worry about artifacts related to new and multiple sensors. Modelers and managers are moving from imagery to pixel-based graphical representations and need tools to easily access, manipulate, integrate, analyze, and correctly interpret these data. Measurement error for parameters and variables are often not provided with SVI products as they vary spatially and seasonally. In the best cases (e.g., MODIS products) it is difficult to translate the current quality assurance flags into an uncertainty, but this could be improved by providing a better data ratings system, providing a level of confidence for each image, and providing visually interpretable, spatially explicit companion products that characterize uncertainty (or our level of confidence in each pixel value) on the whole and by major contributing factors. Implementing a feedback mechanism between SVI developers and end-users would also generate new perspectives on the utility and visualization of SVI products [6] and their associated uncertainty fields.

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Light Absorption by Leaf Chlorophyll and Maximum Light Use Efficiency

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***Abstract*—The MODIS Land Science Team has produced a standard product of gross primary production (GPP) for the global land biosphere, using a satellite-based Production Efficiency Model. In this special issue for the validation studies, two papers have examined the accuracy, error, and uncertainty of the GPP product. Here, we present a user's perspective on accuracy assessment of the data products and discuss two large sources of uncertainty in the context of model variables and parameters: 1) light absorption by chlorophyll versus light absorption by canopy and 2) maximum light use efficiency.**

***Index Terms*—Gross primary production (GPP), Production Efficiency Model (PEM), remote sensing, vegetation.**

I. INTRODUCTION

Photosynthesis occurs in the chloroplasts of plant leaves and is composed of: 1) a light absorption process, i.e., chlorophyll absorbs photosynthetically active radiation (PAR) from sunlight and 2) a carbon fixation process, i.e., absorbed energy is then used to combine water and CO_2 to produce sugar. Although photosynthesis is well understood at the chloroplast and leaf levels, there is still large uncertainty in estimating gross primary production (GPP) at the canopy and landscape scales, particularly its seasonal dynamics and spatial variation due to changes in climate, soils, land use, and management.

A number of satellite-based Production Efficiency Models (PEMs) have been developed to estimate GPP, e.g., GLO-PEM [1], TURC [2], and PSN [3], and these models have the following mathematic formulation:

$$\mathrm{GPP} = \varepsilon_g \times \mathrm{FPAR}_{\mathrm{canopy}} \times \mathrm{PAR} \tag{1}$$

where ε_g is the light use efficiency (g C/mol PAR) for calculation of GPP; and $\mathrm{FPAR}_{\mathrm{canopy}}$ is the fraction of PAR absorbed by the vegetation canopy. These models differ in their approaches for calculating ε_g (Table I).

The PSN model is now used to generate a standard GPP product (MOD17; 1-km spatial resolution, eight-day temporal resolution) from images of the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the NASA Terra and Aqua satellites. The PSN model and associated MOD17 product [4] represent significant progress in remote sensing science and applications at the global scale. What are the accuracy, error distribution, and uncertainty of the MODIS-based GPP product (MOD17)? In this special issue on validation and accuracy assessment of global land products, two papers compared the MODIS-based GPP product with field data from CO_2 eddy flux tower sites [5], [6]. Turner *et al.* [5] examined interannual variation of MODIS-based GPP against field data from three eddy covariance flux tower sites (deciduous broadleaf forest, evergreen needleleaf forest, and desert grassland). Heinsch *et al.* [6] compared

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TABLE I
COMPARISON OF MAXIMUM LIGHT USE EFFICIENCY (ε_0, g C/MOL PAR) USED IN DIFFERENT PRODUCTION EFFICIENCY MODELS FOR DECIDUOUS BROADLEAF FOREST. T: AIR TEMPERATURE SCALAR; SM: SOIL MOISTURE SCALAR; VPD: WATER VAPOR PRESSURE DEFICIT SCALAR; W: LEAF WATER CONTENT SCALAR

Model	$FPAR_{canopy}$ or $FPAR_{chl}$	ε_g	ε_0
TURC[2]	$FPAR_{canopy} = f(NDVI)$	$\varepsilon_g = \varepsilon_0$	0.24
GLO-PEM[1]	$FPAR_{canopy} = f(NDVI)$	$\varepsilon_g = \varepsilon_0 \times T \times SM \times VPD$	0.146
PSN[3]	$FPAR_{canopy} = f(LAI)$ $FPAR_{canopy} = f(NDVI)$	$\varepsilon_g = \varepsilon_0 \times T \times VPD$	0.227
VPM[12]	$FPAR_{chl} = f(EVI)$	$\varepsilon_g = \varepsilon_0 \times T \times W$	0.528
CO_2 flux site[15]	NEE and PAR data from Harvard Forest	deciduous broadleaf forest	0.528

four years (2000–2003) of MODIS-based GPP with tower-based GPP estimates across 15 flux tower sites in the AmeriFlux network. These validation studies are informative for users with regard to understanding the accuracy of the GPP product.

From the perspective of users, there exist three major issues relevant to the standard product: 1) how accurate the product needs to be; 2) how close currently available data come to meeting those needs; and 3) why it is important to quantify the uncertainty. The answer to "how accurate the product needs to be?" is largely dependent upon individual users who have a variety of applications (e.g., agriculture and weather) in the real world. How much risk those applications can take and/or how sensitive those applications are to the product will largely determine how accurate the product needs to be. Here, we primarily discuss two issues: 1) the accuracy of the standard products—a comparison between model output and estimated/observed data—and 2) the uncertainty of the model associated with its variables and parameters.

II. ACCURACY OF THE AVAILABLE PRODUCT—SOURCES OF ERRORS ASSOCIATED WITH INPUT DATASETS

Simulation results of models are affected by the quality of input data sets. The PSN model requires daily climate (PAR, temperature, and vapor pressure deficit), land cover type, and $\mathrm{FPAR}_{\mathrm{canopy}}$ data. In an earlier study [4], significant variations in GPP estimates were reported when different global climate datasets were used to drive the PSN model. Heinsch *et al.* [6] showed remarkable differences in GPP estimate when the site-specific climate data and the global climate data from the NASA Data Assimilation Office (DAO) were used. Their results clearly suggest that further improvements of climate data are critically needed, which would substantially reduce the error in estimating GPP at regional to global scales.

Accuracy assessment and error attribution are also dependent upon temporal scales (e.g., daily, weekly, monthly, seasonal, and annual) used in a study. At the seasonal scale, the accuracy of seasonally integrated GPP between MODIS-based estimates and tower-based estimates was high in the summer but low in the winter [6]. For a deciduous broadleaf forest at the Harvard Forest site, annual sums of MODIS-based GPP in 2000–2003 agreed well with those of tower-based GPP, but there were remarkable differences in the seasonal dynamics of GPP [5], [7]. One unique and unprecedented value of CO_2 eddy covariance flux towers are their capacity to provide continuous (half-hourly) net ecosystem exchange (NEE) data over time. Therefore, in order to better quantify the accuracy of the MOD17 product, one should also conduct validation analyzes at daily to weekly/eight-day scales, because at those temporal scales, vegetation biochemical and physiological changes associated with leaf age are relatively small.

III. UNCERTAINTY OF MODEL VARIABLE—LIGHT ABSORPTION BY CHLOROPHYLL AND CANOPY

$\mathrm{FPAR}_{\mathrm{canopy}}$ is an important biophysical variable. Ecosystem scientists have traditionally used leaf area index (LAI, $\mathrm{m}^2/\mathrm{m}^2$) to estimate $\mathrm{FPAR}_{\mathrm{canopy}}$. Concurrently, the remote sensing community has estimated $\mathrm{FPAR}_{\mathrm{canopy}}$ from satellite images. The normalized difference vegetation index (NDVI), calculated as a normalized ratio between near infrared (NIR) and red spectral bands, has often been used to approximate $\mathrm{FPAR}_{\mathrm{canopy}}$ [1]. A radiative transfer model was applied to generate standard products of $\mathrm{FPAR}_{\mathrm{canopy}}$ and LAI, using MODIS data [8]. Both Turner *et al.* [5] and Heinsch *et al.* [6] compared the seasonal dynamics of $\mathrm{FPAR}_{\mathrm{canopy}}$ with field-measured LAI and discussed the impact of $\mathrm{FPAR}_{\mathrm{canopy}}$ on the seasonal dynamics of GPP in the context of an input data set for the PSN model.

From the biochemical perspective, vegetation canopies are composed of chlorophyll and nonphotosynthetic vegetation (NPV) that includes both canopy-level (e.g., stem and senescent leaves) and leaf-level (e.g., cell walls, vein, and other pigments) materials. Therefore, $\mathrm{FPAR}_{\mathrm{canopy}}$ should be partitioned into the fraction of PAR absorbed by chlorophyll $(\mathrm{FPAR}_{\mathrm{chl}})$ and by NPV $(\mathrm{FPAR}_{\mathrm{NPV}})$, respectively [9]

$$\mathrm{FPAR}_{\mathrm{canopy}} = \mathrm{FPAR}_{\mathrm{chl}} + \mathrm{FPAR}_{\mathrm{NPV}}. \quad (2)$$

Only the PAR absorbed by chlorophyll (product of $\mathrm{FPAR}_{\mathrm{chl}} \times \mathrm{PAR}$) is responsible for photosynthesis. Recently, a few studies have estimated canopy chlorophyll content of crops by a nondestructive optical method [10], approximated $\mathrm{FPAR}_{\mathrm{chl}}$ by the semi-empirical Enhanced Vegetation Index (EVI) [11] for various types of forests [9], [12] and retrieved leaf chlorophyll content and $\mathrm{FPAR}_{\mathrm{chl}}$ by a radiative transfer model and daily MODIS data [13]. The differences between $\mathrm{FPAR}_{\mathrm{chl}}$ and $\mathrm{FPAR}_{\mathrm{canopy}}$ for a deciduous broadleaf forest are large and vary significantly over time [13].

Conceptual partitioning of $\mathrm{FPAR}_{\mathrm{canopy}}$ into $\mathrm{FPAR}_{\mathrm{chl}}$ and $\mathrm{FPAR}_{\mathrm{NPV}}$ is feasible, but quantifying $\mathrm{FPAR}_{\mathrm{chl}}$ across various terrestrial biomes over time will be a challenging task. It will require: 1) extensive field measurements of chlorophyll content at leaf, canopy and landscape levels; 2) improved radiative transfer models that couple both leaf-level biochemical properties (e.g., chlorophyll, other pigments, dry matter) and canopy-level biophysical properties (e.g., plant area index, stem fraction, LAI); and 3) high-quality satellite images. Most importantly, the comparison between $\mathrm{FPAR}_{\mathrm{chl}}$ and $\mathrm{FPAR}_{\mathrm{canopy}}$ would help define to what degree the PEM models are consistent with the light absorption process of photosynthesis at the chlorophyll level. A model that uses $\mathrm{FPAR}_{\mathrm{canopy}} \times \mathrm{PAR}$ in GPP calculation is likely to overestimate the amount of PAR absorbed by leaf chlorophyll and, consequently, propagates this uncertainty into GPP estimates.

IV. UNCERTAINTY OF MODEL PARAMETER—MAXIMUM LIGHT USE EFFICIENCY

The maximum light use efficiency (ε_0) is an important parameter in PEM models. Land use change, disturbance history, and different successional stages of vegetation may result in the spatial variation and temporal changes of ε_0 within a biome type, so it is possible that ε_0 at the canopy level is site-specific. Information about ε_0 for individual vegetation types can be obtained from a survey of the literature [14] and/or analysis of gross ecosystem exchange of CO_2 and photosynthetic photon flux density (PPFD) at a CO_2 eddy flux tower site [15]. Estimation of the ε_0 parameter is largely determined by the choice of either a linear or nonlinear model (e.g., hyperbolic equation) between

GPP and absorbed PAR (APAR, at one half-hour to hourly) data over a year [2], [14]

$$\mathrm{NEE} = \beta \times \mathrm{APAR} - R \tag{3}$$

$$\mathrm{NEE} = \frac{\alpha \times \mathrm{APAR} \times \mathrm{GPP}_{\max}}{\alpha \times \mathrm{APAR} + \mathrm{GPP}_{\max}} - R \tag{4}$$

where R is ecosystem respiration, α is apparent quantum yield, and β is the slope of the linear fit; both α and β are assumed to be ε_0 in Table I. For example, in a review that examined the relationship between GPP and PAR from 126 published datasets [14], it was reported that in a linear model (3) $\varepsilon_0 = 0.020$ μmol CO_2/μmol PAR (~ 0.24 g C/mol PAR), but in a nonlinear hyperbolic function (4), $\varepsilon_0 = 0.044$ μmol CO_2/μmol PAR or ~ 0.528 g C/mol PAR).

Various PEM models use substantially different ε_0 values for a single biome type (Table I). The PSN model assumes one ε_0 value per biome type [3] and uses a ε_0 value of 0.227 g C/mol PAR for deciduous broadleaf forest, which is slightly smaller than 0.24 g C/mol PAR when the linear model (3) is used, but much smaller than 0.528 g C/mol PAR when the nonlinear model (4) is used. There is also a need to estimate the spatial variation and interannual dynamics of ε_0 values within a biome type. CO_2 eddy flux towers provide continuous flux data, which makes it possible to estimate ε_0 values at the canopy-to-landscape level [15]. A comparison between ε_0 values derived from eddy flux tower data and ε_0 values used in various PEM models in a systematic fashion across multiple flux tower sites is needed, which is likely to shed new insight on the uncertainty of PEM models.

V. Summary

Accuracy assessment and validation of the global GPP products is a long-term effort that requires coordination from both the remote sensing community and the CO_2 eddy flux community. At present, there are more than 200 eddy covariance flux tower sites operating across various biomes in the world, including different land use, management, disturbance and recovery stages. The eddy flux community needs to: 1) partition half-hourly NEE data into GPP and ecosystem respiration, and provide GPP data to users in a timely fashion; and 2) quantify light use efficiency in a consistent approach, using observed NEE and PAR data. As there are a number of methods for estimating GPP from observed NEE data, additional effort is needed to reduce the error of GPP estimates from NEE data using a consistent method across flux tower sites. The terrestrial ecosystem science and remote sensing communities need to undertake regular measurements of both biochemical (chlorophyll, nitrogen, and $\mathrm{FPAR}_{\mathrm{chl}}$) and structural (LAI, $\mathrm{FPAR}_{\mathrm{canopy}}$) variables across the leaf, canopy, and landscape levels, and develop datasets of chlorophyll content over land ecosystems. Furthermore, as a large portion of leaf nitrogen is within leaf chloroplasts, developing the quantitative relationships among chlorophyll, $\mathrm{FPAR}_{\mathrm{chl}}$ and nitrogen could have significant implication for reducing the uncertainty in estimating GPP and the carbon cycle.

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