text{Normalized difference vegetation index (NDVI)} = \frac{(\rho_{\text{red}} - \rho_{\text{nir}})}{(\rho_{\text{red}} + \rho_{\text{nir}})} \tag{7}
\]

\[
\text{2-band enhanced vegetation index (EVI2)} = 2.5\left(\frac{(\rho_{\text{red}} - \rho_{\text{nir}})}{(\rho_{\text{red}} + 2.4\rho_{\text{nir}} + 1.0)}\right) \tag{8}
\]

\[
\text{Ratio vegetation index (RVI)} = \frac{\rho_{\text{blue}}}{\rho_{\text{red}}} \tag{9}
\]

\[
\text{Wide dynamic range vegetation index (WDRVI)} = \frac{(\alpha \rho_{\text{nir}} - \rho_{\text{red}})/(\alpha \rho_{\text{nir}} + \rho_{\text{red}})} {\} \tag{10}
\]

where \(R_{\text{ref}}\) is the ecosystem respiration at the reference temperature 10°C (mg CO₂ m⁻² s⁻¹), \(E_0\) is the activation energy parameter (J/mol), \(T\) is soil temperature (°C, 0.05 m depth), \(T_0 = 273.15\) K, and a 91-day window that can reflect the seasonal dynamics of ecosystem \(R_{\text{eco}}\) was applied to parameterize \(R_{\text{eco}}\) and \(E_0\) (Lloyd & Taylor, 1994). To match simultaneous spectral measurements over a maize canopy, the daily mean midday GPP values measured between 11 and 14 h were used in this study.

Eleven common chlorophyll-related VIs were calculated in this study (Table 1). Additionally, the red edge position (REP) was used, which is particularly sensitive to green vegetation information, and was determined as the wavelength inflection point between 680 and 750 nm (i.e., the point of maximum slope) (Dawson & Curran, 1998). Four widely used VIs, that is, the NDVI, ratio vegetation index (RVI), wide dynamic range vegetation index (WDRVI), and 2-band enhanced vegetation index (EVI2) were used to select the optimal CCC_caption indicators using all of the possible combinations of two separate wavelengths in the range of 400–1300 nm along with 12 chlorophyll-related VIs to explore the relationships between VIs and CCC_caption, Considering the saturation effects of VIs with an increasing CCC_caption linear and exponential regression models were employed.

2.4 | Validation of the models

According to LUE principles (Monteith, 1972, 1977), ecosystem GPP can be accurately estimated using the product of fAPAR and LUE following Equation (7):

\[
GPP = \text{PAR} \times \text{fAPAR} \times \text{LUE} \tag{7}
\]
Considering LUE was closely related to ecosystem chlorophyll (Gitelson et al., 2006; Peng & Gitelson, 2011), thus, Equation (7) can be modified as the following form (Equation 8):

$$\text{GPP} = \text{PAR} \times (\text{APAR} \times \alpha \times \text{CCC}_{\text{canopy}}^2)$$  \hspace{1cm} (8)

where $\alpha$ is a light use coefficient for $\text{CCC}_{\text{canopy}}$ per unit area, which can be parameterized by field observation data sets; PAR is photosynthetically active radiation; $\text{APAR}$ is the fraction of absorbed PAR; and $\text{CCC}_{\text{canopy}}$ is the canopy chlorophyll content.

Half-hourly midday GPP between 11 and 14 h estimated and measured by an open-path EC were used to effectively validate the remote estimation model for the $\text{CCC}_{\text{canopy}}$ derived from hyperspectral data. All statistical analyses were performed with SPSS 17.0 software (SPSS, Chicago, IL, USA) and MATLAB R2009a software (MathWorks, Natick, MA, USA).

3 | RESULTS AND DISCUSSION

3.1 | Environmental variables, LAI, and CCC<sub>canopy</sub>

Figure 1 shows the seasonal variations of the environmental factors, LAI, and CCC<sub>canopy</sub> in the maize field. From late May to mid-August the mean daily temperature ($T_{\text{air}}$) maintained a level above 20°C and met the demands of crop growth and development (Figure 1a). PAR showed higher values during the early stage of the growing season and then remained at a certain level with lower values in late July (Figure 1a). Moisture factors also showed clear dynamics during the growing season (Figure 1b). Relative humidity (RH) showed a single-peak seasonal trend, with values above 80% during the period from late July to early August, and reached its peak value of 89.30% on July 29 (DOY210). Vapor press deficit (VPD) showed large fluctuations at the early stage of the growing cycle and then gradually decreased during the late stage. Compared with RH and VPD, the seasonal variations of SWC were not obvious. Similar to the seasonal variation in LAI, CCC<sub>canopy</sub> showed a notable single-peak seasonal trend, which rapidly increased at the vegetative stage and gradually decreased after its peak value, occurring at the period from late July to early August (Figure 1c).

3.2 | Relationships between chlorophyll-related VIs and CCC<sub>canopy</sub>

Based on the relationships between VIs and CCC<sub>canopy</sub>, VIs were classified into two categories. One type of VIs had closely exponential relationships with CCC<sub>canopy</sub>, including REP, NDVI, red edge NDVI, and WDRVI, with coefficients of determination ($R^2$) of .97, .91, .86, and .78, respectively (Figure 2a–d). The strongest relationships exhibited between REP and CCC<sub>canopy</sub> and NDVI and CCC<sub>canopy</sub>, although VIs gradually lost sensitivity to CCC<sub>canopy</sub> when the latter increased above a certain level.

The other types of VIs, including EVI, PRI, SR, MCARI<sub>710</sub>–<sub>670</sub> Cl<sub>green</sub>, Cl<sub>red edge</sub>, MTCI, and CCI, had obviously linear relationships with CCC<sub>canopy</sub> (Figure 2e–l). The best linear relationship exhibited between EVI and CCC<sub>canopy</sub> with an $R^2$ value of .70 ($p < .01$, Figure 2e).

The worst relationships occurred between PRI and CCC<sub>canopy</sub> with an $R^2$ value of .38 ($p = .08$, Figure 2f), and SR and CCC<sub>canopy</sub> with an $R^2$ value of .39 ($p = .074$, Figure 2g); the other $R^2$ values were approximately .50 (Figure 2h–l). To some degree, the latter could overcome the saturation effects, but the explained variances of CCC<sub>canopy</sub> by the linear relationships were still very limited.

Photochemical reflectance index can detect epoxidation and de-epoxidation changes in xanthophyll relevant to heat dissipation and can be used to indicate rapid changes of the photosynthetic efficiency of photosystem II and LUE of plant leaves (Gamon et al., 1997; Peñuelas et al., 1995). However, at the canopy scale, the sensitivity of PRI to the variation in CCC<sub>canopy</sub> did not perform well in this study. In addition, studies also showed that CCI could indicate changes of the chlorophyll content by the shifting of the red edge (Ida et al., 2010; Sims et al., 2006). In particular, CI<sub>green</sub> [(R<sub>NIR</sub> / R<sub>green</sub>) − 1] and CI<sub>red edge</sub> [(R<sub>NIR</sub> / R<sub>red edge</sub>) − 1] could effectively reflect...
the variation of $\text{CCC}_{\text{canopy}}$ and explain more than 92% of the Chl variation (Gitelson et al., 2005). However, they could not be used as better proxies in this study because the effects of the canopy structure, spatial distribution of the chlorophyll content, LAI, and soil background decreased the reflectance signatures of Chl at the canopy level.
3.3 | Relationships between VIs from the combinations of two separate wavelengths and CCC\textsubscript{canopy}

Figure 3 shows a contour map of \( R^2 \) between the CCC\textsubscript{canopy} and the commonly utilized VIs, NDVI, RVI, WDRVI, and EVI2 using all of the possible combinations of two separate wavelengths in the range 400–1300 nm according to linear and exponential relationships. The \( R^2 \) value of the linear relationship NDVI [1233, 1243] versus CCC\textsubscript{canopy} reached .89 (Figure 3a), while the \( R^2 \) value of the exponential relationship reached .95 at wavelength positions around [405, 1010], [405, 1245], and [405, 890] (Figure 3b). The exponential regression of NDVI-CCC\textsubscript{canopy} showed better statistical relationships between the band combinations of the visible (400–700 nm) and the near-infrared regions (700–1300 nm). The RVI-CCC\textsubscript{canopy} relationship was mostly not strong, with the best linear \( R^2 \) value of .89 for RVI [1233, 1243] (Figure 3c), as well as exponential \( R^2 \) values <.90 (Figure 3d). Compared with NDVI, WDRVI, to some extent, showed a similar linear relationship with CCC\textsubscript{canopy}, but it was not better than NDVI for the exponential \( R^2 \) value (Figure 3e,f).
Most of the VIs exhibited saturation effects with increasing \( \text{CCC}_{\text{canopy}} \), which could result in the exponential relationships between VIs and \( \text{CCC}_{\text{canopy}} \), being better than the linear ones (Figure 3a–f). Among the four VIs used in this study, EVI2 was the best indicator of \( \text{CCC}_{\text{canopy}} \) because the \( R^2 \) values of the exponential relationships between \( \text{CCC}_{\text{canopy}} \) and EVI2 [667, 675], \( \text{CCC}_{\text{canopy}} \) and EVI2 [498, 675] reached .94 and .89 (Figure 3h), respectively. Actually, good linear relationships also existed between \( \text{CCC}_{\text{canopy}} \) and EVI2 [1214, 1259] and \( \text{CCC}_{\text{canopy}} \) and EVI2 [726, 1248], with \( R^2 \) values of .92 and .90, which effectively overcame the saturation effects (Figure 4).

EVI2 proved to be suitable for accurate estimations of \( \text{CCC}_{\text{canopy}} \) and they were very sensitive to the \( \text{CCC}_{\text{canopy}} \) variations in this study. Usually, the chlorophylls have strong absorbance peaks in the red and blue regions of the spectrum. However, the blue peak is not used to estimate Chl because it overlaps with the absorbance of the carotenoids (Wu et al., 2009). In addition, maximal chlorophyll absorbance in the red region occurred at wavelengths from 660 to 680 nm; spectral reflectance at these wavelengths are prone to saturated light information, so they were nonsensitive, while reflectance near 550 nm in the green region and red edge region at 700 nm, where more Chl is required to saturate the absorption, showed greater sensitivity to a wide range of Chl (Wu et al., 2009). This study found that the sensitive regions to the variation in Chl were band combinations of the red edge region at 700–730 and 1150–1300 nm, as well as 1200 and 1250 nm (Figure 3g), which were closely related to water absorption features around 1200 nm. Although linear and exponential relationships between \( \text{CCC}_{\text{canopy}} \) and four VIs using any combinations of two separate wavelengths in the range 400–1300 nm were constructed based on only statistical relationships, from which the possible sensitive spectral features or spectral ranges to the variations of \( \text{CCC}_{\text{canopy}} \) were clearly presented. Certainly, more investigations are necessary to further validate their effectiveness and feasibilities for satellite data at broader spatial scales.

3.4 Validation of the hyperspectral remote estimation of \( \text{CCC}_{\text{canopy}} \)

Crop GPP was strongly related to \( \text{CCC}_{\text{canopy}} \). Chl per unit area to a large extent determined crop productivity, net photosynthesis, and light absorbance (Peng & Gitelson, 2011). Moreover, long- or medium-term changes in \( \text{CCC}_{\text{canopy}} \) were closely related to crop phenology, canopy stresses, and photosynthetic capacity, thus it

**FIGURE 4** Relationships of \( \text{CCC}_{\text{canopy}} \) with the VIs (a) EVI2 [1214, 1259] and (b) EVI2 [726, 1248]. Figures 2 and 3 provide the definitions of acronyms.

**FIGURE 5** Comparisons of the estimated PAR (photosynthetically active radiation) * \( \text{APAR}_{\text{green}} \) (the fraction of absorbed photosynthetically active radiation calibrated by green LAI) * \( \text{CCC}_{\text{canopy}} \) using the VIs and gross primary productivity (GPP) derived from the eddy covariance observations. (a) \( \text{CCC}_{\text{canopy}} \) estimated by NDVI, (b) \( \text{CCC}_{\text{canopy}} \) estimated by REP, (c) \( \text{CCC}_{\text{canopy}} \) estimated by EVI2 [1214, 1259], and (d) \( \text{CCC}_{\text{canopy}} \) estimated by EVI2 [726, 1248]. Figures 2 and 3 provide the definitions of acronyms.
was an important physiological variable that strongly related with productivity at the community level (Gitelson et al., 2005, 2006; Ustin et al., 1998).

Half-hourly midday GPP between 11 and 14 h estimated and measured by an open-path EC, through in combination with the algorithms of fAPAR calibrated by green LAI (fAPAR_{green}) (Zhang et al., 2015) and PAR from meteorological observations were utilized to validate the remote estimation models for the CCC_{canopy}. Studies derived from the same field measurements, including spectral measurements and crop canopy data from fAPAR observations, showed that NDVI was a good predictor of fAPAR_{green} as Equation (9) (Zhang et al., 2015):

\[ fAPAR_{green} = 1.235 \times NDVI - 0.211 (R^2 = .90, P < .001) \]  

Here we established CCC_{canopy} algorithms based on hyperspectral data including NDVI and REP (Figure 2a,b), EVI2 [1214, 1259] and EVI2 [726, 1248] (Figure 4) derived from the optimal band combinations as Equations (10)–(13):

\[ CCC_{canopy} = 0.0067 \times e^{0.6986 \times NDVI} (R^2 = .91, P < .001) \]  

\[ CCC_{canopy} = 6.9002 \times 10^{-5} \times e^{0.1743 \times REP} (R^2 = .97, P < .001) \]  

\[ CCC_{canopy} = 187.97 \times EVI2 [1214, 1259] - 0.98 (R^2 = .92, P < .001) \]  

\[ CCC_{canopy} = 12.33 \times EVI2 [726, 1248] - 1.22 (R^2 = .90, P < .001) \]  

Figure 5 shows that the estimated GPP values driven by LUE principles and the measured GPP derived from EC used to validate were closely related, and satisfactory linear relationships were obtained (R^2 = .58–.95, Figure 5). Among Equations (10)–(13), EVI2 [726, 1248] via Equation (13) was the best algorithm for CCC_{canopy} estimation (R^2 = .95, P < .001, Figure 5d). According to Equation (8), when obtaining the coefficient \( \alpha \) for CCC_{canopy} per unit area, which reflect different radiation use abilities of different monitoring indicators for CCC_{canopy} per gram and per unit area in maize ecosystems, ecosystem GPP in maize could be estimated based on LUE model (Equation 8) and remote sensing data (Equations 9–13). This study further demonstrated that based on LUE principles, a CCC_{canopy} algorithm derived from field spectrometry measurements through in combination with an algorithm of fAPAR_{green} and PAR from meteorological observations could be used to estimate GPP in maize agricultural ecosystems.

4 \| CONCLUSIONS

This study investigated remote estimation of LUE through estimating CCC_{canopy} based on field measurements of spectral reflectance, Chl, LAI, and ecosystem CO₂ fluxes as well as micrometeorological factors conducted during the entire growing season for a maize canopy. Among the common chlorophyll-related VIs, REP and NDVI had better exponential relationships with CCC_{canopy} although there existed a certain saturation effect with increasing CCC_{canopy}; to some degree, EVI, PRI, SR and so on, could overcome the saturation effects, the explained variances of CCC_{canopy} by the linear relationships were still very limited. Thus to select the most sensitive spectral information, when estimating CCC_{canopy} using all of the possible combinations of two separate wavelengths in the range of 400–1300 nm, EVI2 [1214, 1259] and EVI2 [726, 1248] were proved to be the best indicators of CCC_{canopy}. This study demonstrated that hyperspectral remote sensing information could effectively monitor the seasonal variations of CCC_{canopy}. Although more researches are needed to validate the performance of spectral features for estimating CCC_{canopy}, we believe that the selected sensitive indicating spectral information will be attractive for actual applications of satellite data at broader temporal and spatial scales.

This study further demonstrated that based on LUE principles, a CCC_{canopy} algorithm derived from field spectrometry measurements through in combination with an algorithm of fAPAR_{green} and PAR from meteorological observations could be used to monitor midday GPP in maize agricultural ecosystems. We optimized the parameterization of LUE using field spectrometry observation data sets, developed an eco-physiological based LUE model, and it showed a good performance. However, considering limited observations in this study, more studies in the future are still necessary to validate this new conceptual model for monitoring vegetation GPP based on the combination of LUE models with plant physiological properties.

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CONFLICT OF INTEREST

None declared.

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