Monitoring Photosynthesis from Space

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ACRONYMS AND DEFINITIONS

ANPP
Aboveground net primary production

APAR
Absorb photosynthetically active radiation

BIOME-BGC
BioGeochemical Cycles Model

BPLUT
Biome-properties look-up table

DOE
Department of Energy

EC
Eddy covariance

eLUE
Ecosystem LUE

EVI
Enhanced vegetation index

FAO
Food and Agriculture Organization

FLEX
Fluorescence explorer satellite

fAPAR
Fraction of APAR

fPAR
Fraction of PAR

G-R
Greenness and radiation

GOME-2
Global Ozone Monitoring Experiment-2

GOSAT
Greenhouse Gases Observing Satellite

GPP
Gross primary productivity

HyspIRI
Hyperspectral infrared imager

LAI
Leaf area index

Lidar
Light detection and ranging

LST
Land surface temperature

LSWI
Land surface water index

LUE
Light-use efficiency

LUT
Look up table

MTCI
MERIS terrestrial chlorophyll index

MERIS
Medium-resolution imaging spectrometer

MODIS
Moderate-resolution imaging spectroradiometer

NASS
National Agricultural Statistics Service

NCAR
National Centre for Atmospheric Research

NCEP
National Centres for Environmental Prediction

NDVI
Normalized difference vegetation index

NEE
Net ecosystem exchange

NIR
Near infrared

NPP
Net primary production

OCO-2
Orbiting Carbon Observatory-2

PAR
Photosynthetically active radiation

PVI
Perpendicular vegetation index

SIF
Solar-induced chlorophyll fluorescence

SW
Short-wave downward solar radiation

T-G
Temperature and Greenness

Ta
Air temperature

TC-GVI
Tasselled cap green vegetation index

TROPOMI
Tropospheric Monitoring Instrument satellite

USDA
U.S. Department of Agriculture
1.1 Introduction

Vegetation productivity is defined as the process by which plants use sunlight to produce organic matter from carbon dioxide through photosynthesis. Gross primary productivity (GPP), or photosynthesis, is the rate of carbon fixation or total plant organic matter produced per unit of time and over a defined area, whereas the amount of carbon fixed by plants and accumulated as biomass is known as terrestrial net primary production (Cramer et al. 1999; Zhao and Running 2010). Productivity forms the basis of terrestrial biosphere functioning and carbon, energy, and water budgets. Accurate estimates of plant productivity across space and time are thus necessary for quantifying carbon balances at regional to global scales (Lieth 1975; Schimel 1998). Vegetation productivity is generally limited by the availability of spatially and temporally varying plant resources (e.g., nutrients, light, water, and temperature) (Field et al. 1995; Churkina and Running 1998; Nemani et al. 2003) (Figure 1.1). Improved knowledge of the main drivers and resource constraints of plant productivity is thus needed for predictable assessments of climate change.

1.1.1 Measures of Productivity

Measures of productivity are essential in global change studies; yet despite their importance, they are quite challenging to obtain or sample (Baldocchi et al. 2001). The assessment of plant production is carried out in various ways, from plot measurements and plant harvests, micrometeorological fluxes, remote sensing, and through empirical and process-based models that may involve remote sensing data inputs. In situ measures include methods that vary with biome type, for example, tree inventories, litter traps, grassland forage estimates, and agricultural harvests and market statistics. Plot-level methods measure aboveground net primary production (ANPP) that often involves destructive sampling during peak biomass periods. Established long-term experimental plots enable cross-site production comparisons; however, they are also amenable to many uncertainties due to differences in site-based procedures, and in some cases, inconsistent sampling methods over time at a given site (Sala et al. 1988; Biondini et al. 1991; Moran et al. 2014). GPP has traditionally been estimated from plot level ANPP measurements by correcting for respiratory losses (Field et al. 1995). Agricultural yield statistics (USDA NASS) combined with maps of cropland areas provide large-scale NPP estimates from local to national level census statistics (Monfreda et al. 2008; Guanter et al. 2014).

A global network of micrometeorological tower sites, known as FLUXNET, now provide continuous measurements of carbon, water, and energy exchanges between ecosystems and the atmosphere (Running et al. 1999). This yields information on seasonal dynamics and interannual variations of net ecosystem exchange (NEE) of carbon dioxide between the land surface and the atmosphere (Baldocchi et al. 2001; Verma et al. 2005). This has yielded quite valuable in situ data to independently evaluate and assess uncertainties in carbon models and satellite carbon products, as they are applied to global change studies.

Satellite imaging sensors offer synoptic-scale observations of ecosystem states and landscape dynamics, and are seen as invaluable tools to help fill the large spatial gaps of in situ measurements, and constrain and improve the accuracies of models. Remote sensing complements the restrictive coverage afforded by experimental plots and eddy covariance (EC) tower flux measurements.

**FIGURE 1.1** Potential limits to vegetation net primary production based on fundamental physiological limits of solar radiation, water balance, and temperature. Greener colors depict biomes increasingly limited by radiation, while red colors are water-limited and blue colors temperature-limited. Many regions are limited by more than one factor. (Adapted from Nemani, R.R. et al., *Science*, 300(5625), 1560, 2003.)
measurements, facilitating observations of broad-scale patterns of ecosystem functioning. This renders remote sensing a powerful tool for studying vegetation productivity at local, regional, and global scales (Gitelson et al. 2006).

The integration of independently derived tower measured carbon fluxes with satellite data is the focus of many investigations across many ecosystems from sparse shrublands to mesic grasslands, and to temperate forests. Estimates of daily GPP and annual NPP are now routinely produced operationally over the global terrestrial surface at 1 km spatial resolution through production efficiency models with near real-time satellite data inputs from the moderate-resolution imaging spectroradiometer (MODIS) (Turner et al. 2006) (Figure 1.2).

Finally, there are many empirical, diagnostic, and process-based models that have been developed over the past decades to monitor and assess vegetation productivity, with many of these methods employing remote sensing data in conjunction with micrometeorological carbon flux measurements to varying extents.

1.1.2 Lidar

Traditionally, national-scale carbon monitoring has been accomplished with networks of field inventory plots (FAO 2007), which provide direct carbon measurements of only very small areas of forest, and are further difficult to install, monitor, and maintain over time (Chambers et al. 2009). Airborne laser technology called light detection and ranging (lidar) offers much potential for terrestrial carbon assessments. Lidar measures the physical structure of woody vegetation, from sparse shrublands to dense forests, and can serve as a reliable replacement for inventory plots in areas lacking field data (Lefsky et al. 2002; Zolkos et al. 2013). Thus, lidar integration with field inventory plots can provide calibrated lidar estimates of aboveground carbon stocks, which can then be scaled up using satellite data on vegetation cover, topography, and rainfall from satellite data to model carbon stocks (Asner et al. 2013). Opportunities to fuse temporally dynamic vegetation optical measurements with lidar have promising potential for better assessments of not only standing wood biomass, but also forest disturbance, biomass loss, and carbon accumulation through forest regrowth (Lefsky et al. 2002; Asner et al. 2010).

1.2 Remote Sensing and Net Primary Production

1.2.1 NDVI–fAPAR Relationships

Remote sensing approaches to estimate productivity generally employ spectral measures of vegetation, which are used for estimating their capacity to absorb photosynthetically active radiation (APAR). Vegetation productivity is directly related to the interaction of solar radiation with the plant canopy, based on the original logic of Monteith (1972), who suggested that productivity of stress-free annual crops was linearly related to vegetation absorbed PAR. Spectral vegetation indices (VIs) such as the normalized difference vegetation index (NDVI) (Tucker 1979), the perpendicular vegetation index (PVI) (Richardson and Wiegand 1977), and the tasselled cap green vegetation index (TC-GVI) (Kauth and Thomas 1976) were consequently developed over croplands and grasslands.

![Figure 1.2 MODIS net primary production satellite product (MOD17). Example showing the mean NPP across years 2000–2005 for the global terrestrial surface. The highest production is seen across the equatorial zone encompassing southeast Asia, the Amazon basin, and equatorial Africa. The least productive regions appear in Australia and the Sahelian region. (Courtesy of Numerical Terradynamic Simulation Group, University of Montana, Missoula, MT.)](image-url)
The NDVI is written as follows:

\[
\text{NDVI} = \frac{(\rho_{\text{NIR}} - \rho_{\text{red}})}{(\rho_{\text{NIR}} + \rho_{\text{red}})}
\] (1.1)

where \(\rho_{\text{NIR}}\) and \(\rho_{\text{red}}\) are spectral reflectance values (unitless) that exploit the chlorophyll-absorbing red band relative to the non-absorbing and high scattering near-infrared (NIR) band. Asrar et al. (1984) showed the NDVI was linearly related with vegetation absorption of light energy (APAR) or fraction of APAR (fAPAR), and thereby related to productivity through the potential capacity of vegetation to absorb light for photosynthesis (Figure 1.3). The linear relationship between NDVI and fAPAR has been documented through field measurements (Ruimy et al. 1994; Fensholt et al. 2004) and theoretical analyses (Sellers 1985; Goward and Huemmrich 1992; Myneni and Williams 1994).

### 1.2.2 Annual Integrated Estimates of Productivity

Several studies suggest that annual vegetation productivity status can be captured with the annual NDVI integral, used as surrogate measures of fAPAR. Goward et al. (1985) used integrated NDVI values derived from the advanced-very-high-resolution radiometer (AVHRR) and found good relationships between NPP and integrated NDVI over annual growing periods of North American biomes (Figure 1.4). Wang et al. (2004) found that the NDVI integral over the early growing season was strongly correlated to in situ forest measurements of diameter increase and tree ring width in the U.S. central Great Plains. They also found the previous year integrated NDVI was well correlated with current year increases in tree height growth.

The annual integrated VI offers a robust approximation of vegetation productivity, because, in general, VI s provide both a measure of the capacity to absorb light energy, as well as reflect recent environmental stress acting on the canopy, with stress forcings showing up as reductions in NDVI expressed as either less chlorophyll and/or less foliage (Running et al. 2004). Photosynthesis or primary production is essentially integrator of resource availability, and according to the resource optimization theory (Field et al. 1995), ecological processes tend to adjust plant characteristics over time periods of weeks or months to match the capacity of the environment to support photosynthesis and maximize growth.

Ponce-Campos et al. (2013) compiled in situ field measures of ANPP across 10 sites in the United States, ranging from arid grassland to forest and directly compared annual integrated values of the MODIS enhanced vegetation index (EVI, or iEVI) (Figure 1.5). Using a log–log relation to account for the uneven distribution of ANPP estimates over time, the iEVI was found to be an effective surrogate to estimate ANPP and quantify vegetation dynamics:

\[
\text{ANPP} = 51.42 \times \text{iEVI}^{1.15},
\] (1.2)
The annual life cycle of plant species and vegetation canopies have large effects on rates of photosynthesis and annual productivity. Phenological factors such as leaf age and life expectancy play important roles on productivity (Wilson et al. 2001) with some production models explicitly incorporating phenophase periods, such as bud burst to full leaf expansion, and full expansion to dormancy (Xiao et al. 2004). LST satellite data and/or meteorological air temperature data (Ta) are also used to identify biologic inactive seasonal periods, for example, masking cold temperature time intervals from the EVI or NDVI integrals.

Often, there is also a need to synchronize the satellite data with scheduled or variable destructive sampling dates. Generally, in situ measures of productivity are made at discrete times within the growing season or may be associated with variable sampling times with uncertain estimates of the dates of peak greenness. In such cases, remote sensing data provides better temporal stability and opportunities to reduce productivity uncertainties. For example, Moran et al. (2014) found significant improvements in productivity–iEVI relationships across a range of grassland sites, when the EVI was only partially integrated from the beginning to the peak of the growing season period (rather than the full season). This was due to the synchronization of time periods to peak biomass periods when grassland ANPP destructive sampling are typically conducted.

Numerous efforts have been made to improve upon the characterization of the plant growing season at regional scales using satellite-based phenology models. Software packages such as Timesat (Jönsson and Eklundh 2004) can be used to quantitatively model the growing season and facilitate the temporal synchronization of in situ production measures with satellite data. A summary of the various remote sensing methods that have been used in estimating net primary productivity is shown in Table 1.1.

1.2.3 Growing Season Phenology Relationships

The annual life cycle of plant species and vegetation canopies have large effects on rates of photosynthesis and annual productivity. Phenological factors such as leaf age and life expectancy play important roles on productivity (Wilson et al. 2001) with some production models explicitly incorporating phenophase periods, such as bud burst to full leaf expansion, and full expansion to dormancy (Xiao et al. 2004). LST satellite data and/or meteorological air temperature data (Ta) are also used to identify biologic inactive seasonal periods, for example, masking cold temperature time intervals from the EVI or NDVI integrals.

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<table>
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<tr>
<th>Net Primary Productivity Measurement</th>
<th>Biome/Location</th>
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<th>Equation</th>
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<td>Annual NPP</td>
<td>Across different North American biomes from tundra to forest to crops and deserts</td>
<td>Integrated growing season NDVI from NOAA/AVHRR</td>
<td>Linear regression between NPP and integrated NDVI</td>
<td>NA</td>
<td>0.89, 0.94 (excl. crops)</td>
<td>Goward et al. (1985)</td>
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<td>Growing season NPPgs, Early growing season NPPgs, Tree ring width, stem growth, and litterfall</td>
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<td>NA</td>
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<td>Wang et al. (2004)</td>
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<tr>
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<td>0.82</td>
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</tr>
<tr>
<td>Annual above ground net primary productivity (ANPP)</td>
<td>Arid to mesic grasslands</td>
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<td>Log-log relation between ANPP and iEVI</td>
<td>NA</td>
<td>0.71</td>
<td>Moran et al. (2014)</td>
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<td>0.86, calibration plots 0.92, validation plots</td>
<td>Asner et al. (2013)</td>
</tr>
</tbody>
</table>
1.3 Remotely Sensed Production Efficiency Models

Remote sensing estimates of GPP and net primary production (NPP) have been implemented at global scales, based on the light-use efficiency (LUE) equation that defines the amount of carbon fixed through photosynthesis as proportional to the solar energy absorbed by green vegetation multiplied by the efficiency with which the absorbed light is used in carbon fixation (Monteith 1972; Monteith and Unsworth 1990):

\[
GPP = \varepsilon \times APAR = \varepsilon \times f_{APAR} \times PAR
\] (1.4)

where \( \varepsilon \) is the efficiency of conversion of absorbed light into aboveground biomass, or light-use efficiency.

APAR is integrated over a time period.

\( f_{APAR} \) is derived through spectral VI relationships (Asrar et al. 1984; Sellers 1985; Goward and Huemmrich 1992; Ruimy et al. 1994).

The LUE concept has been widely adopted by the remote sensing community to assess and extrapolate carbon processes through knowledge of two conversion coefficients: the \( f_{APAR} \) and \( \varepsilon \). Although \( f_{APAR} \) is readily estimated using remotely sensed “greenness” measures, \( \varepsilon \) is very difficult to measure as it dynamically varies with plant functional type, vegetation phenophase, and different environmental stress conditions (Ruimy et al. 1995; Turner et al. 2003; Sims et al. 2006; Jenkins et al. 2007). As a result, there are scarce measurements of \( \varepsilon \) available, particularly at the landscape scale, and potential or maximum LUE values have only been specified for a limited set of biome types, with these values downregulated by environmental stress scalars derived from meteorological inputs (Zhao et al. 2005; Heinsch et al. 2006).

1.3.1 BIOME-BGC Model

The BIOME-BGC (BioGeochemical Cycles) model calculates daily GPP as a function of incoming solar radiation, conversion coefficients, and environmental stresses (Running et al. 2004). This was implemented as the first operational standard satellite product for MODIS (MOD17), providing global estimates of global GPP (Figure 1.7), expressed as follows:

\[
GPP = \varepsilon_{\text{max}} \times 0.45 \times SW_{\text{rad}} \times f_{(VPD)} \times f_{(T_{\text{min}})}
\] (1.5)

where

\( \varepsilon_{\text{max}} \) is the maximum light-use efficiency (g C MJ\(^{-1}\)) obtained from a biome-properties look-up table (BPLUT).

\( SW_{\text{rad}} \) is short-wave downward solar radiation (MJ \( \cdot \) day\(^{-1}\)), of which 45% is assumed to be PAR.

\( f_{(VPD)} \) and \( f_{(T_{\text{min}})} \) are vapor pressure deficit and air temperature reduction scalars for the biome specific \( \varepsilon_{\text{max}} \) values.

\( f_{APAR} \) is directly input from the MODIS FPAR (MOD15) product (Running et al. 2004; Zhao et al. 2005)

MODIS FPAR retrievals are physically based and use biome-specific look-up tables (LUTs) generated using a three-dimensional radiative transfer model (Myneni et al. 2002).

**FIGURE 1.7** MODIS gross primary production satellite product (MOD17). Example showing the mean GPP across years 2000–2005 for the global terrestrial surface. The highest rates of photosynthesis are seen in the tropical forests of southeast Asia, the Amazon basin, and equatorial Africa. The lowest rates of photosynthesis are seen in Australia, South Africa, western North America, the Sahel, and Atacama desert. (Courtesy of Numerical Terradynamic Simulation Group, University of Montana, Montana, MT.)
The reduction scalars encompass LUE variability resulting from water stress (high daily VPD) and low temperatures (low daily minimum temperature $T_{min}$) (Running et al. 2004). The MODIS GPP product is directly linked to remote sensing and weather forecast products and can provide near real-time information on productivity and the influence of anomalies such as droughts. A consistent forcing meteorology is based upon the NCEP/NCAR (National Centres for Environmental Prediction/National Centre for Atmospheric Research) Reanalysis II datasets (Kanamitsu et al. 2002) (Figure 1.7).

Using these satellite products, Zhao and Running (2010) found that global NPP declined slightly by 0.55 petagram carbon ($Pg\ C$, with $Pg = 10^{15}$ g = 1 billion metric tonnes) due to drought from 2000 to 2009. Ichii et al. (2007) used the BIOME-BGC model to simulate seasonal variations in GPP for different rooting depths, from 1 to 10 m, over Amazon forests and determine which rooting depths best estimated GPP consistent with satellite-based EVI, and thereby were able to map rooting depths at regional scales and improve the assessments of carbon, water, and energy cycles in tropical forests.

The utility and accuracy of MODIS GPP/NPP products have been validated in various FLUXNET studies, which have also demonstrated the value of independent tower flux measures to better understand the satellite-based GPP/NPP products (Kang et al. 2005; Leuning et al. 2005; Zhao et al. 2005, 2006; Turner et al. 2006). These studies highlight the capabilities of MODIS GPP to correctly predict observed fluxes at tower sites, but also draw attention to some of the uncertainties associated with use of coarse resolution and interpolated meteorology inputs, uncertainties with the LUT-based values, noise and uncertainties in the satellite fAPAR inputs, and difficulties in constraining the light-use efficiency term (Zhao et al. 2005; Heinsch et al. 2006; Yuan et al. 2010; Sjöström et al. 2013). Since meteorological inputs are often not available at sufficiently detailed temporal and spatial scales, they can introduce substantial errors into the carbon exchange estimates.

Turner et al. (2006) concluded that although the MODIS NPP/GPP products are generally responsive to spatial-temporal trends associated with climate, land cover, and land use, they tend to overestimate GPP at low productivity sites and underestimate GPP at high productivity sites. Similarly, Sjostrom et al. (2013) found that although MODIS-GPP described seasonality at 12 African flux tower sites quite well, it tended to underestimate tower GPP at the dry sites in the Sahel region due to uncertainties in the meteorological and fAPAR input data and the underestimation of $e_{max}$. Jin et al. (2013) reported the MODIS GPP product to substantially underestimate tower GPP during the green-up phase at a woodland savanna site in Botswana, while overestimating tower-GPP during the brown-down phase.

Some studies have found that when properly parameterized with site-level meteorological measurements, MODIS GPP becomes more closely aligned with flux tower derived GPP (Turner et al. 2003; Kanniah et al. 2009; Sjostrom et al. 2013). Kanniah et al. (2011), however, found that utilizing site-based meteorology could only improve GPP estimates during the wet season over northern Australian savannas, and suggested the MODIS GPP product has a systematic limitation in the estimation of savanna GPP in arid and semi-arid areas due to the lack of the representation of soil moisture. Sjöström et al. (2013) also found soil moisture information to be quite important for accurate GPP estimates in drier African savannas.

### 1.3.2 Vegetation Index: Tower GPP Relationships

There have also been many attempts to estimate GPP based solely on remote sensing inputs, thereby minimizing or eliminating the need for meteorological and LUE information. Spectral VIs have been directly related to EC tower carbon flux measurements (Rahman et al. 2005; Gitelson et al. 2006; Sims et al. 2006; Sjöström et al. 2011). Monteith and Unsworth (1990) noted that VIs can legitimately be used to estimate the rate of processes that depend on absorbed light, such as photosynthesis and transpiration.

Wylie et al. (2003) reported a strong relationship between biweekly aggregated NDVI and daytime CO$_2$ flux in a sagebrush-steppe ecosystem, while Rahman et al. (2005) found that EVI can provide reasonably accurate estimates of GPP across a wide range of North American ecosystems, including dense forests. However, the strength of the linear relationships between EVI and tower GPP in temperate forests was greater in seasonally contrasting deciduous forests compared with evergreen forests (Rahman et al. 2005; Sims et al. 2006). Sims et al. (2006) further noted that when data from the winter period of inactive photosynthesis were excluded, the EVI—tower GPP relationship was better than that between tower GPP and MODIS GPP (Figure 1.8). Olofsson et al. (2008) reported strong correlations between EVI and GPP across Northern Europe, while NDVI showed problems with saturation in such areas of high biomass. NDVI saturation is attributed to the strong weighing of the red band, which is primarily absorbed by the uppermost leaf layer of a dense crop or forest canopy while the nonabsorbing NIR band is able to penetrate 5–7 leaf layers. Thus, the more NIR-sensitive indices, such as EVI, PVI, TC-GVI, and linear mixture models are less prone to saturate (Huete et al. 2002, 2006).

Sjöström et al. (2011) found EVI was able to track the seasonal dynamics of tower GPP closely across African tropical savanna ecosystems. Ma et al. (2013) similarly observed good convergences between MODIS EVI and tower GPP across northern Australian mesic and xeric tropical savannas, confirming the potentials to link these two independent data sources for accurate estimation of savanna GPP. Strongly linear and consistent relationships between EVI and tower GPP were also shown in dry to humid tropical forest sites in Southeast Asia and the Amazon (Xiao et al. 2005; Huete et al. 2006, 2008).

These relationships have shown the EVI to estimate GPP with relatively high accuracy, thus greatly simplifying carbon balance models and potentially offering opportunities for
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region-wide scaling of carbon fluxes. The relationships between EVI and tower GPP are partly a result of fairly good correlations between LUE and EVI that make an independent estimate of LUE less necessary. Sims et al. (2006) reported that LUE derived from nine flux towers in North America was well correlated with EVI ($R^2 = 0.76$; Figure 1.8), while Wu et al. (2011) reported moderate correlation between EVI and tower LUE in temperate and boreal forest ecosystems in North America. Further, the 16-day averaging period removes much of the influences of short-term fluctuations in solar radiation and other environmental parameters, thereby minimizing the need for climatic drivers. On the other hand, such relationships were weaker in evergreen forests relative to deciduous ones and one study in an evergreen oak forest showed no correlation between EVI and LUE (Goerner et al. 2009); thus, correlations between EVI and LUE may be a result of covariances between fAPAR and LUE.

1.3.3 Temperature and Greenness Model (T-G)

The simple VI “greenness” model, defined as the straightforward relationship between VIs and GPP, although potentially useful in certain cases, exhibits various limitations due to its inability to always recognize between growth and inactive growth periods, in which spectral “greenness” may show little change. These inactive periods are associated with evergreen vegetation in winter months with low temperatures as well as evergreen vegetation growing in Mediterranean climates in which high temperature, vapor pressure deficit, and soil drought limit growth (Sims et al. 2008; Vickers et al. 2012).

For these reasons, Sims et al. (2008) introduced the temperature and greenness (T-G) model, using combined daytime LST (Wan 2008) and EVI products from MODIS. They found the T-G model substantially improved the correlation between predicted and measured GPP at 11 EC flux tower sites across

![Figure 1.8](image.png)

**FIGURE 1.8** Flux tower measurements of GPP and LUE compared with satellite measures, MODIS GPP and MODIS EVI, respectively, over a range of North American biome types. (From Sims, D.A. et al., *J. Geophys. Res.*, 111, 2006.)
North American biomes compared with the MODIS GPP product or MODIS EVI alone, while keeping the model based entirely on remotely sensed variables without any ground-based meteorological inputs (Sims et al. 2008). The T-G model may be described as follows:

\[
GPP = (EVI_{scaled} \times LST_{scaled}) \times m \quad (1.6)
\]

\[
LST_{scaled} = \min \left[ \frac{LST}{30}, \left( 2.5 - (0.05 \times LST) \right) \right] \quad (1.7)
\]

\[
EVI_{scaled} = EVI - 0.10 \quad (1.8)
\]

where

- \( LST_{scaled} \) sets GPP to zero when LST is less than zero, and defines the inactive winter period
- \( EVI_{scaled} \) adjusts EVI values to a zero baseline value in which GPP is known to be zero
- \( m \) is a scalar that varies between deciduous and evergreen sites, with units of mol C m\(^{-2}\) day\(^{-1}\)

\( LST_{scaled} \) also accounts for low temperature limitations to photosynthesis when LST is between 0°C and 30°C, and accounts for high temperature and high VPD stress in sites that exceed LST values of 30°C (Sims et al. 2008) (Figure 1.9).

LST is closely related to VPD and thus can provide a measure of drought stress (Hashimoto et al. 2008), consistent with the BIOME-BGC model, where temperature and VPD are used as scalars directly modifying LUE (Running et al. 2004). LST is a useful measure of physiological activity of the upper canopy leaves, provided that leaf cover is great enough that LST is not significantly affected by soil surface temperature. Thus, the T-G model has been found less useful in sparsely vegetated ecosystems (e.g., shrubs) where soil surface temperatures significantly influence derived LST values, rendering them less useful as indicators of plant physiology. As an example, Ma et al. (2014) found coupling EVI with LST showed no improvements in predicting savanna GPP compared with using EVI alone over the relatively open tropical savannas in northern Australia, with appreciable soil exposure. This may also be due to temperature not being a limiting factor or significant driver of photosynthesis in tropical savannas (Leuning et al. 2005; Cleverly et al. 2013; Kanniah et al. 2013b).

### 1.3.4 Greenness and Radiation (G-R) Model

Chlorophyll-related spectral indices have also been coupled with measures of light energy, PAR, to provide robust estimates of GPP:

\[
GPP = VI_{chl} \times PAR_{toc} \quad (1.9)
\]

where

- \( PAR_{toc} \) is the top-of-canopy measured PAR (MJ m\(^{-2}\) day\(^{-1}\))
- \( VI_{chl} \) is a chlorophyll-related spectral index

Peng et al. (2013) described two types of chlorophyll spectral indices, (1) commonly used VIs, such as EVI and the wide dynamic range vegetation index (WDRVI), which indirectly indicate total chlorophyll content through “greenness” estimates and (2) chlorophyll indices, such as the MERIS terrestrial chlorophyll index (MTCI), which directly represent the leaf chlorophyll content. The WDRVI equation is,

\[
WDRVI = \frac{a^* (\rho_{753.75} - \rho_{708.75})}{a^* (\rho_{753.75} + \rho_{708.75})} \quad (1.10)
\]

where

- \( a \) is a weighing coefficient with value between 0.1 and 0.2 (Gitelson 2004; Gitelson et al. 2006)

\( MTCI \) is the ratio of the difference in reflectance between an NIR and red edge band and the difference in reflectance between red edge and red band as

\[
MTCI = \frac{\rho_{753.75} - \rho_{708.75}}{\rho_{753.75} + \rho_{708.75}} \quad (1.11)
\]

where \( \rho_{753.75}, \rho_{708.75}, \) and \( \rho_{641.25} \) are reflectances in the center wavelengths of the MERIS narrow-band channel settings (Dash and Curran 2004).

Canopy level chlorophyll represents a community property that is most relevant in quantifying the amount of absorbed radiation used for productivity (Whittaker and Marks 1975; Dawson et al. 2003). Long- or medium-term changes (weeks to months) in canopy chlorophyll are related to canopy stress, phenology, and photosynthetic capacity of the vegetation (Ustin et al. 1998; Zarco-Tejada et al. 2002). Ciganda et al. (2008) showed that for the same LAI amount, the chlorophyll content during the...
green-up stage might be more than two times higher than the chlorophyll content in leaves in the reproductive and senescence stages. In the G-R model, both fAPAR and LUE are driven by total chlorophyll content with strong correlations between GPP/PAR and canopy chlorophyll content (Gitelson et al. 2006; Peng et al. 2011).

Ma et al. (2014) found significant improvements in the use of G-R models, relative to EVI alone, for predicting tower GPP, demonstrating the importance of this quantity as a critical driver of savanna vegetation productivity (Whitley et al. 2011; Kanniah et al. 2013a). The R-G model has been successfully applied in estimating GPP in natural ecosystems (Sjöström et al. 2011; Wu et al. 2011, 2014) and croplands, including maize, soybeans, and wheat (Wu et al. 2010; Peng et al. 2011; Peng and Gitelson 2012).

Site-based PARtoc measurements, however, may exhibit uncertainties associated with high-frequency fluctuations that are difficult to extrapolate beyond the tower sensor footprint and, moreover, scale regionally. Therefore, other measures of PAR that have been used include "potential" PAR, or maximal clear-sky PAR (PARpotential) (Gitelson et al. 2012; Peng et al. 2013; Rossini et al. 2014) and top-of-atmosphere PAR (PARtoa). PARpotential can be calibrated from long-term PARtrans measurements or modeled using an atmosphere radiative transfer code (Kotchenova and Vermote 2007).

Gitelson et al. (2012) found an improved performance of PARpotential relative to PARtrans noting that decreases in PARtrans during the day do not always imply a decrease in GPP. Further, Kanniah et al. (2013a) showed that the negative forcings of wet season cloud cover on Australian tropical savannas were partly compensated by enhanced LUE resulting from a greater proportion of diffuse radiation. Ma et al. (2014) found that coupling of EVI with PARtrans better predicted GPP than coupling EVI with PARtrans and attributed this to tower-based measurement uncertainties of PARtrans as well as better approximations of meteorological controls on GPP by PARtrans.

Two definitions of LUE become apparent in G-R models, with this term either defined as the ratio of GPP to PAR or defined as the ratio of GPP to PAR (Gower et al. 1999), with the latter sometimes referred to as ecosystem-LUE or eLUE:

\[ \varepsilon = \frac{GPP}{PAR} = \frac{GPP}{fAPAR \times PAR} \]  \hspace{1cm} (1.12)

\[ eLUE = \frac{GPP}{PAR} = fAPAR \times \varepsilon \]  \hspace{1cm} (1.13)

An advantage of using chlorophyll-based VIs in G-R models is that the biological drivers of photosynthesis, fAPAR and light-use efficiency (\( \varepsilon \)) resulting from environmental stress and leaf age phenology, are combined into eLUE, thereby simplifying remote sensing–based productivity estimates.

### 1.3.5 Vegetation Photosynthesis Model (VPM)

Xiao et al. (2004) developed a mostly satellite-based vegetation photosynthesis model (VPM) that estimates GPP using satellite inputs of EVI and the land surface water index (LSWI):

\[ GPP = \varepsilon \times fAPAR_{chl} \times PAR_{toc} \]  \hspace{1cm} (1.14)

\[ \varepsilon = \varepsilon_{max} \times T_{scalar} \times W_{scalar} \times P_{scalar} \]  \hspace{1cm} (1.15)

where

- fAPAR_{chl} is estimated as a linear function of EVI
- PAR_{toc} is measured at the site
- T_{scalar}, W_{scalar}, P_{scalar} are scalars for the effects of temperature, water, and leaf phenology on vegetation, respectively (Figure 1.10)

T_{scalar} is based on air temperature and uses minimum, maximum, and optimum temperature for photosynthesis at each time step; W_{scalar} is based on satellite-derived LSWI that accounts for the effect of water stress on photosynthesis:

\[ W_{scalar} = \frac{(1 + LSWI)}{(1 + LSWI_{max})} \]  \hspace{1cm} (1.16)

**Figure 1.10** Schematic diagram of the VPRM utilizing EVI, LSWI, and scalars for temperature, leaf phenology, and canopy water content, T_{scalar}, P_{scalar}, and W_{scalar}, respectively. The VPM model uses primarily remote sensing data along with air temperatures, while the VPRM model additionally assimilates tower flux and meteorological information. (From Mahadevan, P. et al., Global Biogeochem. Cycles, 22(2), GB2005, 2008.)


\[
LSWI = \left( \frac{\rho_{\text{near}} - \rho_{\text{nir}}}{\rho_{\text{near}} + \rho_{\text{nir}}} \right) = \frac{\rho(531\text{ nm}) - \rho(670\text{ nm})}{\rho(531\text{ nm}) + \rho(670\text{ nm})} \tag{1.17}
\]

where

\( \rho_{\text{near}} \) is the reflectance in a broadband shortwave infrared band (e.g., MODIS, 1580–1750 nm)

\( LSWI_{\text{max}} \) is the maximum value for the growing season

\( P_{\text{scalar}} \) accounts for the effect of leaf age on photosynthesis and is dependent on the growing season life expectancy of the leaves (Wilson et al. 2001). \( P_{\text{scalar}} \) is calculated over two phenophases as

\[
P_{\text{scalar}} = \frac{(1 + LSWI)}{2} \tag{1.18}
\]

from bud burst to full leaf expansion, and \( P_{\text{scalar}} = 1 \), after full expansion (Xiao et al. 2004).

The VPM model has been applied to both MODIS and SPOT-4 VEGETATION sensor data to produce tower-calibrated estimates of GPP across a wide range of biomes, including evergreen and deciduous forests, grasslands, and shrub sites in temperate North America and in seasonally moist tropical evergreen forests in the Amazon (Xiao et al. 2005; Mahadevan et al. 2008; Jin et al. 2013).

Mahadevan et al. (2008) further developed the vegetation photosynthesis and respiration model (VPRM), a satellite-based assimilation scheme that estimates hourly values of NEE using EVI, LSWI, and high-resolution meteorology observations of sunlight and air temperature (Figure 1.10). NEE represents the difference between uptake (photosynthesis) and loss (respiration) processes that vary over a wide range of timescales (Goulden et al. 1996; Katul et al. 2001). The VPRM model provides fine-grained fields of surface CO\(_2\) fluxes for application in inverse models at continental and smaller scales (Mahadevan et al. 2008). This capability is presently limited by the number of vegetation classes for which NEE can be constrained using EC tower flux data. A summary of the various remote-sensing-based estimates of GPP is shown in Table 1.2.

### 1.3.6 Photochemical Reflectance Index (PRI)

There is also much interest in reducing the uncertainties in GPP models through direct remote sensing assessments of LUE. The photochemical reflectance index (PRI) is a hyperspectral index that provides a scaled LUE measure, or photosynthetic efficiency, based on light absorption processes by carotenoids (Gamon et al. 1992; Middleton et al. 2011).

\[
PRI = \left( \frac{\rho_{531\text{ nm}} - \rho_{670\text{ nm}}}{\rho_{531\text{ nm}} + \rho_{670\text{ nm}}} \right) \tag{1.19}
\]

Spectral variations at 531 nm are closely associated with the dissipation of excess light energy by xanthophyll pigments (a major carotenoid group of yellow pigments) in order to protect the photosynthetic leaf apparatus (Ripullone et al. 2011). Carotenoids function in processes of light absorption in plants as well as protecting plants from the harmful effects of high light conditions; hence, lower carotenoid/chlorophyll ratios indicate lower physiological stress (Penuelas et al. 1995; Guo and Trotter 2004).

Several studies have shown the linear relationship between PRI and LUE over different vegetation types (e.g., Nichol et al. 2000, 2002). Rahman et al. (2004) produced a “continuous field” retrieval of LUE from satellite data, using the PRI as a proxy of LUE, without the need of LUTs or predetermined biome-specific LUE values. They suggested that the variations found in the continuous LUE fields must be taken into account to accurately estimate CO\(_2\) fluxes of terrestrial vegetation. However, Barton and North (2001) showed that PRI was most sensitive to changes in leaf area index (LAI), and Gitelson et al. (2006) noted that in order to use PRI to predict LUE, one would need an independent estimate of LAI.

The upcoming potential launches of new hyperspectral missions, such as hyperspectral infrared imager (HyspIRI), will provide future data fusion opportunities for the scaling and extension of leaf physiologic processes and phenology from species and ecosystem to regional and global scales.

### 1.4 Spaceborne Fluorescence Measures

Sunlight absorbed by chlorophyll in photosynthetic organisms is mostly used to drive photosynthesis, but some radiation can also be dissipated as heat or reradiated at longer wavelengths (650–850 nm). This NIR light re-emitted from illuminated plants, as a by-product of photosynthesis, is termed as solar-induced chlorophyll fluorescence (SIF), and it has been found to strongly correlate with GPP (Baker 2008; Meroni et al. 2009). Chlorophyll fluorescence may be conceptualized as

\[
SIF = \varepsilon_f \times PAR \times f\text{APAR} \tag{1.20}
\]

where \( \varepsilon_f \) is the yield of fluorescence photons (i.e., the fraction of absorbed PAR photons that are re-emitted from the canopy as SIF photons). This expression can be combined with the GPP-based LUE equation to remove the parallel dependence of both processes on APAR to yield

\[
GPP = \frac{SIF \times \varepsilon_f}{\varepsilon_f} \tag{1.21}
\]

Empirical studies at the leaf and canopy scale indicate that the two LUE terms tend to covary under the conditions of the satellite measurement (Flexas et al. 2002). SIF data provides information on both the light absorbed and the efficiency with which it is being used for photosynthesis. It is an independent measurement, linked to chlorophyll absorption, providing unique information on photosynthesis relative to VIS. Further, SIF is more dynamic than greenness, and will respond much more quickly to environmental stress, through both change in stress-induced light-use efficiency and canopy light absorption (Porcar-Castell et al. 2014).
### TABLE 1.2 Examples of Remote Sensing Methods of Deriving Gross Primary Productivity with Some References

<table>
<thead>
<tr>
<th>Gross Primary Productivity Measurement</th>
<th>Biome/Location</th>
<th>Satellite Products Used</th>
<th>Other Non-Satellite Drivers</th>
<th>Method/Approach</th>
<th>Equation</th>
<th>R²</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>BIOME-BGC (BioGeochemical Cycles) MODIS GPP/NPP, where GPP is Gross Primary Productivity and NPP is Net Primary Productivity</td>
<td>Continental</td>
<td>MODIS FPAR (MODIS): photosynthetic active radiation (PAR) as 0.45 × SWrad (shortwave downward solar radiation)</td>
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<td>See equation</td>
<td>GPP = $e_{max} \times 0.45 \times \text{SWrad} \times f\text{PAR} \times (f\text{VPD} \times f\text{Ta})$</td>
<td>NA</td>
<td>Running et al. (2004)</td>
</tr>
<tr>
<td>GPP and light use efficiency (LUE)</td>
<td>North American ecosystems from evergreen needleleaf and deciduous forest to grassland to savanna</td>
<td>MODIS EVI</td>
<td>NA</td>
<td>Linear regression</td>
<td>GPP = $m \times \text{EVI} + b$ LUE = $m \times \text{EVI} + b$</td>
<td>0.76 MODIS GPP–GPP 0.92 EVI–GPP 0.76 EVI–LUE 0.62 MODIS LUE–LUE</td>
<td>0.5</td>
</tr>
<tr>
<td>GPP</td>
<td>Tropical forests and converted pastures at the Amazon basin</td>
<td>MODIS EVI</td>
<td>NA</td>
<td>Linear regression</td>
<td>GPP = $m \times \text{EVI} + b$</td>
<td>GPP–EVI: 0.81 deciduous, 0.69, coniferous forests NEE$_{max}$–EVI:0.83 deciduous, 0.72, coniferous forests</td>
<td>Olofsson et al. (2008)</td>
</tr>
<tr>
<td>GPP and maximum Net Ecosystem Exchange (NEE$_{max}$)</td>
<td>Northern Europe ecosystems from evergreen needleleaf and deciduous forest to grasslands</td>
<td>MODIS EVI</td>
<td>NA</td>
<td>Linear regression</td>
<td>GPP = $m \times \text{EVI} + b$ NEE$_{max}$ = $m \times \text{EVI} + b$</td>
<td>GPP–NEE: 0.81 deciduous, 0.69, coniferous forests NEE$_{max}$–EVI:0.83 deciduous, 0.72, coniferous forests</td>
<td>Olofsson et al. (2008)</td>
</tr>
<tr>
<td>GPP</td>
<td>Dry to humid tropical forest sites in Southeast Asia</td>
<td>MODIS EVI</td>
<td>NA</td>
<td>Linear regression</td>
<td>GPP = $8282 \times \text{EVI} + 2118$, GPP (kgC ha$^{-1}$ month$^{-1}$)</td>
<td>0.74</td>
<td>Huete et al. (2008)</td>
</tr>
<tr>
<td>GPP</td>
<td>African tropical savanna ecosystems including shrubland, woodlands, crops and grasslands</td>
<td>MODIS EVI</td>
<td>NA</td>
<td>Linear regression</td>
<td>GPP = $m \times \text{EVI} + b$</td>
<td>NA</td>
<td>Sjöström et al. (2011)</td>
</tr>
<tr>
<td>GPP</td>
<td>Northern Australian mesic and xeric tropical savannas</td>
<td>MODIS EVI MODIS GPP product</td>
<td>Eddy covariance measured water availability index (EF) and PAR</td>
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<td>Linear regression</td>
<td>GPP–EVI ranges from 0.89 (woodyland) to 0.52 (wooded grassland)</td>
</tr>
<tr>
<td>Temperature and Greenness Model (T–G)</td>
<td>North American ecosystems from evergreen needleleaf and deciduous forest to grassland to savanna</td>
<td>MODIS daytime land surface temperature (LST) and EVI</td>
<td>NA</td>
<td>See equation</td>
<td>GPP = $(\text{EVI}<em>{\text{std}} \times \text{LST}</em>{\text{std}}) \times m$ LST$<em>{\text{std}} = \min((\text{LST}/30); (2.5 – (0.05 \times \text{LST}))$ $\text{EVI}</em>{\text{std}} = \text{EVI} – 0.10$</td>
<td>NA</td>
<td>Sims et al. (2008)</td>
</tr>
<tr>
<td>Greenness and Radiation (G–R) model</td>
<td>Crops, including soybean and maize–soybean rotation</td>
<td>MODIS NDVI and a chlorophyll-related spectral index ($V_{LH}$); EVI or wide dynamic range vegetation index (WDRVI)</td>
<td>PAR$_{\text{canopy}}$ is the top of canopy measured PAR</td>
<td>See equation</td>
<td>GPP = $V_{LH} \times \text{PAR}<em>{\text{canopy}}$ GPP = $\text{NDVI} \times \text{PAR}</em>{\text{canopy}}$</td>
<td>0.84 GPP = EVI$<em>{2} \times \text{PAR}</em>{\text{canopy}}$ 0.87 GPP = Red edge NDVI $\times \text{PAR}<em>{\text{canopy}}$ 0.9–0.9 GPP = EVI $\times \text{PAR}</em>{\text{canopy}}$</td>
<td>Peng and Gitelson (2012)</td>
</tr>
<tr>
<td>Gross Primary Productivity Measurement</td>
<td>Biome/Location</td>
<td>Satellite Products Used</td>
<td>Other Non-Satellite Drivers</td>
<td>Method/Approach</td>
<td>Equation</td>
<td>( R^2 )</td>
<td>Reference</td>
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<tr>
<td>Greemness and Radiation (G–R) model</td>
<td>Northern Australian mesic and xeric tropical savannas</td>
<td>MODIS EVI</td>
<td>( \text{PAR}_{\text{top}} ) is the top of atmosphere PAR</td>
<td>See equation</td>
<td>( \text{GPP} = \text{EVI} \times \text{PAR}_{\text{top}} )</td>
<td>NA</td>
<td>Ma et al. (2014)</td>
</tr>
<tr>
<td>Temperature and Greemness Model (T–G) and Greemness and Radiation (G–R) model</td>
<td>Temperate and boreal forest ecosystems in North America</td>
<td>MODIS EVI</td>
<td>NA</td>
<td>Linear regression</td>
<td>( \text{GPP} = \text{m} \times \text{EVI} + \text{b} )</td>
<td>( \text{T–G model GPP: 0.27 to 0.91 at non-forests ( ~0.9 ) at deciduous forests ( 0.28–0.91 ) evergreen forests} )</td>
<td>Wu et al. (2011)</td>
</tr>
<tr>
<td>Vegetation Photosynthesis Model (VPM)</td>
<td>Single temperate deciduous broadleaf ecosystem forest</td>
<td>MODIS EVI, NDVI, LSWI, water (( W_{\text{chl}} )), leaf phenology (( P_{\text{chl}} ))</td>
<td>Temperature (air) and leaf phenology information ( T_{\text{chl}} ), ( P_{\text{chl}} ), respectively</td>
<td>See equation</td>
<td>( \text{GPP} = \epsilon \times \text{fAPARchl} \times \text{PARtoct} )</td>
<td>( \text{GPP–NDVI, 0.64} ) ( \text{GPP–EVI, 0.84} ) ( \text{GPP–VPM GPP, 0.92} )</td>
<td>Xiao et al. (2004)</td>
</tr>
<tr>
<td>Vegetation Photosynthesis and Respiration Model (VPRM)</td>
<td>Nine vegetation classes, including evergreen and deciduous forests, grasslands, and shrub sites in North America</td>
<td>MODIS EVI, and LSWI</td>
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<td>Model</td>
<td>NA</td>
<td>Monthly NEE – VPRM NEE ranges from 0.96 (deciduous temperate forest) to ( &gt;1 ) at grasses and agricultural areas</td>
<td>Mahadevan et al. (2008)</td>
</tr>
<tr>
<td>Light use efficiency, LUE</td>
<td>Crops: sunflower</td>
<td>Photochemical reflectance index (PRI)</td>
<td>NA</td>
<td>Linear regression</td>
<td>( \text{LUE} = \text{m} \times \text{PRI} + \text{b} )</td>
<td>NA</td>
<td>Gamon et al. (1992)</td>
</tr>
<tr>
<td>LUE</td>
<td>Crops: corn</td>
<td>PRI</td>
<td>NA</td>
<td>Linear regression</td>
<td>( \text{LUE} = 1.37 \times \text{PRI}_{\text{VIS}} - 0.04 ) ( \text{LUE (mol C mol}^{-1} \text{ APAR)} )</td>
<td>0.66</td>
<td>Middleton et al. (2011)</td>
</tr>
<tr>
<td>GPP</td>
<td>Cropland and grassland ecosystems</td>
<td>Solar-induced chlorophyll fluorescence (SIF)</td>
<td>NA</td>
<td>Linear regression</td>
<td>US croplands: ( \text{GPP} = -0.88 + 3.55 \times \text{SIF} ) ( \text{Europe grasslands: GPP = 0.35 + 3.71 \times SIF} ) ( \text{All sites: GPP = -0.17 + 3.48 \times SIF, GPP (gC m}^{-2} \text{ day}^{-1})} )</td>
<td>0.92, US croplands 0.79, Europe grasslands 0.87, All sites</td>
<td>Guanter et al. (2014)</td>
</tr>
</tbody>
</table>
Global space-based estimates of SIF have recently become available through the Japanese Greenhouse Gases Observing Satellite (GOSAT) using solar absorption, where Fraunhofer lines are used to derive fluorescence estimates. Subsequently, global SIF data with better spatial and temporal sampling are now produced from the Global Ozone Monitoring Experiment-2 (GOME-2) instrument onboard the Metop-A platform (Joiner et al. 2013) and the Orbiting Carbon Observatory-2 (OCO-2) launched in July 2014 (Frankenberg et al. 2014). Preparatory studies are also underway for the future European fluorescence explorer (FLEX) satellite mission (Meroni et al. 2009). Whereas OCO-2 and GOME-2 were not designed specifically to measure fluorescence and estimate only a single-wavelength SIF, the FLEX mission will provide measurements characterizing the spectral shape of fluorescence emission and enable estimates of photosynthesis rates under different vegetation stress conditions. In addition, the future Sentinel-5 Precursor Tropospheric Monitoring Instrument (TROPOMI) (Veefkind et al. 2012) satellite mission will provide advance spectrometer and fluorescence data with significantly finer spatial resolution.

Chlorophyll fluorescence provides estimates of actual photosynthetic rates, as opposed to estimates of potential photosynthesis that are typically derived using spectral VIs, fAPAR and LAI products. Satellite-based SIF retrievals have thus been shown to be highly correlated with GPP estimates derived at global and seasonal scales (Frankenberg et al. 2011; Guanter et al. 2012). Guanter et al. (2014) showed satellite SIF retrievals provided direct measures of GPP of cropland and grassland ecosystems and a more direct link with photosynthesis than found with vegetation greenness measures, such as VIs. Their SIF-based GPP estimates were similar to flux-tower comparisons and found to be significantly more accurate than empirical and process-based productivity models, which underestimated GPP by as much as 50%–75%. This study, along with Zhang et al. (2014), has shown the potential of SIF data to improve carbon cycle models and provide more accurate projections of ecosystem and agricultural productivity and climate impacts on production.

1.5 Discussion

The simple LUE-based productivity equation introduced by Monteith (1972) comprises a great deal of biological and biophysical complexity, resulting in numerous productivity modeling approaches that attempt to deal with this complexity in different ways. GPP is proportional to the incident shortwave radiation, the fractional absorption of that energy (fAPAR), and the efficiency with which the absorbed radiation is converted to fixed carbon, ε. The different modeling approaches tend to emphasize one term or the other of the LUE equation, with remote sensing-based algorithms focusing on the fAPAR term, or more recently, the fAPAR_plant component. Others have focused on the LUE term as the primary determining factor of productivity either focusing on the biome level versus species specificity of LUE variability (e.g., Ahl et al. 2004) or focusing on the meteorologic scalars of LUE with potential incorporation of soil moisture as an LUE regulator. Kanniah et al. (2009) noted that strong seasonal variations in LUE at tropical mesic savanna sites are primarily driven by the dynamics in understory grasses. There is also much attention on the role of the PAR term in explaining seasonal and year-to-year growth variability of plant productivity, including the incorporation of light quality (direct and diffuse) to complement data of radiation quantities.

With the increasing use of satellite data for large-scale productivity assessments, it has become appealing to calibrate such data with in situ productivity measures, such as from EC tower sites. Glenn et al. (2008) suggested that remote sensing is very suitable as a scaling tool of productivity when ground data are available. Remote sensing can greatly simplify the upsampling of ecosystem processes, such as photosynthesis, from an expansive network of flux towers to larger landscape units and to regional scales, as the measurement footprint of flux towers at least partially overlaps the pixel size of daily return satellites (e.g., 250 m for MODIS). Further, as top-of-canopy measurements, flux towers do not require knowledge of LAI or details of canopy architecture to estimate fluxes facilitating their comparisons with remote sensing measures that similarly involve community properties resulting from integrative, top-of-canopy radiation interactions. However, tower data of fluxes potentially offer much more than simply validating and/or calibrating remote sensing products and models. An understanding of why satellite–flux tower relationships hold, or do not hold, will greatly advance and contribute to our comprehension of the carbon cycle mechanisms and scaling factors at play.

The validation of satellite-based productivity products remains challenging due to a variety of spatial and temporal scaling issues (Morisette et al. 2002; Turner et al. 2004). These include the matching of large satellite pixels (~1 km) with field plot scale measurements in both time and space. Li et al. (2008) demonstrated limitations associated with disparate footprints between satellite and tower flux measurements and the need for Landsat spatial resolutions for flux footprint matching, particularly in nonforest canopies. Plot-level ANPP measurements are commonly made at scales from 1 m² to 0.01 km², while the matching MODIS footprint may range from 62.500 m² to 1 km².

From a temporal perspective, plants respond to the dynamics of environmental variables through stomatal closure and other diurnal adjustments that cannot be easily sensed by satellite sensors (e.g., MODIS). Variation in LUE is likely to be significant over shorter, daily time frames when water or temperature stress develops. However, at moderate to longer (e.g., weekly to monthly) time scales, plants tend to increase leaf area under favorable environments as an investment of resources into their photosynthetic apparatus, and reduce LAI under stress when leaves are expensive to produce and maintain. Thus, at longer time scales, there would be a convergence of satellite greenness signals with biologic and structural canopy properties. SIF, however, is seen as one way to increase the effective temporal remote sensing of vegetation photosynthesis, essentially to near real-time.
Despite these challenges, continuing advances made in global weather-forecasting accuracies and the development of new satellite sensor technologies, including fluorescence, hyperspectral, thermal, and lidar, now enable a more thorough coupling of the environmental conditions that plants experience with improved characterization of their biophysical states, and with better monitoring capabilities to track plant responses to environmental changes. These advances are providing a better understanding of the dynamics of terrestrial productivity and the use of satellite data to drive productivity models of the land surface.

References


Monitoring Photosynthesis from Space


