Integrating chlorophyll fAPAR and nadir photochemical reflectance index from EO-1/Hyperion to predict cornfield daily gross primary production

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Abstract – The concept of light use efficiency (ϵ) and the concept of the fraction of photosynthetically active radiation (PAR) absorbed for vegetation photosynthesis (PSN), i.e., $fAPAR_{PSN}$, have been widely utilized to estimate vegetation gross primary productivity (GPP). It has been demonstrated that the photochemical reflectance index (PRI) is empirically related to ϵ . An experimental US Department of Agriculture (USDA) cornfield in Maryland was selected as our study field. We explored the potential of integrating $fAPAR_{chl}$ (defined as the fraction of PAR absorbed by chlorophyll) and nadir PRI (PRI_{nadir}) to predict cornfield daily GPP. We acquired nadir or near-nadir EO-1/Hyperion satellite images that covered the cornfield and took nadir *in-situ* field spectral measurements. Those data were used to derive the PRI_{nadir} and $fAPAR_{chl}$. The $fAPAR_{chl}$ is retrieved with the advanced radiative transfer model PROSAIL2 and the Metropolis approach, a type of Markov Chain Monte Carlo (MCMC) estimation procedure. We define chlorophyll light use efficiency (ϵ_{chl}) as the ratio of vegetation GPP as measured by eddy covariance techniques to PAR absorbed by chlorophyll ($\epsilon_{chl} = GPP/APAR_{chl}$). Daily ϵ_{chl} retrieved with the EO-1 Hyperion images was regressed with a linear equation of PRI_{nadir} ($\epsilon_{chl} = \alpha \times PRI_{nadir} + \beta$). The satellite ϵ_{chl} - PRI_{nadir} linear relationship for the cornfield was implemented to develop an integrated daily GPP model [$GPP = (\alpha \times PRI_{nadir} + \beta) \times fAPAR_{chl} \times PAR$], which was evaluated with $fAPAR_{chl}$ and PRI_{nadir} retrieved from field measurements. Daily GPP estimated with this $fAPAR_{chl}$ - PRI_{nadir} integration model was strongly correlated with the observed tower *in-situ* daily GPP ($R^2 = 0.93$); with a root mean square error (RMSE) of $1.71 \text{ g C mol}^{-1} \text{ PPFD}$ and coefficient of variation (CV) of 16.57%. Both seasonal ϵ_{chl} and PRI_{nadir} were strongly correlated with $fAPAR_{chl}$ retrieved from field measurements, which indicates that chlorophyll content

strongly affects seasonal ϵ_{chl} and PRI_{nadir} . We demonstrate the potential capacity to monitor GPP with space-based visible through shortwave infrared (VSWIR) imaging spectrometers such as NASA's soon to be decommissioned EO-1/Hyperion and the future Hyperspectral Infrared Imager (HyspIRI).

Keywords – Daily GPP, $fAPAR_{chl}$, chlorophyll, PRI, cornfield, EO-1/Hyperion, HyspIRI

1. INTRODUCTION

From the perspective of plant biochemistry, canopy photosynthesis is a pigment level process, primarily associated with chlorophylls, which is initiated in the chloroplasts of leaf mesophyll cells to absorb radiation for the photochemical process. Nitrogen content is a necessary component in vegetation photosynthesis and plant growth, and drives the canopy carbon balance (Aber et al. 1996; Gillon et al. 1999; Green et al. 2003; Kergoat et al. 2008). Leaf chlorophyll molecules require incorporation of nitrogen (e.g., Evans 1989; Houborg et al. 2015; Pierce et al. 1994; Sage et al. 1987; Serbin et al. 2011; Smith et al. 2002) and canopy chlorophyll content is strongly related to canopy nitrogen content (Baret and Fourty 1997). The ability to quantify chlorophyll and nitrogen as important drivers of photosynthesis using remote sensing data would enhance our capability to study carbon cycles and climate change (Croft et al. 2015; Gitelson et al. 2006; Houborg et al. 2013; Moorthy et al. 2008; Ollinger 2011; Richardson et al. 2002; Zhang et al. 2005).

Employing the concept of light use efficiency (ϵ) and the concept of the fraction of photosynthetically active radiation (PAR) absorbed for vegetation photosynthesis (PSN), i.e., $fAPAR_{PSN}$, to estimate vegetation gross primary productivity (GPP) was proposed more than four decades ago by Monteith (1972):

$$GPP = \epsilon \times APAR_{PSN} \quad (1)$$

where $APAR_{PSN} = PAR \times fAPAR_{PSN}$ and ϵ is a measure of $APAR_{PSN}$ conversion efficiency into photosynthetically fixed CO_2 . Vegetation light use efficiency depends on vegetation types and is affected by environmental factors, such as nutrient supplies (e.g., nitrogen and phosphorus), temperature, water, canopy growth stage, and leaf phenology or age (Field et al. 1995; Goetz and Prince 1999; Malmstrom et al. 1997; Potter et al. 1993; Raich et al. 1991; Running et al. 2004). Empirically, scientists have estimated ϵ directly with the photochemical reflectance index (PRI) or variations of the PRI (e.g., Drolet et al. 2005; Gamon et al. 1997; Hall et al. 2011; Hilker et al. 2010; Merlier et al. 2015; Middleton, Cheng, Hilker et al. 2009; Nichol et al. 2000); with climate data alone or with combination of climate data and remote sensing information (e.g., Dong et al. 2015; Potter et al. 1993; Prince and Goward 1996; Running et al. 2004; Sellers et al. 1996; Wu et al. 2012; Wu et al. 2015; Xiao et al. 2004; Yebra et al. 2015). The PRI has been proposed to detect the relative down regulation of photosynthesis (Gamon et al. 1997; Nichol et al. 2000; Middleton, Cheng, Hilker et al. 2009), which is a normalized difference reflectance index that uses two narrow bands: an essential physiologically active band centered at 531 nm coupled with a reference band (e.g., 570 nm) with the formula:

$$PRI = \frac{\rho_{531} - \rho_{570}}{\rho_{531} + \rho_{570}} \quad (2)$$

where ρ_{531} and ρ_{570} are surface reflectance values at spectral wavelength 531 nm and 570 nm.

Most remote sensing of GPP is currently based on the ε concept coupled with a satellite product that estimates the fraction of PAR absorbed by a canopy ($fAPAR_{canopy}$), such as MOD15A2 FPAR derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) images (Myneni et al. 2002) and/or $fAPAR_{canopy}$ retrieved from the Advanced Very High Resolution Radiometer (AVHRR) images (Sellers et al. 1996). These $fAPAR_{canopy}$ products are either associated with spectral vegetation indices or retrieved through radiative transfer models (Myneni et al. 1997; Myneni and Williams 1994). This modeling approach assumes that $fAPAR_{PSN} = fAPAR_{canopy}$ (Myneni et al. 2002; Running et al. 2000; Sellers 1987; Zhao and Running 2010). The GPP models that are based on this assumption ($fAPAR_{PSN} = fAPAR_{canopy}$; e.g., SiB2, Sellers et al. 1996) operationally define ε as ε_{canopy} , i.e., the ratio of GPP to $APAR_{canopy}$:

$$\varepsilon_{canopy} = GPP/APAR_{canopy}, \quad (3)$$

where $APAR_{canopy} = fAPAR_{canopy} \times PAR$. However, part of $fAPAR_{canopy}$ is associated with non-chlorophyll containing components of the canopy, thus comprising a non-photosynthetic fraction. GPP is only directly tied to the PAR absorbed by photosynthetic pigments (chlorophyll) of the canopy ($APAR_{chl}$). $APAR_{chl}$ is the product of $fAPAR_{chl}$ and PAR, and $fAPAR_{chl}$ is fraction of PAR absorbed by chlorophyll of the canopy. The

GPP models that assume $fAPAR_{PSN}=fAPAR_{chl}$ operationally define ϵ as ϵ_{chl} , i.e., the ratio of GPP to $APAR_{chl}$:

$$\epsilon_{chl} = GPP / APAR_{chl} \quad (4)$$

The $fAPAR_{chl} - \epsilon_{chl}$ definitions are more consistent with the process of vegetation photosynthesis than the $fAPAR_{canopy} - \epsilon_{canopy}$ definitions (Zhang et al., 2009; Zhang et al., 2014).

When environmentally stressful conditions dominate, the photosynthesis process is usually limited by factors such as nutrient availability, water supply and temperature, so excess $APAR_{chl}$ must be discarded to protect the photosystems. This is accomplished through two key energy pathways that dissipate energy as either heat from non-photochemical quenching (NPQ) generated through chemical reactions in the xanthophyll pigment cycle or as chlorophyll fluorescence. NPQ is typically a process via xanthophyll pigment cycling within plant cells under stress that creates increased acidity in leaf chloroplasts (Baker 2008). However, it is challenging to quantify plant stress and/or NPQ with currently available satellite products.

It has been demonstrated that PRI is empirically related to ϵ (Gamon et al. 1997; Gamon et al. 2015; Gamon et al. 1992; Hilker et al. 2008; Mänd et al. 2010; Peñuelas et al. 2011; Soudani et al. 2014; Suárez et al. 2009; Wu et al. 2014). For a given canopy at a given moment, the directly sunlit foliage is more likely to have lower PRI values than shaded foliage (Cheng et al. 2012; Hall et al. 2008; Hilker et al. 2008; Middleton, Cheng, Hilker et al. 2009). Previous studies have investigated the applications of the PRI as proxy for ϵ_{canopy} and ϵ at foliage and leaf levels (Gamon et al. 1990; Gamon et al. 2015;

Gamon et al. 1992; Garbulsky et al. 2011; Hall et al. 2011; Hilker et al. 2010; Merlier et al. 2015; Middleton, Cheng, Hilker et al. 2009; Peñuelas et al. 2011). PRI may vary with environmental conditions, illumination and viewing geometry, and background (Magney et al., 2016; Zhang, Ju, et al., 2015; Gamon and Bond, 2013), and the remote sensing-based ϵ_{canopy} :PRI relationship has been reported to be linear or non-linear depending on the influence of various factors including canopy structure, leaf area index (LAI), chlorophyll content, growth stage and the sunlit/shaded canopy ratio (Barton and North 2001; Cheng et al. 2012; Drolet et al. 2008; Garbulsky et al. 2008; Hall et al. 2011; Hall et al. 2008; Hilker et al. 2008; Nichol and Grace 2010; Sims et al. 2006). Middleton, Cheng, Hilker et al. (2009) used an extinction coefficient for canopy APAR transmittance with the Normalized Difference Vegetation Index (NDVI) to estimate $f\text{APAR}_{\text{foliage}}$ and reported a general linear $\epsilon_{\text{foliage}}$:PRI relationship for three foliage groups (sunlit, sublit-shaded, and shaded) at the Canadian Douglas-fir forest DF49 using directional measurements acquired from the flux tower. Field experiments have provided seasonal nadir PRI ($\text{PRI}_{\text{nadir}}$) behaviors (Middleton et al. 2010). However, there is no study explicitly exploring seasonal ϵ_{chl} :PRI relationship at canopy level in the literature.

Our study for the first time utilizes nadir or near-nadir PRI ($\text{PRI}_{\text{nadir}}$) to estimate ϵ_{chl} . The two-fold objectives of this study are: (1) to develop an $f\text{APAR}_{\text{chl}}$ - $\text{PRI}_{\text{nadir}}$ integration GPP model: $\text{GPP} = \epsilon_{\text{chl}} \times f\text{APAR}_{\text{chl}} \times \text{PAR}$ for a cornfield, where $\epsilon_{\text{chl}} = \alpha * \text{PRI}_{\text{nadir}} + \beta$ derived from EO-1/Hyperion imagery, α and β are slope and intercept; and (2) to evaluate the $f\text{APAR}_{\text{chl}}$ - $\text{PRI}_{\text{nadir}}$ integration GPP model with *in-situ* measurements acquired in a USDA research cornfield. In addition, we will discuss how seasonal $\text{PRI}_{\text{nadir}}$ and ϵ_{chl} vary with $f\text{APAR}_{\text{chl}}$ using field measurements.

2. METHODOLOGY

A. Field methods

Croplands are managed agro-ecosystems containing vegetation that have been bred/genetically altered to maximize productivity and yield, making them convenient systems to investigate retrievals of photosynthetic parameters with remote sensing approaches. In this study, we chose the 21 ha experimental USDA-ARS watershed (39.030° N, 76.845° W) at the Beltsville Agricultural Research Center, Beltsville, Maryland, referred to as the Optimizing Production inputs for Economic and Environmental Enhancement (OPE3) (Houborg and Anderson 2009; Scanlon and Kustas 2010) (for further details see <http://hydrolab.arsusda.gov/oep3/>). This site is surrounded by forest (Fig. 1) and is close to the NASA/Goddard Space Flight Center (GSFC). Corn (*Zea mays* L.) was planted on Day of Year (DOY) 178 (June 28) in 2008, and reached maturity by late August and senescence in late September.

Fig. 1 The location of the USDA-ARS OPE3 experimental watershed in Beltsville of Maryland where the field campaign was conducted.

In order to evaluate the $fAPAR_{chl}$ - PRI_{nadir} integration GPP model developed with the Hyperion images (see section 2.C), we made nadir hyperspectral visible through shortwave infrared (VSWIR) measurements in the field with an 18-degree field of view (FOV). Canopy measurements under clear sky conditions began one month after planting (DOY 207), and were acquired from a pole-mount using a FieldSpec VSWIR Spectroradiometer (ASD Inc., Boulder, CO, USA) along a representative 100-m north-south direction transect of the field (Fig. 1). Canopy reflectance field measurements were taken on twelve dates, about one day a week during the course of the 2008 growing season throughout the summer and early fall (Tab. 1).

Table 1 A list of the dates when the EO-1 Hyperion images (H) covering the OPE3 field were acquired in 2008 and the dates when the field measurements (M) were made at the field. Vn stands for the vegetative stage with the n^{th} leaf fully expanded, VT stands for the tasselling stage, and Rn stands for the n^{th} reproductive stage (R1 – Silking, R2 – Blister, R3 – Milk, R4 – Dough, R5 – Dent, and R6 – physiological maturity).

Date (Day of Year)	Hyperion (H) or field Measurement (M)	Season/ Growth Stage
6/20 (172)	H	Late Spring/Early Summer
7/8 (190)	H	Summer
7/13(195)	H	Summer
7/25 (207)	M	Summer/V8
8/2 (215)	M	Summer/V10

8/8 (221)	M	Summer/V13
8/12 (225)	M	Summer/VT
8/18 (231)	H	Summer
8/19 (232)	M	Summer/R1
8/26 (239)	M	Summer/R2
9/2 (246)	M	Late Summer/R3
9/9 (253)	M	Late Summer/R4
9/19 (263)	M	Late Summer/R5
9/25 (269)	M	Early Fall/R5
10/02 (276)	M	Fall/R6
10/3 (277)	H	Fall/R6
10/07 (281)	M	Fall/R6

Micrometeorological tower measurements of sensible, latent and carbon exchange using the eddy covariance technique at the OPE3 field were used in an approach developed by Cook et al. (2004) to estimate daytime ecosystem respiration (ER). Daily GPP was computed by subtracting ER from net ecosystem exchange (NEE) measured at the flux tower site, i.e., $GPP = NEE - ER$ (Cook et al. 2004; Twine et al. 2000).

B. EO-1/Hyperion images: acquisition, atmospheric correction and computation of PRI_{nadir} and fAPAR variables

The EO-1 satellite mission has been a technology demonstration mission since early 2001 to collect VSWIR spectral data over a wide variety of study sites in response to user/system requests. The EO-1/Hyperion (one of two onboard instruments) is the only civilian space-borne spectrometer for Earth observations and views 7.5 km wide ground

swaths at 30 m spatial resolution. The Hyperion VSWIR spectrometer has a nominal spectral resolution of 10 nm and covers the spectral range of the MODIS bands 1-7. We acquired EO-1/Hyperion VSWIR spectrometer images that covered the site. Five nadir or near-nadir cloud free EO-1 Hyperion images of the OPE3 field were acquired during the growing season, from just before the planting of corn through the course of the growing/senescence season (Tab. 1). Spatial moment matching was used to destripe the five Hyperion Level One radiometrically corrected radiance (L1R) images (Sun et al. 2008), and the L1R images were atmospherically corrected using the Atmosphere Removal Algorithm (ATREM) (Gao and Davis 1997; Gao et al. 1993). In ATREM, the scattering effect due to atmospheric molecules and aerosols was determined with the 6S computer code (Vermote et al. 1997). The atmospherically corrected Hyperion 30 m surface reflectance images and the field measured canopy surface reflectance spectra were utilized to compute the PRI. The atmospherically corrected Hyperion surface reflectance, as well as the field measured canopy surface reflectance data, were utilized to derive the broader spectrally MODIS-like bands used for the $fAPAR_{chl}$ and related parameters, by convolving the 10 nm Hyperion bands or the 3 nm ASD Spectroradiometer bands, using the spectral response functions (Barry et al. 2002) for the MODIS bands (Zhang et al. 2013).

The synthesized spectrally MODIS-like data from Hyperion and from field measurements (Tab. 1) were used for computation of the fraction of PAR absorbed by foliage ($fAPAR_{foliage}$), $fAPAR_{chl}$ and the fraction of PAR absorbed by foliage non-chlorophyll components ($fAPAR_{non-chl}$) with the algorithm developed for these retrievals using the MODIS bands (Zhang et al. 2013). Each directional surface reflectance

observation $[\rho_{obs}]$ always contains some noise, and is associated with a specific view zenith angle $[\theta_v, \text{ in degrees}]$, relative view azimuth angle $[\phi, \text{ in degrees}]$, and solar zenith angle $[\theta_s, \text{ in degrees}]$. Therefore, we treated each reflectance observation as a sample of the following distribution:

$$\rho \sim \{\rho_{obs}(\lambda, \theta_v(1 + 3N(0,1)), \theta_s(1 + 3N(0,1)), \phi(1 + 3N(0,1)))\} \cdot (1 + 0.05N(0,1)) \quad (5)$$

where $N(0,1)$ was the normal distribution with a mean of zero and $SD = 1$. We used multiple samples from this distribution (Eq. 5) for the sequential computations for canopy components. Using the previously published algorithms (Zhang et al., 2013), we initially partitioned the canopy into foliage and non-foliage (referred to as **stem**) components, and then further partitioned the foliage component into chlorophyll (chl) and non-chlorophyll (non-chl) components; the non-chl component is composed of non-photosynthetic pigments (referred to as **brown** pigment) and leaf dry matter. The fAPAR values for the foliage non-chlorophyll sector ($fAPAR_{non-chl}$) and for total foliage ($fAPAR_{foliage}$) were computed as:

$$fAPAR_{foliage} = fAPAR_{chl} + fAPAR_{non-chl} \quad (6)$$

$$fAPAR_{non-chl} = fAPAR_{brown_pigment} + fAPAR_{dry_matter} \quad (7)$$

A modified version of the canopy-level radiative transfer model, SAIL (Verhoef 1984, 1985; Verhoef 1998), referred to as SAIL2 (Braswell et al. 1996), was coupled with an improved version of the leaf-level radiative transfer model, PROSPECT (Baret and Fourty 1997; Jacquemoud and Baret 1990), to produce the coupled PROSAIL2 model (Zhang et al. 2013; Zhang et al. 2012; Zhang et al. 2009; Zhang et al. 2006; Zhang et al.

2005) for this study [see Appendix for the list of model parameters]. We employed the Metropolis algorithm (Metropolis et al. 1953), a type of Markov Chain Monte Carlo (MCMC) estimation procedure (Gelman et al. 2000), to invert the PROSAIL2 model and compute these parameters: $fAPAR_{\text{foliage}}$, $fAPAR_{\text{chl}}$, $fAPAR_{\text{non-chl}}$, $fAPAR_{\text{non-chl}}/fAPAR_{\text{foliage}}$ and $fAPAR_{\text{non-chl}}/fAPAR_{\text{chl}}$ [see Appendix].

C. Developing the $\epsilon_{\text{chl}}\text{-}PRI_{\text{nadir}}$ function from EO-1/Hyperion satellite images

Daily GPP and daily PAR from the OPE3 tower measurements were combined with the $fAPAR_{\text{chl}}$ for the OPE3 cornfield retrieved from EO-1/Hyperion images on the same dates to compute daily ϵ_{chl} (see Eq. 3) on those days. We found that daily ϵ_{chl} and PRI_{nadir} from the Hyperion images were linearly correlated, the $\epsilon_{\text{chl}}\text{-}PRI_{\text{nadir}}$ function was expressed as: $\epsilon_{\text{chl}} = \alpha \times PRI + \beta$. Then GPP can be predicted:

$$GPP = (\alpha \times PRI_{\text{nadir}} + \beta) \times fAPAR_{\text{chl}} \times PAR \quad (8)$$

D. Evaluation of the GPP model based on $fAPAR_{\text{chl}}\text{-}PRI_{\text{nadir}}$ integration

The EO-1/Hyperion satellite $fAPAR_{\text{chl}}\text{-}PRI_{\text{nadir}}$ integration GPP model (Eq. 8) was evaluated with $fAPAR_{\text{chl}}$ and PRI_{nadir} retrieved from repetitive field nadir canopy reflectance measurements. The field measured canopy surface reflectance spectra were employed to compute $fAPAR_{\text{chl}}$ and related parameters in the same fashion as for the Hyperion images. The $fAPAR_{\text{chl}}$ and PRI_{nadir} from field measurements were implemented to predict daily GPP with Eq. 8, which were compared to daily tower flux GPP (see second paragraph of

section 2.A). We computed standard statistics, including the coefficient of determination R^2 between tower flux GPP and predicted GPP, the root mean square error (RMSE), and the coefficient of variation (CV).

3. RESULTS

A. Seasonal courses of climate conditions and GPP

Climate conditions influence vegetation GPP. The average daily temperatures increased from June (23.2°C) to July (24.4°C), then decreased in August (21.8°C) and September (20.1°C) in 2008, and total precipitation in those months was 116, 107, 25, and 106 mm, respectively (Fig. 2). The crop (corn) was planted later in 2008 than usual due to a wet springtime. The average daily PAR gradually decreased from June to September (44, 39, 36, and 27 mol m⁻² d⁻¹ in each month) and average daily GPP for June, July, August and September was 2.17, 7.96, 15.15 and 7.55 g C m⁻² d⁻¹, respectively (Fig. 3). Average daily GPP reached its summer peak in August.

Fig. 2 The daily precipitation (mm) and temperature (°C) during day of year (DOY) 170 – 300 of 2008 at the USDA-ARS OPE3 experimental watershed in Beltsville, MD.

Fig. 3 The daily ecosystem gross primary production (GPP) and PAR during DOY 170 – 300 of 2008 at the USDA-ARS OPE3 experimental watershed in Beltsville, MD.

B. Maps of fAPAR variables and $\text{PRI}_{\text{nadir}}$ from Hyperion images

Figure 4 shows maps of $fAPAR_{\text{foliage}}$, $fAPAR_{\text{chl}}$, $fAPAR_{\text{non-chl}}$, $fAPAR_{\text{non-chl}}/fAPAR_{\text{foliage}}$, $fAPAR_{\text{non-chl}}/fAPAR_{\text{chl}}$, and PRI_{nadir} at the spatial resolution of 30 m derived from Hyperion images on DOY 172, 190, 195, 231 and 277 of 2008. The maps illustrated in Figure 4 (a) – (c) reveal significant differences in the three $fAPAR$ values ($fAPAR_{\text{foliage}}$, $fAPAR_{\text{chl}}$ and $fAPAR_{\text{non-chl}}$). The contrast in the magnitude and phenology is obvious between the managed OPE3 agricultural site and the surrounding deciduous forest, a natural ecosystem, with distinctly different $fAPAR_{\text{foliage}}$, $fAPAR_{\text{chl}}$ and $fAPAR_{\text{non-chl}}$ seasonality. Before corn was planted, values for both $fAPAR_{\text{chl}}$ and $fAPAR_{\text{non-chl}}$ of the cornfield were low, while those for the forest were already high in mid/late June (on DOY 172), and remained high through the summer (DOYs 190, 195; Fig. 4 (a)-(c)). Cornfield $fAPAR_{\text{chl}}$ on DOY 231 was the highest of all acquisition dates and was higher than that for the forest. The cornfield $fAPAR_{\text{non-chl}}$ was lower than forest $fAPAR_{\text{non-chl}}$ in spring and summer, but increased in fall when senescence occurred. The ratios $fAPAR_{\text{non-chl}}/fAPAR_{\text{foliage}}$ and $fAPAR_{\text{non-chl}}/fAPAR_{\text{chl}}$ of the cornfield were also lower than the comparable ratios for the forest before senescence. The forest $fAPAR_{\text{foliage}}$ did not change during summer (Fig. 4(a)). However, over this time period (DOY 172 – 277), the forest $fAPAR_{\text{chl}}$, $fAPAR_{\text{non-chl}}$, $fAPAR_{\text{non-chl}}/fAPAR_{\text{foliage}}$ and $fAPAR_{\text{non-chl}}/fAPAR_{\text{chl}}$ varied with leaf age (Fig. 4). Forest $fAPAR_{\text{chl}}$ decreased from late spring/early summer (DOY 172) to summer, and retained stable values during summer (Fig. 4 (b)). Forest $fAPAR_{\text{non-chl}}$ increased from late spring/early summer to summer, before decreasing in early fall (Fig. 4 (c)), producing seasonally higher summer ratios for $fAPAR_{\text{non-chl}}/fAPAR_{\text{foliage}}$ and $fAPAR_{\text{non-chl}}/fAPAR_{\text{chl}}$ (Fig. 4 (d) – (e)). Figure 4 (f) expresses how PRI_{nadir} changed over the seasons and with plant functional types. Values

for PRI_{nadir} of the cornfield in the summer (DOYs 190, 195) were lower than those of the forest. Cornfield PRI_{nadir} on DOY 231 was similar as the forest. When senescence occurred, values for PRI_{nadir} of both the cornfield and the forest decreased. It may be due to decrease of green leaf area index/canopy chlorophyll content, and/or increasing photosynthetic stress.

Fig. 4 (a) the foliage fAPAR ($fAPAR_{foliage}$); (b) the chlorophyll fAPAR ($fAPAR_{chl}$); (c) the foliage non-chlorophyll fAPAR ($fAPAR_{non-chl}$); (d) the ratio of $fAPAR_{non-chl}$: $fAPAR_{foliage}$; (e) the ratio of $fAPAR_{non-chl}$: $fAPAR_{chl}$; and (f) PRI_{nadir} derived from Hyperion images acquired on DOYs 172, 190, 195, 231 and 277 of 2008 for the USDA-ARS OPE3 experimental watershed in Beltsville, MD.

C. The ϵ_{chl} – PRI_{nadir} function developed with EO-1/Hyperion images

Tower daily PAR, tower daily GPP and the $fAPAR_{chl}$ from EO-1 Hyperion images were utilized to compute ϵ_{chl} with Eq. 3. Daily ϵ_{chl} ranged from 0.23 to 0.68 g C mol⁻¹ PPFD and cornfield PRI_{nadir} retrieved from the Hyperion images ranged from -0.037 to -0.108 (Fig. 5). The satellite PRI_{nadir} of the cornfield and the retrieved ϵ_{chl} were deployed to find the coefficients α and β with the least squares best fit algorithm: $\epsilon_{chl} = \alpha \times PRI_{nadir} + \beta$. The slope α was 6.31 (g C mol⁻¹ PPFD) and the intercept β was 0.91 (g C mol⁻¹ PPFD). Therefore the $fAPAR_{chl}$ - PRI_{nadir} integration GPP model (Eq. 8) developed with the EO-1 Hyperion data is: $GPP = (6.31 \times PRI_{nadir} + 0.91) \times fAPAR_{chl} \times PAR$.

D. Evaluation of the $fAPAR_{chl}$ - PRI_{nadir} integration GPP model

Repetitive nadir field measured spectral observations under clear skies were utilized to retrieve $fAPAR_{chl}$ and PRI_{nadir} . Seasonal variations in $fAPAR_{chl}$ and PRI_{nadir} over the experimental cornfield are shown in Fig. 5. The $fAPAR_{chl}$ values retrieved from field measurements ranged from 0.37 on Oct. 6 (DOY 281) to 0.74 on Aug. 1 (DOY 215) and PRI_{nadir} values ranged from -0.092 on Oct. 6 to -0.039 on Aug. 11 (DOY 225).

Values for both $fAPAR_{chl}$ and PRI_{nadir} of the cornfield reached peak values in August. The $fAPAR_{chl}$ and PRI_{nadir} retrieved from field measurements were employed to evaluate the $fAPAR_{chl}$ - PRI_{nadir} integration GPP model developed in Section 3.C [$GPP = (6.31 \times PRI_{nadir} + 0.91) \times fAPAR_{chl} \times PAR$]. When these field values for $fAPAR_{chl}$ and PRI_{nadir} , along with the tower daily PAR values were implemented into the GPP model, a comparison of the predicted daily GPP with the observed tower flux GPP was made (Fig. 6). This combination of canopy-level PRI_{nadir} and $fAPAR_{chl}$ produced a satisfying correlation to tower *in-situ* daily GPP ($R^2 = 0.93$), achieving a RMSE of $1.71 \text{ g C mol}^{-1} \text{ PPFD}$ and a CV of 16.57%.

Fig. 5 $fAPAR_{chl}$ and PRI_{nadir} retrieved with field measurements of nadir surface reflectance and the Hyperion images in 2008 at the USDA-ARS OPE3 experimental watershed in Beltsville, MD.

Fig. 6 Comparison between tower flux GPP and the GPP estimated with the $fAPAR_{chl}$ – PRI_{nadir} integration GPP model [$GPP = (6.31 \times PRI_{nadir} + 0.91) \times fAPAR_{chl} \times PAR$] from field measurements and the Hyperion images for the USDA-ARS OPE3 experimental watershed.

4. DISCUSSIONS

Both canopy level non-photosynthetic vegetation components (NPV) and leaf level NPV contribute to $fAPAR_{canopy}$ (Asner et al. 1998; Gamon et al. 1995; Hanan et al. 2002; Hanan et al. 1998; Hilker et al. 2010; Zhang et al. 2013), in accordance with this study (Fig. 4). Partition of $fAPAR_{foliage}$ into $fAPAR_{chl}$ and $fAPAR_{non-chl}$ is essential. The PAR absorbed by chlorophyll throughout the canopy ($APAR_{chl} = fAPAR_{chl} \times PAR$) is potentially available to power vegetation photosynthesis, for which the indispensable

parameter is $fAPAR_{chl}$. Studies show that canopy chlorophyll content in deciduous broadleaf forests, evergreen needle leaf forests and crops varies seasonally, which contributes to the seasonality of plant GPP (Croft et al. 2015; Hmimina et al. 2015; Houborg et al. 2015; Merlier et al. 2015; Peng et al. 2011). To obtain $APAR_{chl}$, the traditionally used $fAPAR_{canopy}$ must be partitioned into the various components described. We found that NDVI calibrated with $fAPAR_{chl}$, also referred to as scaled NDVI, can improve performance of GPP estimation over original un-calibrated NDVI (Zhang, Cheng et al. 2015). Our current study and other studies support the use of $fAPAR_{chl}$ in place of $fAPAR_{canopy}$ in plant GPP modeling activities (Cheng et al. 2014; Croft et al. 2015; Zhang et al. 2014; Zhang et al. 2009; Flanagan et al. 2015).

Fig. 7 Relationship between PRI_{nadir} and $fAPAR_{chl}$. Data are derived from field measurements for the USDA-ARS OPE3 experimental watershed.

Fig. 8 Relationship between ϵ_{chl} and PRI_{nadir} . Data are derived from field measurements for the USDA-ARS OPE3 experimental watershed. The inset shows seasonal behavior of both ϵ_{chl} and PRI_{nadir} .

Fig. 9 Comparison between tower flux GPP and the GPP estimated with the model GPP

$$= (0.87 \times fAPAR_{chl} - 0.01) \times fAPAR_{chl} \times PAR \text{ from field measurements and the Hyperion images for the USDA-ARS OPE3 experimental watershed.}$$

Green band reflectance values vary with leaf chlorophyll content (Gitelson et al. 1996) and chlorophyll content has a strong impact on PRI responses (Gamon and Berry 2012; Hmimina et al. 2015; Merlier et al. 2015). There is a close relationship between $fAPAR_{chl}$ and PRI_{nadir} of this field (Fig. 7, $PRI_{nadir} = 0.10 \times fAPAR_{chl} - 0.12$, $R^2 = 0.69$), which hints that seasonal PRI_{nadir} might be a proxy of seasonal green leaf area index/canopy chlorophyll content. Seasonal chlorophyll content might also drive seasonal ϵ_{chl} since ϵ_{chl} is also linearly correlated with $fAPAR_{chl}$ ($\epsilon_{chl} = 0.87 \times fAPAR_{chl} - 0.01$, $R^2 = 0.78$, figure not shown). Because both PRI_{nadir} and ϵ_{chl} are correlated with $fAPAR_{chl}$, there is a close relationship between PRI_{nadir} and ϵ_{chl} (Fig. 8, $\epsilon_{chl} = 6.62 \times PRI_{nadir} + 0.90$, $R^2 = 0.69$). The close relationship between PRI_{nadir} and $fAPAR_{chl}$ hints that slowing changing “constitutive” components affect seasonal PRI (Gamon and Berry, 2012). When GPP is estimated with the model $GPP = (0.87 \times fAPAR_{chl} - 0.01) \times fAPAR_{chl} \times PAR$ (Fig. 9), the predicted GPP values agree well with tower flux GPP. Chlorophyll fluorescence is the second pathway for transformation of excess $APAR_{chl}$. Our additional, related field experiments and lab exercises find that both fluorescence and PRI_{nadir} can capture physiological stress by corn canopies (Middleton et al. 2010; Middleton, Cheng, Corp et al. 2009). Canopy fluorescence for the full emission spectrum can be potentially mapped at a useful 300 m scale with the Fluorescence Explorer (FLEX) mission

(http://esamultimedia.esa.int/docs/EarthObservation/SP1330-2_FLEX.pdf), selected for Phase-A development in Nov. 2015 and expected to be in space by 2022.

Both the Hyperion imager on EO-1 and the ASD Fieldspec Spectroradiometer are not suitable for fluorescence retrieval. Further well-conceived, comprehensive experiments and analysis are required to understand how $APAR_{chl}$ is partitioned for photosynthesis, NPQ and fluorescence. We believe this understanding will require near-surface airborne and drone-based spectrometer research, incorporating instrument/sensor fusion (e.g., Cook et al. 2013; Corp et al. 2010; Hmimina et al. 2014; Zarco-Tejada et al. 2012) to simultaneously measure $fAPAR_{chl}$, PRI and fluorescence over identical areas (e.g., selected tower flux areas in North America).

Such a study using satellites requires hyperspectral VSWIR imagery at a high enough spatial resolution (≤ 30 m) for use over agriculture. Currently, this is only possible with the Earth Observing One (EO-1)/Hyperion imaging spectrometer, but its image collection capacity is limited, and after more than fifteen years EO-1 is planned for decommissioning at the end of 2016. There is no immediate plan for a NASA spaceborne spectrometer replacement for Hyperion that will enable us to utilize the approach we describe herein at ~ 30 m. However, the German EnMAP satellite (<http://www.enmap.org/>) will have a VSWIR imaging spectrometer with ~ 25 m spatial resolution and ~ 5 nm spectral resolution, and is planned for launch in 2018. EnMAP will have global biweekly coverage but will concentrate on European targets. Another satellite mission sponsored by the European Space Agency (ESA) is expected for launch in 2022, a tandem mission that couples the separate Fluorescence Explorer (FLEX) and Sentinel-3 platforms, from which hyperspectral bands will allow retrieval of PRI_{nadir} at

300 m spatial resolution. The next NASA VSWIR spectrometer which is under pre-Phase A development is the Hyperspectral Infrared Imager (HyspIRI), with 5-10 nm spectral resolution and 30-60 m spatial resolution, biweekly. The other existing NASA satellite sensors that can be used to retrieve PRI_{nadir} and $fAPAR_{chl}$ are the MODIS instruments on Terra and Aqua, but the 531 band is a coarse (1 km) spatial resolution band (Drolet et al., 2005; Zhang et al., 2014).

5. CONCLUSIONS

In this paper, EO-1/Hyperion hyperspectral images enabled us to develop a spectrally based daily $fAPAR_{chl}$ - PRI_{nadir} integration GPP model that could be routinely implemented from space. We developed and evaluated this GPP retrieval approach for a USDA experimental cornfield. This GPP model integrates these two spectral vegetation parameters related to photosynthetic function: PRI_{nadir} and $fAPAR_{chl}$. Field measurements manifest that both seasonal PRI_{nadir} and ϵ_{chl} are highly correlated with $fAPAR_{chl}$. We also show that foliage $fAPAR_{non-chl}$ and the ratios $fAPAR_{non-chl}/fAPAR_{foliage}$ and $fAPAR_{non-chl}/fAPAR_{chl}$ are useful for vegetation phenology studies. They quantitatively provide the allocation of APAR within the photosynthetic versus non-photosynthetic sections in foliage, which vary with plant functional types and over seasons.

We demonstrated that incorporating either PRI_{nadir} or $fAPAR_{chl}$ to provide ϵ_{chl} , may significantly decrease uncertainty and improve the accuracy of daily GPP estimates, via an ϵ model. We are aware that $fAPAR_{chl}$ has clear physiological meaning and is

derived with physical models while PRI is an empirical index, analogous to NDVI. We will investigate whether seasonal ϵ_{chl} is strongly correlated with $fAPAR_{chl}$ for other plant functional types in future. If so, we may develop a GPP model with only $fAPAR_{chl}$ and PAR. We also show that ϵ_{chl} derived from EO-1/Hyperion (or similar) hyperspectral images provides finer spatial variations than meteorology data that have coarser spatial resolution including temperature and vapor pressure deficit from reanalyses (Zhao et al., 2010). We note that although we convolved Hyperion bands to match seven MODIS VSWIR land bands to obtain $fAPAR_{chl}$, the standard PRI (using wavelengths centered at 530 and 570 nm) cannot be computed with MODIS observations. Instead, a variation of PRI using a coarse 1 km ocean green band (530 nm) and a replacement reference band is used (Drolet et al., 2008), which limits use of MODIS PRI for agriculture at site scale. Future research will need to verify this daily GPP model at the stand and satellite levels across a large number of sites and plant functional types.

It is critically needed to design and develop instruments capable of measuring $fAPAR_{chl}$, PRI, and fluorescence at scales from sites, to regions, and to the globe. Another measurement needed for GPP estimation is PAR, which is readily available from other satellite data products. Science-oriented field experiments, airborne campaigns and satellite missions are needed to improve the understanding of ecosystem carbon cycles. We support the HypsIRI mission's measurement concept (Lee et al. 2015), which would allow us to simultaneously measure $fAPAR_{chl}$, PRI and surface temperature for regional/global GPP monitoring every two weeks with a spatial resolution of 30-60 m, and could be implemented into the design of the next generation of global vegetation-climate missions.

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Appendix

Table A1 A list of variables in the PROSAIL2 model and their search ranges

	Variable	Description	Unit	Search range
Biophysical /biochemical variables	PAI	plant area index, i.e., leaf +stem area index	m ² /m ²	0.0 – 9.5
	SFRAC	Stem fraction		0.0 –1.0
	CF	Cover fraction: area of land covered by vegetation/ total area of land		0.0 –1.0
	C _{ab}	Leaf chlorophyll a+b content	µg/cm ²	0 – 80
	N	Leaf structure variable: measure of the internal structure of the leaf		1.0 – 4.5
	C _w	Leaf equivalent water thickness	cm	0.001 – 0.04
	C _m	Leaf dry matter content	g/cm ²	0.001 – 0.04
	C _{brown}	Leaf brown pigment content		0.00001 –

				8
	LFINC	Mean leaf inclination angle	degree	10 – 89
	STINC	Mean stem inclination angle	degree	10 – 89
	LFHOT	Leaf BRDF variable: length of leaf/ height of vegetation	m/m	0 – 0.9
	STHOT	Stem BRDF variable: length of stem / height of vegetation	m/m	0 – 0.9
	STEM _A	Stem reflectance variable range (for a fitted function)		0.0 – 1.0
	SOIL _A	Soil reflectance variable range (for a fitted function)		0.0 – 1.0
Atmospheric condition variable	VIS	Diffuse/ direct variable: scope of atmospheric clarity	km	50

Description of the Metropolis algorithm to invert the PROSAIL2 model (Zhang et al., (2011))

In the following formalism, $\Pr(\cdot)$ denotes probability in a general sense, or more specifically, the value of a probability density function. $\Pr(v)$ denotes the prior distribution assumed for the set of variables. $\Pr(v_{\text{new}}|\text{data})$ and $\Pr(v_{\text{old}}|\text{data})$ refer to the conditional probabilities of “new” and “old” variable estimates (variable points) given the known “data”.

According to Bayes’ theorem,

$$\Pr(v | \text{data}) \propto \Pr(v) \Pr(\text{data} | v)$$

$$\text{Let } L(v) = \Pr(\text{data} | v)$$

$$\Pr(v | \text{data}) \propto \Pr(v) L(v)$$

where $L(\cdot)$ is the likelihood function. In this study we assume a set of independent uniform prior distributions for the variables. Let $X_i = [x_{i1}, \dots, x_{ip}]$ ($p=7$, the 7 MODIS

bands, see Tab 1), i is the subscript of data point, subscripts 1, ..., p mean spectral bands, and x is reflectance.

This study assumes that the observed spectral values X_i differ from the model predicted values $U_i = [u_{i1}, \dots, u_{ip}]$ according to a mean zero p -variate Gaussian error model that results in the likelihood function

$$L = \prod_{i=1}^n \frac{1}{(\sqrt{2\pi})^p |\Sigma|^{1/2}} e^{-(X_i - U_i)' \Sigma^{-1} (X_i - U_i) / 2}, \quad (A1)$$

where n is the number of data points sampled according to Eq. 18 and Σ is the variance-covariance matrix of X . Σ is estimated by the usual sample variances and covariances in each step of the algorithm:

$$\begin{aligned} \Sigma_e &= (s_{ij})_{p \times p} \\ s_{ij} &= \frac{1}{n} \sum_{k=1}^n (x_{ki} - u_{ki})(x_{kj} - u_{kj}) \end{aligned} \quad i, j = 1, \dots, p \quad (A2)$$

The natural logarithm of the likelihood, the “log-likelihood” ($\log(L)$), is used in the algorithm during its operation (e.g., (Bishop 1995)).

The algorithm defines the probability of accepting the new point as following:

$$\Pr_{accept} = \min \left(1, \frac{\Pr(v_{new} | data)}{\Pr(v_{old} | data)} \right), \quad (A3)$$

If the algorithm accepts the new point, it will become the “old” point in next iteration; otherwise, the old point will still be the “old” point in the next iteration.

To accelerate the speed of convergence of the Metropolis algorithm, we modified the adaptive algorithm used in other studies (e.g., (Braswell et al. 2005; Hurtt and Armstrong 1996)) as follows:

In each iteration, one variable is selected to change as

$$v_{new,s} = v_{old,s} + r \times (v_{\max,s} - v_{\min,s}) \quad (\text{A4})$$

where $s=1, \dots, 14$, is the number of variables in PROSAIL-2 model that are allowed to search for solutions, r is randomly selected at each step between $\pm 0.5 \cdot T_s$, $v_{\max,s}, v_{\min,s}$ are the maximum and minimum values allowed for the search, and T_s is the adaptive length parameter. If $v_{new,s}$ is accepted, then T_s is increased by a factor of 1.006569. If it is rejected, then T_s is decreased by a factor of 0.99. By changing *the adaptive length parameters* in this way, the T_s ($s=1, \dots, 14$) of all variables are adjusted until varying any given variable leads to acceptance of about 23% to 44% of the time, which is considered an ideal acceptance rate for the Metropolis algorithm (Gelman et al. 2000).