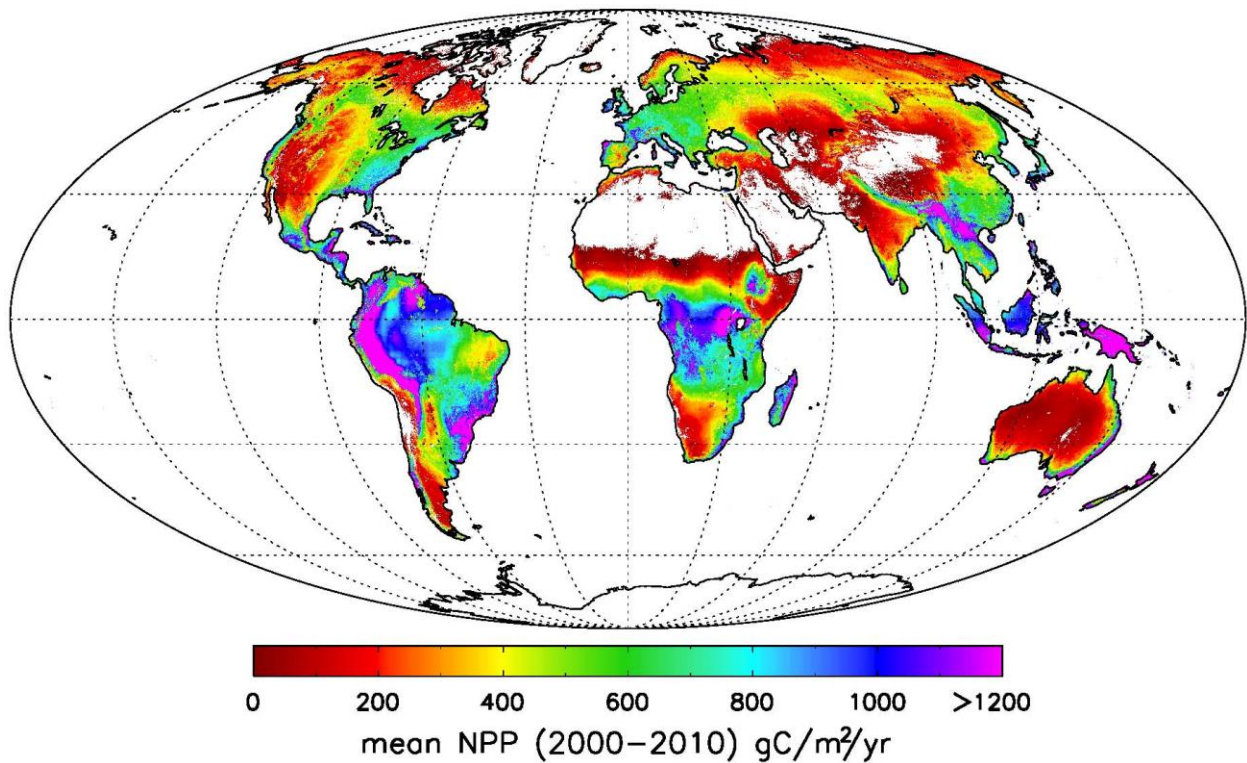


User's Guide
Daily GPP and Annual NPP (MOD17A2/A3) Products
NASA Earth Observing System MODIS Land Algorithm

Steven W. Running
Maosheng Zhao



Version 3.0
For Collection 6
October 7, 2015

Synopsis

The U.S. National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) currently “produces a regular global estimate of daily gross primary productivity (GPP) and annual net primary productivity (NPP) of the entire terrestrial earth surface at 1-km spatial resolution, 110 million cells, each having GPP and NPP computed individually” (Running et al. 2004). This guide provides a description of the Gross and Net Primary Productivity algorithms (MOD17A2/A3) designed for the MODIS sensor aboard the Aqua and Terra platforms. The resulting 8-day products, beginning in 2000 and continuing to the present, are archived at a NASA DAAC (Distributed Active Archive Center). This document is intended to provide both a broad overview and sufficient detail to allow for the successful use of the data in research and applications.

1. The Algorithm, Background and Overview

The derivation of a satellite estimate of terrestrial NPP has three theoretical components: (1) the idea that plant NPP is directly related to absorbed solar energy, (2) the theory that a connection exists between absorbed solar energy and satellite-derived spectral indices of vegetation, and (3) the assumption that there are biophysical reasons why the actual conversion efficiency of absorbed solar energy may be reduced below the theoretical potential value. We will briefly consider each of these components.

1.1. Relating NDVI, APAR, GPP, and NPP

The original logic of John L. Monteith (1972) suggested that the NPP of well-watered and fertilized annual crop plants was linearly related to the amount of solar energy the plants absorbed over a growing season. This logic combined the meteorological constraint of available sunlight reaching a site with the ecological constraint of the amount of leaf area absorbing the solar energy, while avoiding many complexities of canopy micrometeorology and carbon balance theory. Measures of absorbed photosynthetically active radiation (APAR) integrate the geographic and seasonal variability of day length and potential incident radiation with daily cloud cover and aerosol attenuation of sunlight. In addition, APAR implicitly quantifies the amount of leafy canopy that is displayed to absorb radiation (i.e., LAI). A conversion efficiency, ϵ , translates APAR (in energy units) to final tissue growth, or NPP (in biomass). GPP is the initial daily total of photosynthesis, and daily net photosynthesis (PSN_{net}) subtracts leaf and fine-root respiration over a 24-hour day. NPP is the annual sum of daily net PSN minus the cost of growth and maintenance of living cells in permanent woody tissue. Monteith's logic, therefore, combines the meteorological constraint of available sunlight reaching a site with the ecological constraint of the amount of leaf-area capable of absorbing that solar energy. Such a combination avoids many of the complexities of carbon balance theory.

The radiation use efficiency logic requires an estimate of APAR, while the more typical application of remote sensing data is to provide an estimate of FPAR, the fraction of incident PAR absorbed by the surface. Sellers (1987) showed that APAR could be estimated from remote sensing. Spectral vegetation indexes such as NDVI most directly quantify the fraction of photosynthetically active radiation (FPAR) that is absorbed (ranging from 0 to 1): $FPAR = APAR/PAR \approx NDVI$. APAR depends upon (1) the geographic and seasonal variability of day

length and potential incident radiation, as modified by cloud cover and aerosols, and (2) the amount and geometry of displayed leaf material.

Measurements or estimates of PAR are therefore required in addition to the remotely sensed FPAR. Fortunately, for studies over small spatial domains with *in situ* measurements of PAR at the surface, the derivation of APAR from satellite-derived FPAR is straightforward. Implementation of radiation use efficiency for the MODIS productivity algorithm depends on global daily estimates of PAR, ideally at the same spatial resolution as the remote sensing inputs, a challenging problem. Currently, large-scale meteorological data are provided by the NASA GMAO, see details below.

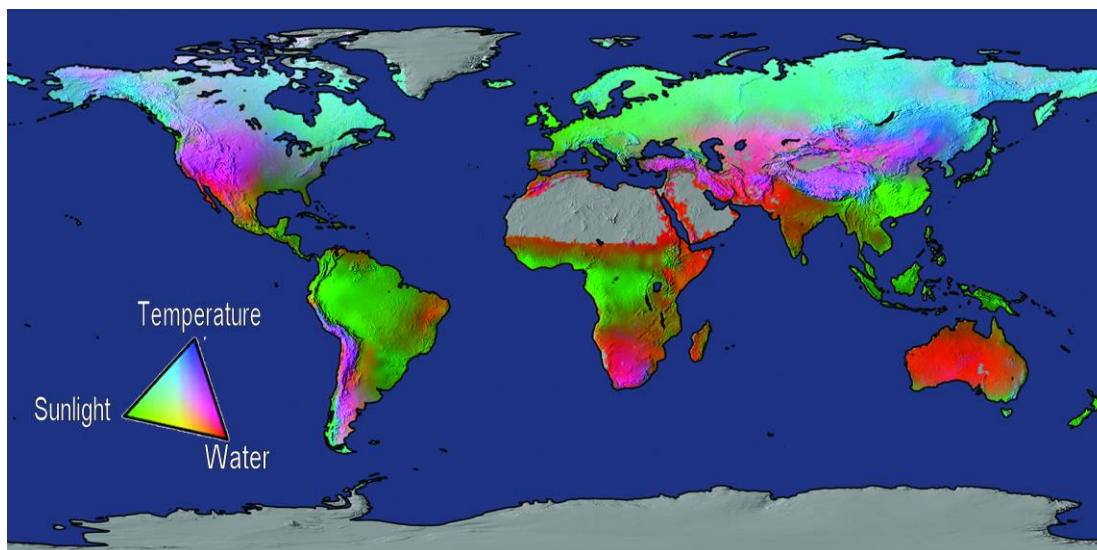


Figure 1. Analysis of the geographic variation in climatic controls of terrestrial net primary production from water, temperature, and radiation limitations. Data are from Nemani and colleagues (2003).

1.2. Biophysical variability of ϵ

The PAR conversion efficiency ϵ , varies widely with different vegetation types (Field et al. 1995, Prince and Goward 1995, Turner et al. 2003). There are two principle sources of this variability. First, with any vegetation, some photosynthesis is immediately used for maintenance respiration. For the annual crop plants from the original theory of Monteith (1972), these respiration costs were minimal, so ϵ was typically around 2 gC/MJ. Respiration costs, however, increase with the size of perennial plants. Hunt (1994) found published ϵ values for woody vegetation were much lower, from about 0.2 to 1.5 gC/MJ, and hypothesized that this was the result of respiration from the 6-27% of living cells in the sapwood of woody stems (Waring and Running 2010).

The second source of variability in ϵ is attributed to suboptimal climatic conditions. To extrapolate Monteith's original theory, designed for well-watered crops only during the growing season, to perennial plants living year around, certain severe climatic constraints must be recognized. Evergreen vegetation such as conifer trees or sclerophyllous shrubs absorb PAR all during the non-growing season, yet sub-freezing temperatures stop photosynthesis because leaf stomata are forced to close (Waring and Running 2010). As a global generalization, we truncate GPP on days when the air temperature is below 0 °C. Additionally, high vapor pressure deficits, > 2000 Pa, have been shown to induce stomatal closure in many species. This level of daily

atmospheric water deficit is commonly reached in semi-arid regions of the world for much of the growing season. So, our algorithm mimics this physiological control by progressively limiting daily GPP by reducing ϵ when high vapor pressure deficits are computed from the surface meteorology. We also assume nutrient constraints on vegetation growth to be quantified by limiting leaf area, rather than attempting to compute a constraint through ϵ . This assumption isn't entirely accurate, as ranges of leaf nitrogen and photosynthetic capacity occur in all vegetation types (Reich et al. 1994, Reich et al. 1995, Turner et al. 2003). Spectral reflectances are somewhat sensitive to leaf chemistry, so the MODIS derived FPAR and LAI may represent some differences in leaf nitrogen content, but in an undetermined way.

To quantify these biome- and climate-induced ranges of ϵ , we simulated global NPP in advance with a complex ecosystem model, BIOME-BGC, and computed the ϵ or conversion efficiency from APAR to final NPP. This Biome Parameter Look-Up Table or BPLUT contains parameters for temperature and VPD limits, specific leaf area and respiration coefficients for representative vegetation in each biome type (Running et al. 2000, White et al. 2000). The BPLUT also defines biome differences in carbon storage and turnover rates.

Since the relationships of temperature to the processes controlling GPP and those controlling autotrophic respiration have fundamentally different, it seems likely that the empirical parameterization of the influence of temperature on production efficiency would be more robust if the gross production and autotrophic respiration processes were separated. This is the approach employed in the MOD17 algorithm.

1.3. The MOD17A2/MOD17A3 algorithm logic

1.3a. Gross primary productivity. The core science of the algorithm is an application of the described radiation conversion efficiency concept to predictions of daily GPP, using satellite-derived FPAR (from MOD15) and independent estimates of PAR and other surface meteorological fields (from DAO data, now renamed to GMAO/NASA), and the subsequent estimation of maintenance and growth respiration terms that are subtracted from GPP to arrive at annual NPP. The maintenance respiration (MR) and growth respiration (GR) components arise from allometric relationships linking daily biomass and annual growth of plant tissues to satellite-derived estimates of leaf area index (LAI, MOD15). These allometric relationships have been developed from an extensive literature review, and incorporate the same parameters as those used in the BIOME-BGC ecosystem process model (Running and Hunt 1993; White et al. 2000).

For any given pixel within the global set of 1-km land pixels, estimates of both GPP and NPP are calculated. The calculations, summarized in Figure 1.1, are a series of steps, some (e.g., GPP) are calculated daily, and others (e.g., NPP) on an annual basis. Calculations of daily photosynthesis (GPP) are shown in the upper flowchart of Figure 1.1. An 8-day estimate of FPAR from MOD15 and daily estimated PAR from GMAO/NASA are multiplied to produce daily APAR for the pixel. Based on the at-launch landcover product (MOD12), a set of biome-specific radiation use efficiency parameters are extracted from the Biome Properties Look-Up Table (BPLUT) for each pixel. There are five parameters used to calculate GPP, as shown in Table 1.1. The actual biome-specific values associated with these parameters will be discussed in Section 3, and the entire BPLUT is shown in Table 2.1.

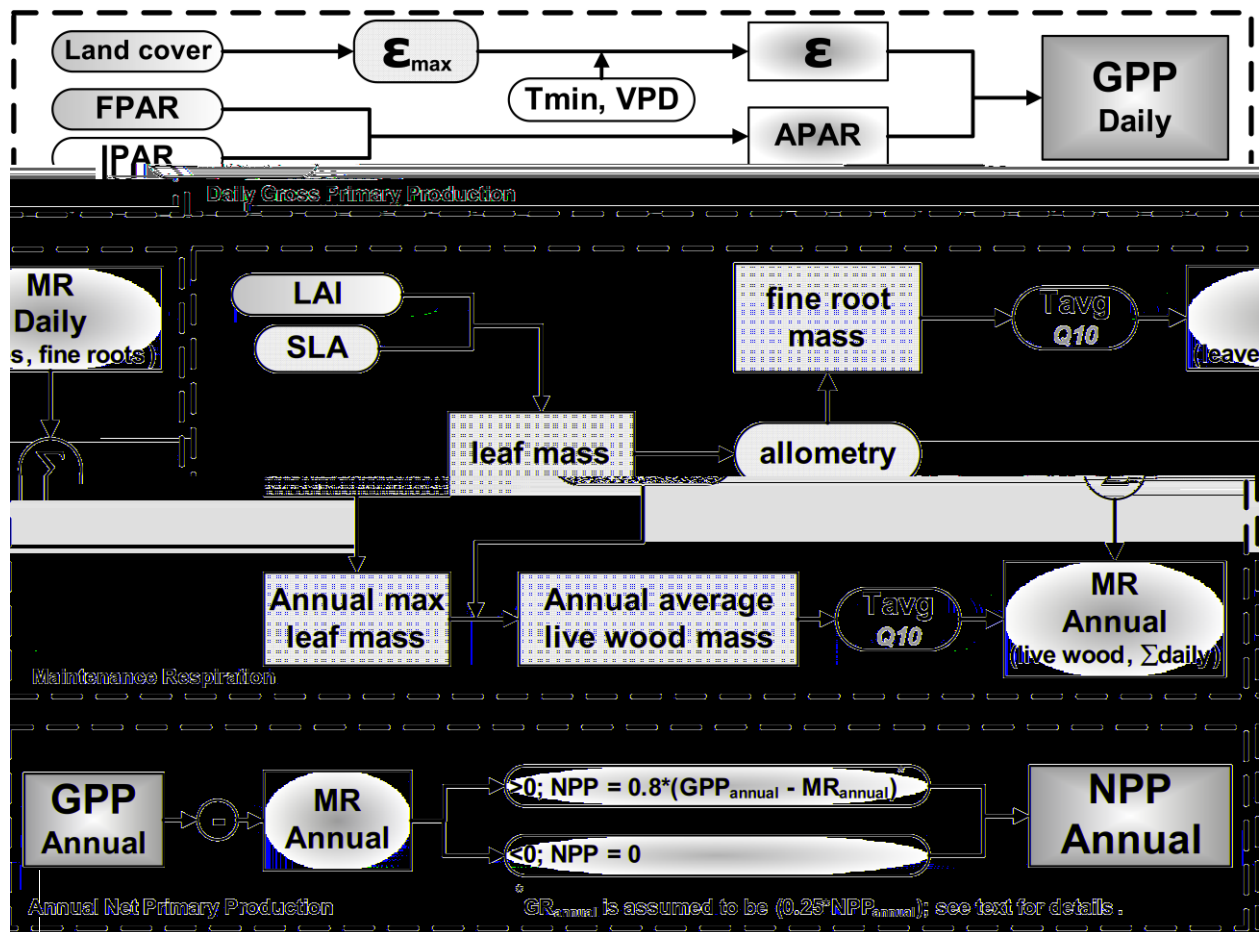


Figure 1.1. Flowcharts showing the logic behind the MOD17 Algorithm in calculating both 8-day average GPP and annual NPP.

Table 1.1. BPLUT parameters for daily gross primary productivity.

Parameter	Units	Description
ϵ_{max}	(kg C MJ ⁻¹)	The maximum radiation conversion efficiency
TMINmax	(°C)	The daily minimum temperature at which $\epsilon = \epsilon_{max}$ (for optimal VPD)
TMINmin	(°C)	The daily minimum temperature at which $\epsilon = 0.0$ (at any VPD)
VPDmax	(Pa)	The daylight average vapor pressure deficit at which $\epsilon = \epsilon_{max}$ (for optimal TMIN)
VPDmin	(Pa)	The daylight average vapor pressure deficit at which $\epsilon = 0.0$ (at any TMIN)

The two parameters for TMIN and the two parameters for VPD are used to calculate the scalars that attenuate ϵ_{\max} to produce the final ϵ (kg C MJ⁻¹) used to predict GPP such that

$$\epsilon = \epsilon_{\max} * \text{TMIN_scalar} * \text{VPD_scalar} \quad (1.1)$$

The attenuation scalars are simple linear ramp functions of daily TMIN and VPD, as illustrated for TMIN in Figure 1.2. Values of TMIN and VPD are obtained from the GMAO/NASA dataset, while the value of ϵ_{\max} is obtained from the BPLUT.

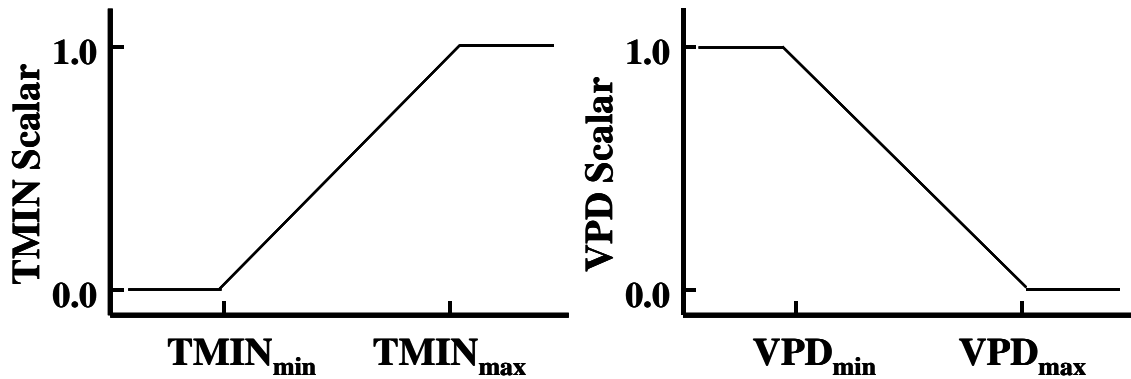


Figure 1.2. The TMIN and VPD attenuation scalars are simple linear ramp functions of daily TMIN and VPD.

The resulting radiation use efficiency coefficient ϵ is combined with estimates of APAR to calculate GPP (kg C day⁻¹) as

$$\text{GPP} = \epsilon * \text{APAR} \quad (1.2)$$

where $\text{APAR} = \text{IPAR} * \text{FPAR}$. IPAR (PAR incident on the vegetative surface) must be estimated from incident shortwave radiation (SWRad, provided in the GMAO/NASA dataset) as

$$\text{IPAR} = (\text{SWRad} * 0.45) \quad (1.3)$$

While GPP (Equation 1.2) is calculated on a daily basis, 8-day summations of GPP are created and these summations are available to the public. The summations are named for the first day included in the 8-day period.

✦ Each summation consists of 8 consecutive days of data, and there are 46 such summations created for each calendar year of data collection. To obtain an estimate of daily GPP for this 8-day period, it is necessary to divide the value obtained during a data download by eight for the first 45 values/year and by five (or six in a leap year) for the final period.

1.3b. Daily maintenance respiration and net photosynthesis. Maintenance respiration costs (MR) for leaves and fine roots are summarized in the center flowchart of Figure 1.1 and are also calculated on a daily basis. There are five parameters within the BPLUT (Table 1.2) needed to calculate daily MR, which is dependent upon leaf or fine root mass, base MR at 20 °C, and daily average temperature. Leaf mass (kg) is calculated as

$$\text{Leaf_Mass} = \text{LAI} / \text{SLA} \quad (1.4)$$

where LAI, the leaf area index ($\text{m}^2 \text{ leaf m}^{-2} \text{ ground area}$), is obtained from MOD15 and the specific leaf area (SLA, projected leaf area $\text{kg}^{-1} \text{ leaf C}$) for a given pixel is obtained from the BPLUT.

Table 1.2. BPLUT parameters for daily maintenance respiration.

Parameter	Units	Description
SLA	($\text{m}^2 \text{ kg C}^{-1}$)	Projected leaf area per unit mass of leaf carbon
froot_leaf_ratio	None	Ratio of fine root carbon to leaf carbon
leaf_mr_base	($\text{kg C kg C}^{-1} \text{ day}^{-1}$)	Maintenance respiration per unit leaf carbon per day at 20 °C
froot_mr_base	($\text{kg C kg C}^{-1} \text{ day}^{-1}$)	Maintenance respiration per unit fine root carbon per day at 20 °C
Q _{10_mr}	None	Exponent shape parameter controlling respiration as a function of temperature

Fine root mass (Fine_Root_Mass, kg) is then estimated as

$$\text{Fine_Root_Mass} = \text{Leaf_Mass} * \text{froot_leaf_ratio} \quad (1.5)$$

where froot_leaf_ratio is the ratio of fine root to leaf mass (unitless) as obtained from the BPLUT.

Leaf maintenance respiration (Leaf_MR, kg C day^{-1}) is calculated as

$$\text{Leaf_MR} = \text{Leaf_Mass} * \text{leaf_mr_base} * \text{Q}_{10_mr}^{[(T_{\text{avg}} - 20.0) / 10.0]} \quad (1.6)$$

where leaf_mr_base is the maintenance respiration of leaves ($\text{kg C kg C}^{-1} \text{ day}^{-1}$) as obtained from the BPLUT and T_{avg} is the average daily temperature (°C) as estimated from the GMAO/NASA meteorological data.

The maintenance respiration of the fine root mass (Froot_MR, kg C day^{-1}) is calculated as

$$\text{Froot_MR} = \text{Fine_Root_Mass} * \text{froot_mr_base} * \text{Q}_{10_mr}^{[(T_{\text{avg}} - 20.0) / 10.0]} \quad (1.7)$$

where froot_mr_base is the maintenance respiration per unit of fine roots ($\text{kg C kg C}^{-1} \text{ day}^{-1}$) at 20 °C as obtained from the BPLUT.

Finally, PSNnet (kg C day^{-1}) can be calculated from GPP (Equation 1.2) and maintenance respiration (Equations 1.6, 1.7) as

$$\text{PSNnet} = \text{GPP} - \text{Leaf_MR} - \text{Froot_MR} \quad (1.8)$$

As with GPP, PSNnet is summed over an 8-day period.

✎ *This product does not include the maintenance respiration associated with live wood (Livewood_MR), nor does it include growth respiration (GR).*

1.3c. Annual maintenance respiration. Given a calendar year's worth of outputs from the daily algorithm, the annual algorithm (Figure 1.1, lower flowchart) estimates annual NPP by first calculating live woody tissue maintenance respiration, and then estimating growth respiration costs for leaves, fine roots, and woody tissue using values defined in Table 1.3. Finally, these components are subtracted from the accumulated daily PSNnet to produce an estimate of annual NPP.

Table 1.3. BPLUT parameters for annual maintenance and growth respiration.

Parameter	Units	Description
livewood_leaf_ratio	None	Ratio of live wood carbon to annual maximum leaf carbon
livewood_mr_base	($\text{kg C kg C}^{-1} \text{ day}^{-1}$)	Maintenance respiration per unit live wood carbon per day at 20 °C
leaf_longevity	(yrs)	Average leaf lifespan
leaf_gr_base	(kg C kg C^{-1})	Respiration cost to grow a unit of leaf carbon
froot_leaf_gr_ratio	None	Ratio of live wood to leaf annual growth respiration
livewood_leaf_gr_ratio	None	Ratio of live wood to leaf annual growth respiration
deadwood_leaf_gr_ratio	None	Ratio of dead wood to leaf annual growth respiration
ann_turnover_proportion	None	Annual proportion of leaf turnover

Annual maximum leaf mass, the maximum value of daily leaf mass, is the primary input for both live wood maintenance respiration (Livewood_MR) and whole-plant growth respiration (GR). To account for Livewood_MR, it is assumed that the amount of live woody tissue is (1) constant throughout the year, and (2) related to annual maximum leaf mass. Once the live woody tissue mass has been determined, it can be used to estimate total annual livewood maintenance respiration. This approach relies on empirical studies relating the annual growth of leaves to the annual growth of other plant tissues. The compilation study by Cannell (1982) is an excellent resource, providing the basis for many of the relationships developed for this portion of the MOD17 algorithm and tested with the BIOME-BGC ecosystem processes model. Leaf longevity is required to estimate annual leaf growth for evergreen forests but is assumed to be less than one year for deciduous forests, which replace all foliage annually. This logic further assumes that there is no litterfall in deciduous forests until after maximum annual leaf mass has been attained.

The parameters relating annual leaf growth respiration costs to annual fine root, live wood, and dead wood growth respiration were calculated directly from similar parameters developed for the BIOME-BGC model (White et al. 2000).

To create the annual NPP term, the MOD17 algorithm maintains a series of daily pixel-wise terms to appropriately account for plant respiration. To determine livewood maintenance respiration, the mass of livewood (Livewood_Mass, kg C) is calculated as

$$\text{Livewood_Mass} = \text{ann_leaf_mass_max} * \text{livewood_leaf_ratio} \quad (1.9)$$

where ann_leaf_mass_max is the annual maximum leaf mass for a given pixel (kg C) obtained from the daily Leaf_Mass calculation (Equation 1.4). The livewood_leaf_ratio is the ratio of live wood mass to leaf mass (unitless), and is obtained from the BPLUT.

Once the mass of live wood has been determined, it is possible to calculate the associated maintenance respiration (Livewood_MR, kg C day⁻¹) as

$$\text{Livewood_MR} = \text{Livewood_Mass} * \text{livewood_mr_base} * \text{annsum_mrindex} \quad (1.10)$$

where livewood_mr_base (kg C kg C⁻¹ day⁻¹) is the maintenance respiration per unit of live wood carbon per day from the BPLUT and annsum_mrindex is the annual sum of the maintenance respiration term $Q_{10_mr}^{[(T_{\text{avg}}-20.0)/10.0]}$.

Q_{10} is a constant value of 2.0 for fine root and live wood. For leaf, we adopted a temperature acclimated Q_{10} equation proposed by Tjoelker et al. (2001),

$$Q_{10} = 3.22 - 0.046 * T_{\text{avg}} \quad (1.11)$$

1.3d. Annual growth respiration and net primary productivity. The original algorithm calculated growth respiration (R_g) as a function of annual maximum LAI, and thus, the accuracy of R_g is determined by the accuracy of LAI_{max} . However, when LAI is greater than 3.0, surface reflectances have low sensitivity to LAI and the MODIS LAI is retrieved, in most cases, under reflectance saturation conditions (Myneni et al., 2002). Generally, for forests, annual MODIS LAI_{max} is set to be 6.8 for pixels classified as forests. This logic can generate R_g values that are greater than NPP. R_g is the energy cost for constructing organic compounds fixed by photosynthesis, and it is empirically parameterized as 25% of NPP (Ryan 1991, Cannell et al. 2000). To improve the algorithm, we replaced the LAI_{max} dependent R_g with $R_g = 0.25 * \text{NPP}$, and annual MODIS NPP can be computed as

$$\text{NPP} = \text{GPP} - R_m - R_g = \text{GPP} - R_m - 0.25 * \text{NPP} \quad (1.12)$$

where R_m is annual plant maintenance respiration, and therefore,

$$\begin{aligned} \text{NPP} &= 0.8 * (\text{GPP} - R_m) && \text{when } \text{GPP} - R_m \geq 0, \text{ and} \\ \text{NPP} &= 0 && \text{when } \text{GPP} - R_m < 0 \end{aligned} \quad (1.13)$$

2. Operational Details of MOD17 and Primary Uncertainties in the MOD17 Logic

A number of issues are important in implementing this algorithm for a global NPP. This section discusses some of the assumptions and special issues involved in development of the input variables, and their influence on the final NPP.

2.1. Dependence on MODIS Land Cover Classification (MOD12Q1)

One of the first MODIS products used in the MOD17 algorithm is the Land Cover Product, MOD12Q1. The importance of this product cannot be overstated as the MOD17 algorithm relies heavily on land cover type through use of the BPLUT. While the primary product created by MOD12 is a 17-class IGBP (International Geosphere-Biosphere Programme) landcover classification map (Running et al. 1994, Belward et al. 1999, Friedl et al. 2010), the MOD17 algorithm employs Boston University's UMD classification scheme (Table 2.1). More details on these and other schemes and their quality control considerations can be found at: https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1

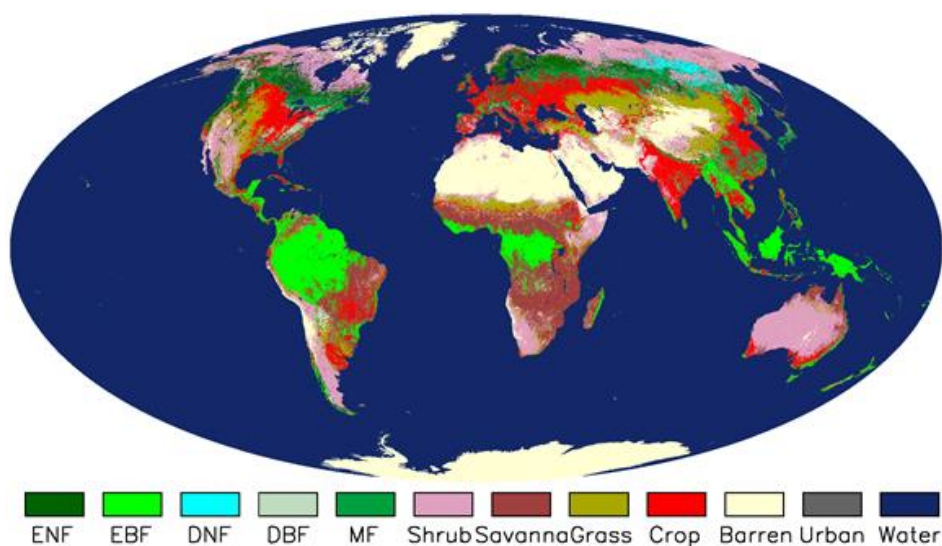


Figure 2.1. University of Maryland land cover classification system defined land covers from MOD12Q1 (land cover type 2 in MOD12Q1 dataset). Evergreen Needleleaf Forest (ENF), Evergreen Broadleaf Forest (EBF), Deciduous Needleleaf Forest (DNF), Deciduous Broadleaf Forest (DBF), Mixed forests (MF), Closed Shrublands (CShrub), Open Shrublands (OShrub), Woody Savannas (WSavanna), Savannas (Savanna), grassland (Grass), and Croplands (Crop). Note that in this figure, we combined CShrub and OShrub into Shrub, and WSavanna and Savannas into Savanna.

Given the global nature and daily time-step of the MODIS project, a broad classification scheme, which retains the essence of land cover, is necessary. Since Collection 6 MODIS products are designed at a 0.5-km grid scale, it can be difficult to obtain accurate land cover in areas with complex vegetation, and misclassification can occur. However, studies have suggested that the MODIS vegetation maps are accurate to within 65-80%, with higher

accuracies for pixels that are largely homogeneous, and allow for consistent monitoring of the global land cover (Friedl et al. 2010).

2.2. The BPLUT and constant biome properties

Arguably, the most significant assumption made in the MOD17 logic is that biome-specific physiological parameters do not vary with space or time. These parameters are outlined in the BPLUT (Table 2.2) within the MOD17 algorithm. The BPLUT constitutes the physiological framework for controlling simulated carbon sequestration. These biome-specific properties are not differentiated for different expressions of a given biome, nor are they varied at any time during the year. In other words, a semi-desert grassland in Mongolia is treated the same as a tallgrass prairie in the Midwestern United States. Likewise, a sparsely vegetated boreal evergreen needleleaf forest in Canada is functionally equivalent to its coastal temperate evergreen needleleaf forest counterpart.

At NTSG we are exploring new logic that will allow both geospatial and seasonal variation in the ϵ_{max} parameter (Madani et al. 2014, Reich 2012). We will be developing global implementation, and doing global testing of this in coming years.

Table 2.1. The land cover types used in the MOD17 Algorithm.

UMD Land Cover Types	
Class Value	Class Description
0	Water
1	Evergreen Needleleaf Forest
2	Evergreen Broadleaf Forest
3	Deciduous Needleleaf Forest
4	Deciduous Broadleaf Forest
5	Mixed Forest
6	Closed Shrubland
7	Open Shrubland
8	Woody Savanna
9	Savanna
10	Grassland
12	Cropland
13	Urban or Built-Up
16	Barren or Sparsely Vegetated
254	Unclassified
255	Missing Data

Table 2.2. Biome-Property-Look-Up-Table (BPLUT) for MODIS GPP/NPP algorithm with NCEP-DOE reanalysis II and the Collection5 FPAR/LAI as inputs. The full names for the University of Maryland land cover classification system (UMD_VEG_LC) in MOD12Q1 dataset (fieldname: Land_Cover_Type_2) are, Evergreen Needleleaf Forest (ENF), Evergreen Broadleaf Forest (EBF), Deciduous Needleleaf Forest (DNF), Deciduous Broadleaf Forest (DBF), Mixed forests (MF), Closed Shrublands (CShrub), Open Shrublands (OShrub), Woody Savannas (WSavanna), Savannas (Savanna), Grassland (Grass), and Croplands (Crop).

UMD_VEG_LC	ENF	EBF	DNF	DBF	MF	CShrub	OShrub	WSavanna	Savanna	Grass	Crop
LUEmax (KgC/m ² /d/MJ)	0.000962	0.001268	0.001086	0.001165	0.001051	0.001281	0.000841	0.001239	0.001206	0.000860	0.001044
Tmin_min (C)	-8.00	-8.00	-8.00	-6.00	-7.00	-8.00	-8.00	-8.00	-8.00	-8.00	-8.00
Tmin_max (C)	8.31	9.09	10.44	9.94	9.50	8.61	8.80	11.39	11.39	12.02	12.02
VPD_min (Pa)	650.0	800.0	650.0	650.0	650.0	650.0	650.0	650.0	650.0	650.0	650.0
VPD_max (Pa)	4600.0	3100.0	2300.0	1650.0	2400.0	4700.0	4800.0	3200.0	3100.0	5300.0	4300.0
SLA (LAI/KgC)	14.1	25.9	15.5	21.8	21.5	9.0	11.5	27.4	27.1	37.5	30.4
Q ₁₀ *	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
froot_leaf_ratio	1.2	1.1	1.7	1.1	1.1	1.0	1.3	1.8	1.8	2.6	2.0
livewood_leaf_ratio	0.182	0.162	0.165	0.203	0.203	0.079	0.040	0.091	0.051	0.000	0.000
leaf_mr_base	0.00604	0.00604	0.00815	0.00778	0.00778	0.00869	0.00519	0.00869	0.00869	0.0098	0.0098
froot_mr_base	0.00519	0.00519	0.00519	0.00519	0.00519	0.00519	0.00519	0.00519	0.00519	0.00819	0.00819
livewood_mr_base	0.00397	0.00397	0.00397	0.00371	0.00371	0.00436	0.00218	0.00312	0.00100	0.00000	0.00000

*: The constant Q₁₀ = 2.0 is applied to fine roots and live wood, while for leaves, a temperature acclimation Q₁₀ value is used as described in Equation.

3. Leaf area index and fraction of absorbed photosynthetically active radiation

As illustrated in Figure 2.1, the primary productivity at a pixel is dependent upon, among other things, LAI and FPAR, calculated with the MOD15 algorithm. The LAI/FPAR product is an eight-day composite product

(https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod15a2).

The MOD15 compositing algorithm uses a simple selection rule whereby the maximum FPAR (across the eight days) is chosen for the inclusion as the output pixel. The same day chosen to represent the FPAR measure also contributes the current pixel's LAI value. This means that although primary productivity is calculated daily, the MOD17 algorithm necessarily assumes that leaf area and FPAR do not vary during a given 8-day period. Compositing of LAI and FPAR is required to provide an accurate depiction of global leaf area dynamics with consideration of spectral cloud contamination, particularly in the tropics.

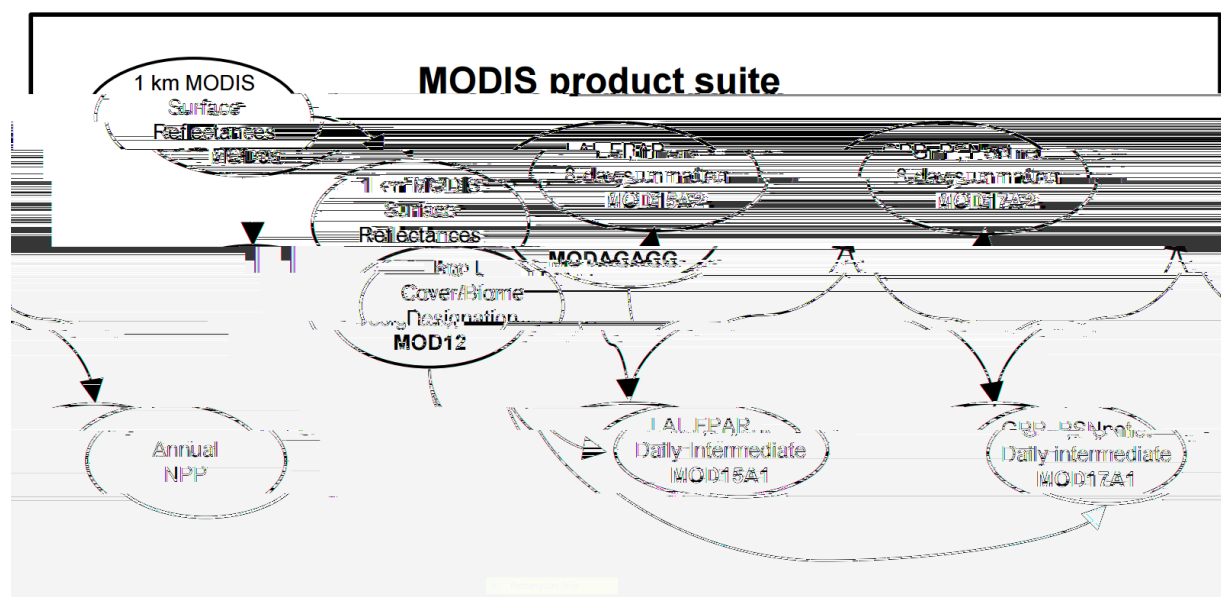


Figure 2.1. The linkages among MODIS land products.

4. Additional Cloud/Aerosol Screening

The 8-day MOD15A2 is still contaminated by clouds and/or aerosols in certain regions and times of year. As a result, in regions with higher frequencies of cloud cover, such as tropical rain forests, values of FPAR and LAI will be greatly reduced (Figure 2.1). To distinguish between good quality and contaminated data, MOD15A2 contains Quality Control (QC) fields, enabling users to determine which pixels are suitable for further analysis. The use of contaminated FPAR and LAI inputs will produce incorrect 8-day GPP and consequently, unreliable annual NPP.

✎ The following additional cloud/aerosol screening is only applied to the improved MOD17 for the end of the year when the previous full yearly MOD15A2 is available. The screening processes for the improved MOD17 cannot be applied to NASA's near real time MOD17 (Zhao et al. 2005).

We solved this problem related to MOD15A2 inputs by removing poor quality FPAR and LAI data based on the QC label for every pixel. If any LAI/FPAR pixel did not meet the quality screening criteria, its value is determined through linear interpolation between the previous period's value and that of the next period to pass the screening process. Figure 2.2 illustrates how this temporal filling approach is applied to a MODIS pixel in the Amazon region where higher frequency and persistence of cloud cover exists.

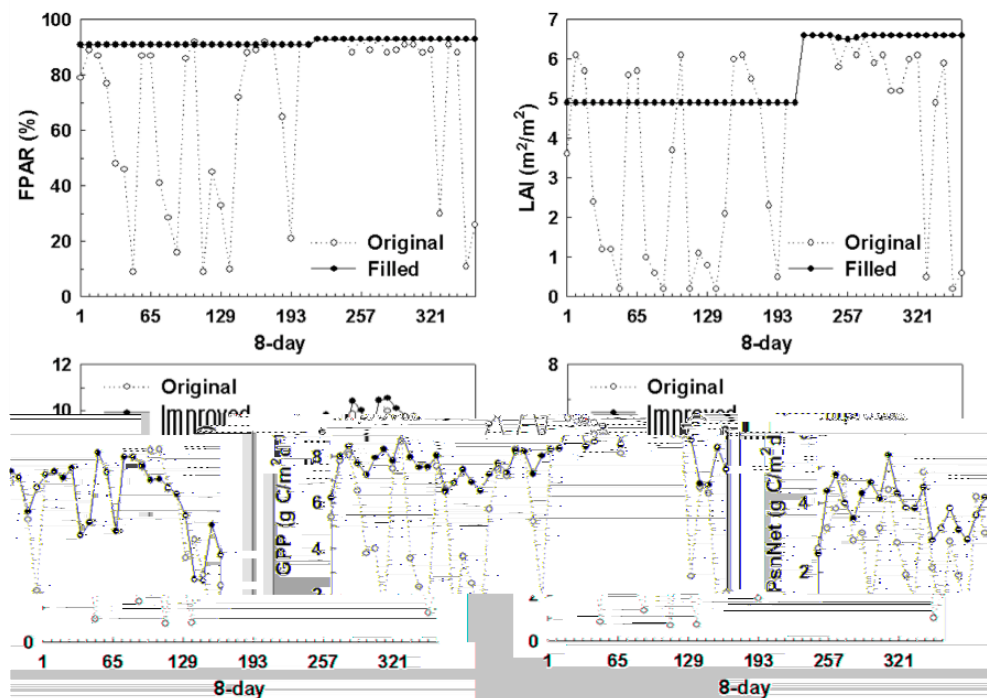


Figure 2.2. An example on how temporal filling unreliable 8-day Collection 4 FPAR/LAI, and therefore improved 8-day GPP and PsnNet for one MODIS 1-km pixel located in Amazon basin ($lat = -5.0$, $lon = -65.0$) (from Zhao et al. 2005).

As depicted in Figure 2.2, contaminated MOD15A2 was improved as the result of the filling process. However, there are some unusual 8-day periods with lower FPAR and LAI but good QC labels. In spite of this, we have to depend on QC label because this is the only source of quality control. Improved MOD15A2 leads to improvements of MOD17. Under most conditions, 8-day composited GPP will increase because the temporal filling process generally acts to increase FPAR.

2.5. GMAO daily meteorological data

The MOD17 algorithm computes productivity at a daily time step. This is made possible by the daily global meteorological reanalysis data, including average and minimum air temperature, incident PAR and specific humidity, provided by the GMAO/NASA. The current version of GMAO/NASA is hourly time step data set with about half-degree spatial resolution (0.5 Latitude degree by 0.67 Longitude degree) generated by GEOS-5 data assimilation system (Rienecker et al. 2008). We aggregated hourly data into daily scale for daily meteorological inputs to MOD17. For VPD, we are using daytime VPD not daily as photosynthesis is largely occurring during daytime. Daytime is determined when hourly downward solar radiation is above zero. Daytime VPD is the difference between daytime saturated vapor pressure estimated with daytime average air temperature and daily vapor pressure. Daily vapor pressure is calculated with specific humidity and surface air pressure. GMAO/NASA, like other global meteorological reanalyses, contains uncertainties, especially for regions with poor weather station coverage and small-scale convection processes which cannot be sufficiently depicted by coarse resolution meteorological data assimilation system. Therefore, uncertainties in GMAO/NASA and subsequent estimated GPP/NPP are higher in tropics than non-tropical regions (Zhao et al. 2006).

One major problem is the inconsistency in spatial resolution between half-degree GMAO/NASA meteorological data and 0.5-km MODIS Collection 6 pixel. We solved the problem by spatially smoothing meteorological data to 0.5-km MODIS pixel level. In the Collection 4 MOD17 system, all 1-km MODIS pixels located within the same “large” GMAO cell will use the same meteorological data without spatial variation. In other words, each 1-km pixel retains the characteristics of the nearest neighbor GMAO cell. As a result, a GMAO cell boundary line may appear in 1-km MOD17 images due to the relatively steep gradients between GMAO cells (Figure 2.3). Such treatment, on a global or regional scale, may be acceptable, while at the local scale, especially for topographically diverse terrain or sites located at the relatively abrupt climatic gradient zones, it may introduce inaccurate climatic predictions for some productivity calculations.

For the problem arising from coarse spatial resolution daily GMAO data, we use spatial interpolation to enhance meteorological inputs. The four GMAO cells nearest to a given 1-km MODIS pixel are used in the interpolation algorithm. There are two reasons for choosing four GMAO cells per 1-km MODIS pixel: (1) this will not slow down the computational efficiency of creating MOD17, which is a global product, and (2) it is more reasonable to assume no elevation variation within four GMAO cells than more GMAO cells.

Although there are many formulae for non-linear spatial interpolation, for simplicity, we use a cosine function because the output value can be constrained between 0 and 1. This function still could not effectively boundary lines in a MOD17 image, and thus we utilized a modified cosine function of the form:

$$D_i = \cos^4((\pi/2) * (d_i / d_{max})) \quad i = 1,2,3,4 \quad (2.1)$$

where, D_i is the non-linear distance between the 1-km MODIS pixel and any one of four surrounding GMAO cells; d_i is the great-circle distance between the 1-km pixel and the same GMAO cell; and d_{max} is the great-circle distance between the two farthest GMAO cells of the four being used. This ensures that $D_i = 1$ when $d_i = 0$, and $D_i = 0$ when $d_i = d_{max}$.

Based on the non-linear distance (D_i), the weighted value W_i can be expressed as

$$W_i = D_i / \sum_{i=1}^4 D_i, \tag{2.2}$$

and therefore, for a given pixel, the corresponding smoothed value V (i.e., interpolated Tmin, Tavg, VPD, SWrad) is

$$V = \sum_{i=1}^4 (W_i * V_i) \tag{2.3}$$

Theoretically, this GMAO spatial interpolation can improve the accuracy of meteorological data for each 1-km pixel because it is unrealistic for meteorological data to abruptly change from one side of GMAO boundary to the other, as in Collection 4. Figure 2.3 shows how this method works for MOD17A2/A3. The degree to which this interpolated GMAO will improve the accuracy of meteorological inputs, however, is largely dependent on the accuracy of GMAO data and the properties of local environmental conditions, such as elevation or weather patterns. To explore the above question, we use observed daily weather data from World Meteorological Organization (WMO) daily surface observation network (>5000 stations) to compare changes in Root Mean Squared Error (RMSE) and Correlation (COR) between the original and enhanced DAO data.

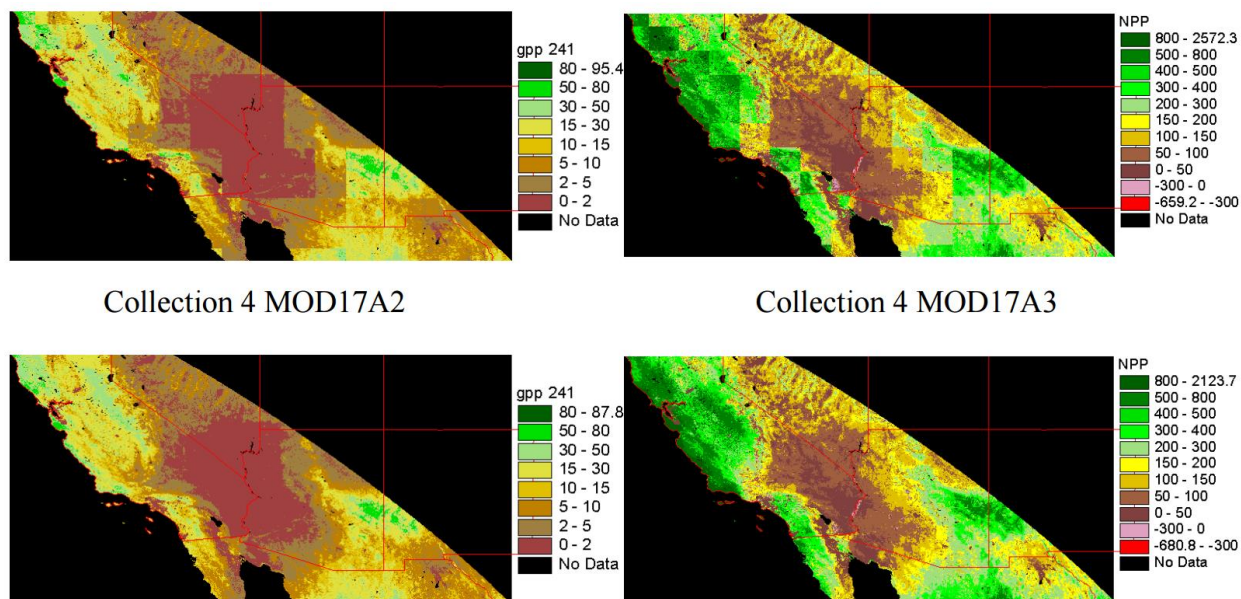


Figure 2.3. Comparison of Collection 4 and Collection 4.5 MOD17A2 GPP (composite period 241) and MOD17A3 NPP for 2001.

As a result of the smoothing process, on average, RMSE is reduced and COR increased for 72.9% and 84% of the WMO stations, respectively, when comparing original and enhanced DAO data to WMO observations for 2001 and 2002. Clearly, the nonlinear spatial interpolation significantly improves GMAO inputs for most stations, although for a few stations, interpolated

GMAO accuracy may be reduced due to the inaccuracy of GMAO in these regions. (Zhao et al. 2005, 2006)

3. Validation of MOD 17 GPP and NPP

The original strategy for validation of the MOD 17 GPP and NPP data can be found in Running et al. 1999. This paper, published before the first MODIS launch, developed an overall plan for integrating MODIS Land data into global terrestrial monitoring. This paper laid the foundation for the interaction between MODLAND and the eddy covariance fluxtower community, illustrating the mutual advantage of fluxtowers providing direct measurement of carbon and water fluxes, while MODIS land products provided a spatial extrapolation of the tower data. It also laid out the conceptual basis for swapping out various components of the MOD17 algorithm in order to isolate points of uncertainty and inaccuracy, shown in Figure 3.1.

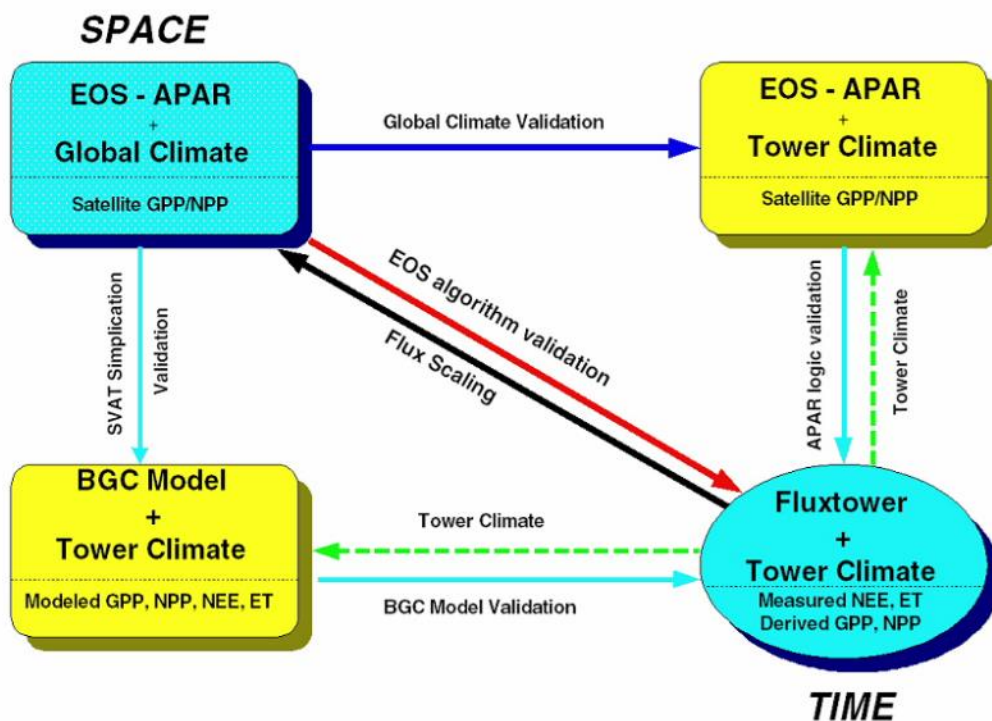


Figure 3.1. The conceptual logic we are following for validation of MOD17 GPP with fluxtower data where tower meteorology, ground measured FPAR and more rigorous ecosystem models are sequentially substituted to evaluate sources of error and variability in MOD17 (based on Running et al. 1999).

Early validation papers using this strategy can be found in Turner et al. 2003, 2004, and 2006, and Heinsch et al. 2006. Google Scholar searches now identify hundreds of similar papers. The current organization of MODIS land product validation is here:

<http://landval.gsfc.nasa.gov/>

and specifics for MODIS NPP can be found here:

<http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD17>

Recent reviews of MODIS NPP validated against other global NPP data can be found in Ito 2011, and Pan et al 2014.

4. Practical Details for downloading and using MOD17 Data

All MODIS land data products are distributed to global users from the Land Processes Distributed Active Archive Center, found here:

<https://lpdaac.usgs.gov/>

Specific details about the MODIS land products can be found here:

https://lpdaac.usgs.gov/dataset_discovery/modis

including details about sensor spectral bands, spatial/temporal resolution, platform overpass timing, datafile naming conventions, tiling formats, processing levels and more.

Specific details about the daily GPP product, including the datafiles, can be found here:

https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod17a2

Specific details about the annual NPP product can be found here:

https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod17a3

including processing notes, definitions and details of earlier product Versions and Collections.

The consistent improved global MOD17 from year to 2000 to the previous year can be downloaded at NTSG ftp site

ftp://ftp.ntsg.umd.edu/pub/NPP_Science_2010/

5. New Science and Applications using MOD17

Because NPP is the first tangible step in the transfer of carbon from the atmosphere to the biosphere, there have been a lot of applications of MOD 17 for global carbon cycle studies. While the net CO₂ balance, NEE, of the land surface is of greatest interest to climate modelers, global NPP avoids the difficult problem of computing soil respiration and decomposition losses. So NPP can be more directly computed globally. Some that NTSG has been part of are looking at time trends of global NPP (Nemani et al. 2003, Zhao and Running 2010). Bastos et al. 2012, and Poulter et al. 2014 explored the causes of the maximum annual global NPP ever recorded, in 2011, and found that abundant rainfall in arid lands produced much of the anomaly. Cleveland et al. 2013 explored the role of NPP in constraining complex biogeochemical cycles globally. And Running 2012, postulated that global NPP might be a carbon cycle planetary boundary, because very little change has occurred in global NPP in the 30+ years of record.

Terrestrial NPP also has high value for evaluating human food, fibre and fuel issues. Haberl et al. 2014 has shown how MODIS NPP is used to define the Human Appropriation of NPP, or HANPP. Abdi et al. 2014 showed how regional food supply/demand balances can be analyzed with MOD 17 data. The global capacity for bioenergy done by Smith et al. 2012 used MODIS NPP. Ecosystem services and natural capital are attempts to give economic value to ecological processes. Tallis et al. 2012 illustrated how MOD17 NPP could be part of a carbon service calculation. Mora et al. 2015 analyzed global food security and agricultural growing season potentials with MOD 17 NPP. Allred et al. 2015 analyzed ecosystem plant production potential lost to industrial activity.

**LIST OF NTSG AUTHORED/CO-AUTHORED PAPERS
USING MOD 17 NPP: 2000 – 2015**

[all available at <http://www.ntsg.umd.edu/biblio>]

- Allred, B. W., Smith, W. K., Twidwell, D., Haggerty, J. H., Running, S. W., Naugle, D. E., and Fuhlendorf, S. D. (2015). Ecosystem services lost to oil and gas in North America. *Science*, 348(6233).
- McDowell, N., Coops N. C., Beck P., Chambers J. Q., Gangodagamage C., Hicke J. A., Huang C., Kennedy R. E., Krofcheck D. J., Litvak M., Meddens A. J. H., Muss J., Litvak M., Negron-Juarez R., Peng C., Schwantes A. M., Swenson J. J., Vernon L. J., Williams A. P., Xu C., Zhao M., Running S. W., and Allen C. D. (2015). Global satellite monitoring of climate-induced vegetation disturbances. *Trends in Plant Science*, 20(2), 114-123.
- Mora, C., Caldwell, I. R., Caldwell, J. M., Fisher, M. R., Genco, B. M., and Running S. W. (2015). Suitable Days for Plant Growth Disappear under Projected Climate Change: Potential Human and Biotic Vulnerability. *PLoS Biol*, 06/2015, 13(6), e1002167
- Madani, N., Kimball, J. S., Affleck, D. L., Kattge, J., Graham, J., Bodegom, P. M., Reich, P. B., and Running, S. W. (2014). Improving ecosystem productivity modeling through spatially explicit estimation of optimal light use efficiency. *Journal of Geophysical Research: Biogeosciences*, 119(9), 1755-1769.
- Pan, S., Tian, H., Dangal, S. R. S., Ouyang, Z., Tao, B., Ren, W., Lu, C., and Running, S. W. (2014). Modeling and Monitoring Terrestrial Primary Production in a Changing Global Environment: Toward a Multiscale Synthesis of Observation and Simulation. *Advances in Meteorology*, 2014, 1-17
- Poulter, B., Frank, D., Ciais, P., Myneni, R. B., Andela, N., Bi, J., Broquet, G., Canadell, J. G., Chevallier, F., Liu, Y. Y., Running, S. W., Sitch, S., and van der Werf, G. R. (2014). Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature*, 509(7502), 600-603.
- Smith, W. K., Cleveland, C. C., Reed, S. C., and Running, S. W. (2014). Agricultural conversion without external water and nutrient inputs reduces terrestrial vegetation productivity. *Geophysical Research Letters*, 41(2), 449-455.
- Bastos, A., Running, S. W., Gouveia, C., and Trigo, R. M. (2013). The global NPP dependence on ENSO: La Niña and the extraordinary year of 2011. *Journal of Geophysical Research: Biogeosciences*, 118(3), 1247-1255.
- Cleveland, C. C., Houlton, B. Z., Smith, W. K., Marklein, A. R., Reed, S. C., Parton, W., Del Grosso, S. J., and Running, S. W. (2013). Patterns of new versus recycled primary production in the terrestrial biosphere. *Proceedings of the National Academy of Sciences*, 110(31), 12733-12737.
- Running, S. W. (2012). A measurable planetary boundary for the biosphere. *Science*, 337(6101), 1458-1459.
- Hasenauer, H., Petritsch, R., Zhao, M., Boisvenue, C., and Running, S. W. (2012). Reconciling satellite with ground data to estimate forest productivity at national scales. *Forest Ecology and Management*, 276, 196-208.
- Smith, W. K., Cleveland, C. C., Reed, S. C., Miller, N. L., and Running S. W. (2012). Bioenergy Potential of the United States Constrained by Satellite Observations of Existing Productivity. *Environmental Science and Technology*, 46(6), 3536-3544.
- Smith, W. K., Zhao, M., and Running, S. W. (2012). Global Bioenergy Capacity as Constrained by Observed Biospheric Productivity Rates. *BioScience*, 62(10), 911-922.

- Tallis, H., Mooney, H., Andelman, S., Balvanera, P., Cramer, W., Karp, D., Polasky, S., Reyers, B., Ricketts, T., Running, S. W., Thonicke, K., Tietjen, B. and Walz, A. (2012). A global system for monitoring ecosystem service change. *Bioscience*, 62(11), 977-986.
- Mu, Q., Zhao M., and Running S. W. (2011) Evolution of hydrological and carbon cycles under a changing climate. *Hydrological Processes*, 25(26), 4093-4102.
- Zhao, M., Running, S., Heinsch, F. A., and Nemani, R. (2011). MODIS-derived terrestrial primary production. In *Land Remote Sensing and Global Environmental Change* (pp. 635-660). Springer New York.
- Zhao, M., and Running, S. W. (2010). Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science*, 329(5994), 940-943.
- Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P., Conway, T. J., Doney, S.C., Feely, R.A., Foster, P., Friedlingsten, P., Gurney, K., Houghton, R.A., House, J. I., Huntingford, C., Levy, P. E., Lomas, M. R., Majkut, J., Metzl, N., Ometto, J. P., Peters, G.P., Prentice, C., Randerson, J. T., Running, S.W., Sarmiento, J. L., Schuster, U., Sitch, S., Takahashi, T., Viovy, N., van der Werf, G.R. , and Woodward, F. I. (2009). Trends in the sources and sinks of carbon dioxide. *Nature Geoscience*, 2(12), 831-836.
- Randerson, J. T., Hoffman, F. M., Thornton, P. E., Mahowald, N. M., Lindsay, K., LEE, Y. H., , Nevison, C.D., Doney, S.C., Bonan, G., Stockli, R., Covey, C., Running, S. W. , and Fung, I. Y. (2009). Systematic assessment of terrestrial biogeochemistry in coupled climate-carbon models. *Global Change Biology*, 15(10), 2462-2484.
- Hashimoto, H., Dungan, J. L., White, M. A., Yang, F., Michaelis, A. R., Running, S. W., and Nemani, R. R. (2008). Satellite-based estimation of surface vapor pressure deficits using MODIS land surface temperature data. *Remote Sensing of Environment*, 112(1), 142-155.
- Zhao, M., and Running, S. W. (2008). Remote Sensing of Terrestrial Primary Production and Carbon Cycle Advances in Land Remote Sensing: System, Modeling, Inversion and Application, S. Liang (Ed.), Springer, 423-444.
- Friend, A. D., Arneeth, A., Kiang, N. Y., Lomas, M., Ogee, J., Rodenbeck, C., Running, S. W., Santaren, J., Sitch, S., Viovy, N., Woodward, F. I., and Zaehle, S. (2007). FLUXNET and modelling the global carbon cycle. *Global Change Biology*, 13(3), 610-633.
- Kimball, J. S., Zhao, M., McGuire, A. D., Heinsch, F. A., Clein, J., Calef, M., Jolly, W. M., Kang, S., Euskirchen, S. E., McDonald, K. C., and Running, S. W. (2007). Recent climate-driven increases in vegetation productivity for the western arctic: evidence of an acceleration of the northern terrestrial carbon cycle. *Earth Interactions*, 11(4), 1-30.
- Liang, S., T. Zheng, D. Wang, K. Wang, R. Liu, S. Tsay, S. W. Running, J. Townshend. (2007) Mapping High-Resolution Incident Photosynthetically Active Radiation over Land from Polar-Orbiting and Geostationary Satellite Data. *Photogrammetric Engineering and Remote Sensing* 1085-1089.
- Mu, Q., Zhao, M., Heinsch, F. A., Liu, M., Tian, H., and Running, S. W. (2007). Evaluating water stress controls on primary production in biogeochemical and remote sensing based models. *Journal of Geophysical Research: Biogeosciences*, 112(G1).
- Reichstein, M., Ciais, P., Papale, D., Valentini, R., Running, S., Viovy, N., Aubinet, M., Bernhofer, Chr., Buchmann, N., Carrara, A., Grünwald, T., Heimann, M., Heinesch, B., Knohl, A., Kutsch, W., Loustau, D., Manca, G., Matteucci, G., Miglietta, F., Ourcival, J. M., Pilegaard, K., Pumpanen, J., Rambal, S., Schaphoff, S., Seufert, G., Soussana, J. F., Sanz, M. J., Vesala, T., and Zhao, M. (2007). Reduction of ecosystem productivity and

- respiration during the European summer 2003 climate anomaly: a joint flux tower, remote sensing and modelling analysis. *Global Change Biology*, 13(3), 634-651.
- Zhang, K., Kimball, J. S., McDonald, K. C., Cassano, J. J., and Running, S.W. (2007). Impacts of large-scale oscillations on pan-Arctic terrestrial net primary production. *Geophysical Research Letters*, 34(21), L21403.
- Zhang, K., Kimball, J. S., Zhao, M., Oechel, W. C., Cassano, J., and Running, S. W. (2007). Sensitivity of pan-Arctic terrestrial net primary productivity simulations to daily surface meteorology from NCEP-NCAR and ERA-40 reanalyses. *Journal of Geophysical Research: Biogeosciences*, 112(G1).
- Chapin III, F. S., Woodwell, G. M., Randerson, J. T., Rastetter, E. B., Lovett, G. M., Baldocchi, D. D., Clark, D. A., Harmon, M. E., Schimel, D. S., Valentini, R., Wirth, C., Aber, J. D., Cole, J. J., Goulden, M. L., Harden, J. W., Heimann, M., Howarth, R. W., Matson, P. A., McGuire, A. D., Melillo, J. M., Mooney, H. A., Neff, J. C., Houghton, R. A., Pace, M. L., Ryan, M. G., Running, S. W., Sala, O. E., Schlesinger, W. H, and Schulze, E. D. (2006). Reconciling carbon-cycle concepts, terminology, and methods. *Ecosystems*, 9(7), 1041-1050.
- Cohen, W. B., Maiersperger, T. K., Turner, D. P., Ritts, W. D., Pflugmacher, D., Kennedy, R. E., Kirschbaum, A., Running, S. W., Costas, M., and Gower, S. T. (2006). MODIS land cover and LAI collection 4 product quality across nine sites in the western hemisphere. *Geoscience and Remote Sensing, IEEE Transactions on*, 44(7), 1843-1857.
- Heinsch, F. A., Zhao, M., Running, S. W., Kimball, J. S., Nemani, R. R., Davis, K. J., Bolstad, P. V., Cook, B. D., Desai, A. R., Ricciuto, D. M., Law, B. E., Oechel, W. C., Kwon, H., Luo, H., Wofsy, S. C., Dunn, A. L., Munger, J. W., Baldocchi, D. D., Xu, L., Hollinger, D. Y., Richardson, A. D., Stoy, P. C., Siqueira, M. B. S., Monson, R. K., Burns, S.P, and Flanagan, L. B. (2006). Evaluation of Remote Sensing Based Terrestrial Productivity from MODIS Using Regional Tower Eddy Flux Network Observations. *IEEE Transactions on Geoscience and Remote Sensing*, 44(7), 1908-1925.
- Kang, S., Kimball, J. S., and Running, S. W. (2006). Simulating effects of fire disturbance and climate change on boreal forest productivity and evapotranspiration. *Science of the Total Environment*, 362(1), 85-102.
- Kimball, J. S., Zhao, M., McDonald, K. C., and Running, S. W. (2006). Satellite remote sensing of terrestrial net primary production for the pan-Arctic basin and Alaska. *Mitigation and Adaptation Strategies for Global Change*, 11(4), 783-804.
- Liang, S., Zheng, T., Liu, R., Fang, H., Tsay, S. C., & Running, S. (2006). Estimation of incident photosynthetically active radiation from Moderate Resolution Imaging Spectrometer data. *Journal of Geophysical Research: Atmospheres*, 111(D15).
- Reeves, M. C., Zhao, M., Running, S. W. (2006). Applying Improved Estimates of MODIS Productivity to Characterize Grassland Vegetation Dynamics. *Rangeland Ecology and Management*, 59(1), 1-10.
- Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Running, S. W., Zhao, M., Costa, M. H., Kirschbaum, A. A., Ham, J. M., Saleska, S. R., and Ahl, D. E. (2006). Evaluation of MODIS NPP and GPP products across multiple biomes. *Remote Sensing of Environment*, 102(3), 282-292.
- Turner, D. P., Ritts, W. D., Zhao, M., Kurc, S., Dunn, A. L., Wofsy, S. C, Small, E.E., and Running, S. W. (2006). Assessing interannual variation in MODIS-based estimates of

- gross primary production. *Geoscience and Remote Sensing, IEEE Transactions on*, 44(7), 1899-1907.
- White, J. D., Scott, N. A., Hirsch, A.L., and Running, S. W. (2006). 3-PG Productivity Modeling of Regeneration Amazon Forests: Climate Sensitivity and Comparison with MODIS-Derived NPP. *Earth Interactions*, 10(0), 1-26.
- Zhao, M., Running, S. W., and Nemani, R. R. (2006). Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. *Journal of Geophysical Research: Biogeosciences*, 111(G1).
- Kang, S., Running, S. W., Zhao, M., Kimball, J. S., and Glassy, J. (2005). Improving continuity of MODIS terrestrial photosynthesis products using an interpolation scheme for cloudy pixels. *International Journal of Remote Sensing*, 26(8), 1659-1676.
- Milesi, C., Hashimoto, H., Running, S. W., and Nemani, R. R. (2005). Climate variability, vegetation productivity and people at risk. *Global and Planetary Change*, 47(2), 221-231
- Martel, M. C., Margolis, H. A., Coursolle, C., Bigras, F. J., Heinsch, F. A., and Running, S. W. (2005). Decreasing photosynthesis at different spatial scales during the late growing season on a boreal cutover. *Tree Physiology*, 25(6), 689-699.
- Meyerson, L. A., Baron, J., Melillo, J. M., Naiman, R. J., O'Malley, R. I., Orians, G., Palmer, M. A., Pfaff, A. S. P., Running, S. W., and Sala, O. E. (2005). Aggregate measures of ecosystem services: can we take the pulse of nature?. *Frontiers in Ecology and the Environment*, 3(1), 56-59.
- Reeves, M. C., Zhao, M., and Running, S. W. (2005). Usefulness and limits of MODIS GPP for estimating wheat yield. *International Journal of Remote Sensing*, 26(7), 1403-1421.
- Turner, D. P., Ritts, W. D., Cohen, W. B., Maeirsperger, T. K., Gower, S. T., Kirschbaum, A. A., Running, S. W., Zhao, M., Wofsy, S. C., Dunn, A. L., Law, B. E., Campbell, J. L., Oechel, W. C., Kwon, H. J., Meyers, T. P., Small, E. E., Kurc, S. A., and Gamon, J. A. (2005). Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. *Global Change Biology*, 11(4), 666-684.
- Zhao, M., Heinsch, F. A., Nemani, R. R., and Running, S. W. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote sensing of Environment*, 95(2), 164-176.
- Hashimoto, H., Nemani, R. R., White, M. A., Jolly, W. M., Piper, S. C., Keeling, C. D., Myneni, R. R., and Running, S. W. (2004). El Nino–Southern Oscillation–induced variability in terrestrial carbon cycling. *Journal of Geophysical Research: Atmospheres*, 109(D23).
- Running, S.W. (2004) Global Land Data Sets for Next Generation Biospheric Monitoring. *American Geophysical Union Eos Transactions*, 85(50), 543-545.
- Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M., and Hashimoto, H. (2004). A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production. *BioScience*, 54(6), 547-560.
- Cohen, W. B., Maersperger, T. K., Yang, Z., Gower, S. T., Turner, D. P., Ritts, W. D., Berterretche, M., and Running, S. W. (2003). Comparisons of land cover and LAI estimates derived from ETM+ and MODIS for four sites in North America: A quality assessment of 2000/2001 provisional MODIS products. *Remote Sensing of Environment*, 88(3), 233-255.
- Nemani, R. R., Keeling, C. D., Hashimoto, H., Jolly, W. M., Piper, S. C., Tucker, C. J., Myneni R. B., and Running, S. W. (2003). Climate-driven increases in global terrestrial net primary production from 1982 to 1999, *Science*, 300(5625), 1560-1563.

- Milesi, C., Elvidge, C. D., Nemani, R. R., and Running, S. W. (2003). Assessing the environmental impacts of human settlements using satellite data. *Management of Environmental Quality*, 14(1), 99-107.
- Milesi, C., Elvidge, C. D., Nemani, R. R., Running, S. W. (2003). Assessing the impact of urban land development on net primary productivity in the southeastern United States. *Remote Sensing of Environment*, 86(3), 401-410.
- Nemani, R., White, M., Pierce, L., Votava, P., Coughlan, J., Running, S. W. (2003). Biospheric Monitoring and Ecological Forecasting. *Earth Observation Magazine*, 12(2), 6-8.
- Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Zhao, M., Running, S. W., Wofsy, S.C., Urbanski, S., Dunn, A. L., and Munger, J. W. (2003). Scaling gross primary production (GPP) over boreal and deciduous forest landscapes in support of MODIS GPP product validation. *Remote Sensing of Environment*, 88(3), 256-270.
- Myneni, R. B., Hoffman, S., Knyazikhin, Y., Privette, J. L., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G. R., Lotsch, A., Friedl, M., Morisette, J. T., Votava, P., Nemani, R. R., and Running, S. W. (2002). Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote sensing of environment*, 83(1), 214-231.
- Nemani, R., White, M., Thornton, P., Nishida, K., Reddy, S., Jenkins, J., and Running, S. (2002). Recent trends in hydrologic balance have enhanced the terrestrial carbon sink in the United States. *Geophysical Research Letters*, 29(10), 106-1.
- Pielke, R. A., Marland, G., Betts, R. A., Chase, T. N., Eastman, J. L., Niles, J. O., and Running, S. W. (2002). The influence of land-use change and landscape dynamics on the climate system: relevance to climate-change policy beyond the radiative effect of greenhouse gases. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 360(1797), 1705-1719.
- Running, S. W. (2002). New Satellite Technologies Enhance Study of Terrestrial Biosphere. *Eos, Transactions. American Geophysical Union*, 83(41), 458-460.
- Schimel, D., Kittel, T. G., Running, S., Monson, R., Turnipseed, A., and Anderson, D. (2002). Carbon sequestration studied in western US mountains. *Eos, Transactions American Geophysical Union*, 83(40), 445-449.
- Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S. W., Anthoni, P., Bernhofer, C., Davis, K., Evans, R., Fuentes, J., Goldstein, A., Katul, G., Law, B., Lee, X., Malhi, Y., Meyers, T., Munger, W., Oechel, W., Paw U, K., Pilegaard, K., Schmid, H., Valentini, R., Verma, S., Vesala, T., Wilson, K., and Wofsy, S. (2001). FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bulletin of the American Meteorological Society*, 82(11), 2415-2434.
- Chase, T. N., Pielke Sr, R., Kittel, T. G. F., Zhao, M., Pitman, A. J., Running, S. W., and Nemani, R. R. (2001). Relative climatic effects of landcover change and elevated carbon dioxide combined with aerosols- A comparison of model results and observations. *Journal of Geophysical Research. D. Atmospheres*, 106, 31.
- Coops, N. C., Waring, R. H., Brown, S. R., and Running, S. W. (2001). Comparisons of predictions of net primary production and seasonal patterns in water use derived with two forest growth models in Southwestern Oregon. *Ecological Modelling*, 142(1), 61-81.

- Nemani, R. R., White, M. A., Cayan, D. R., Jones, G. V., Running, S. W., Coughlan, J. C., and Peterson, D. L. (2001). Asymmetric warming over coastal California and its impact on the premium wine industry. *Climate research*, 19(1), 25-34.
- Reeves, M. C., Winslow, J. C., & Running, S. W. (2001). Mapping weekly rangeland vegetation productivity using MODIS algorithms. *Journal of Range Management*, 54(2), A90-A105.
- Canadell, J. G., Mooney, H. A., Baldocchi, D. D., Berry, J. A., Ehleringer, J. R., Field, C. B., Gower, S. T., Hollinger, D. Y., Hunt, J. E., Jackson, R. B., Running, S. W., Shaver, G. R., Steffen, W., Trumbore, S. E., Valentini, R., and Bond, B. Y. (2000). Commentary: Carbon metabolism of the terrestrial biosphere: A multitechnique approach for improved understanding. *Ecosystems*, 3(2), 115-130.
- Running, S. W. (2000). Why the earth observing system matters to all of us. *The Earth Observer*, 12(1), 9-10.
- Running, S. W., Queen, L., Thornton, M. (2000). The Earth Observing System and Forest Management. *Journal of Forestry*, 98(6), 29-31.
- Running, S. W., Thornton, P. E., Nemani, R., and Glassy, J. M. (2000). Global terrestrial gross and net primary productivity from the earth observing system. In *Methods in ecosystem science* (pp. 44-57). Springer New York.
- Tian, Y., Zhang, Y., Knyazikhin, Y., Myneni, R. B., Glassy, J. M., Dedieu, G., and Running, S. W. (2000). Prototyping of MODIS LAI and FPAR algorithm with LASUR and LANDSAT data. *Geoscience and Remote Sensing, IEEE Transactions on*, 38(5), 2387-2401.
- White, M. A., Thornton, P. E., Running, S. W., and Nemani, R. R. (2000). Parameterization and sensitivity analysis of the BIOME-BGC terrestrial ecosystem model: net primary production controls. *Earth interactions*, 4(3), 1-85.

REFERENCES

- Abdi, H., Seaquist, J., Tenenbaum, D., Eklundh, L., and Ardö, J. (2014). The supply and demand of net primary production in the Sahel. *Environmental Research Letters*, 9(9), 094003-11.
- Allred, B. W., Smith, W. K., Twidwell, D., Haggerty, J. H., Running, S. W., Naugle, D. E., and Fuhlendorf, S. D. (2015). Ecosystem services lost to oil and gas in North America. *Science*, 348(6233).
- Bastos, A., Running, S. W., Gouveia, C., and Trigo, R. M. (2013). The global NPP dependence on ENSO: La Niña and the extraordinary year of 2011. *Journal of Geophysical Research: Biogeosciences*, 118(3), 1247-1255.
- Belward, A. S., Estes, J. E., and Kline, K. D. (1999). The IGBP-DIS global 1-km land-cover data set DISCover: A project overview. *Photogrammetric Engineering and Remote Sensing*, 65(9), 1013-1020.
- Cannell, M. (1982). *World Forest Biomass and Primary Production Data*. Academic Press: London.
- Cannell, M. G. R., and Thornley, J. H. M. (2000). Modelling the components of plant respiration: some guiding principles. *Annals of Botany*, 85(1), 45-54.
- Cleveland, C. C., Houlton, B. Z., Smith, W. K., Marklein, A. R., Reed, S. C., Parton, W., DelGrasso, S. J., and Running, S. W. (2013). Patterns of new versus recycled primary production in the terrestrial biosphere. *Proceedings of the National Academy of Sciences*, 110(31), 12733-12737.
- Cleveland, C. C., Houlton, B. Z., Smith, W. K., Marklein, A. R., Reed, S. C., Parton, W., Del Grosso, S. J., and Running, S. W. (2013). Patterns of new versus recycled primary production in the terrestrial biosphere. *Proceedings of the National Academy of Sciences*, 110(31), 12733-12737.
- Field, C. B., Randerson, J. T., and Malmstrom, C. M. (1995). Global net primary production: Combining ecology and remote sensing. *Remote Sensing of Environment*, 51(1), 74-88.
- Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., and Huang, X. (2010). MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, 114(1), 168-182.
- Haberl, H., Erb, K. H., and Krausmann, F. (2014). Human appropriation of net primary production: patterns, trends, and planetary boundaries. *Annual Review of Environment and Resources*, 39, 363-391.
- Heinsch, F. A., Zhao, M., Running, S. W., Kimball, J. S., Nemani, R. R., Davis, K. J., Bolstad, P. V., Cook, B. D., Desai, A. R., Ricciuto, D. M., Law, B. E., Oechel, W. C., Kwon, H., Luo, H., Wofsy, S. C., Dunn, A. L., Munger, J. W., Baldocchi, D. D., Xu, L., Hollinger, D. Y., Richardson, A. D., Stoy, P. C., Siqueira, M. B. S., Monson, R. K., Burns, S. P., and Flanagan, L. B. (2006). Evaluation of Remote Sensing Based Terrestrial Productivity from MODIS Using Regional Tower Eddy Flux Network Observations. *IEEE Transactions on Geoscience and Remote Sensing*, 44(7), 1908-1925.
- Hunt, E. J. (1994). Relationship between woody biomass and PAR conversion efficiency for estimating net primary production from NDVI. *International Journal of Remote Sensing*, 15(8), 1725-1730.
- Ito, A. (2011). A historical meta-analysis of global terrestrial net primary productivity: are estimates converging?. *Global Change Biology*, 17(10), 3161-3175.

- Madani, N., Kimball, J. S., Affleck, D. L., Kattge, J., Graham, J., Bodegom, P. M., Reich, P. B., and Running, S. W. (2014). Improving ecosystem productivity modeling through spatially explicit estimation of optimal light use efficiency. *Journal of Geophysical Research: Biogeosciences*, 119(9), 1755-1769.
- Monteith, J. (1972). Solar radiation and productivity in tropical ecosystems. *Journal of Applied Ecology*, 9(3), 747-766.
- Mora, C., Caldwell, I. R., Caldwell, J. M., Fisher, M. R., Genco, B. M., & Running, S. W. (2015). Suitable days for plant growth disappear under projected climate change: Potential human and biotic vulnerability. *PLoS biology*, 13(6), e1002167.
- Myneni, R. B., Hoffman S., Knyazikhin, Y., Privette, J., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G. R., Lotsch, A., Friedl, M., Morisette, J. T., Votava, P., Nemani, R. R., Running, S. W.. (2002). Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sensing of Environment*, 83(1), 214-231.
- Nemani R. R., Keeling, C. D., Hashimoto, H., Jolly, W.M., Piper, S. C., Tucker, C. J., Myneni, R. B., Running, S. W., (2003). Climate-Driven Increases in Global Terrestrial Net Primary Production from 1982 to 1999. *Science*, 300(5625),1560-1563.
- Pan, S., Tian, H., Dangal, S. R. S., Ouyang, Z., Tao, B., Ren, W., Lu, C., and Running, S. W. (2014). Modeling and Monitoring Terrestrial Primary Production in a Changing Global Environment: Toward a Multiscale Synthesis of Observation and Simulation. *Advances in Meteorology*, 2014, 1-17.
- Poulter, B., Frank, D., Ciais, P., Myneni, R. B., Andela, N., Bi, J., Broquet, G., Canadell, J. G., Chevallier, F., Liu, Y. Y., Running, S. W., Sitch, S., and van der Werf, G. R. (2014). Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature*, 509(7502), 600-603.
- Prince, S., and Goward, S. (1995). Global primary production: a remote sensing approach. *Journal of Biogeography*, 22(4/5), 815-835.
- Reich, P. B., Walters, M. B., Ellsworth, D. S., and Uhl, C. (1994). Photosynthesis-nitrogen relations in Amazonian tree species. *Oecologia*, 97(1), 62-72.
- Reich, P. B., Walters, M. B., Kloeppel, B. D., and Ellsworth, D. S. (1995). Different photosynthesis-nitrogen relations in deciduous hardwood and evergreen coniferous tree species. *Oecologia*, 104(1), 24-30.
- Reich, P. B. (2012). Key canopy traits drive forest productivity. *Proceedings of the Royal Society of London B: Biological Sciences*, 279(1736), 2128-2134.
- Rienecker, M. M., Suarez, M. J., Todling, R., Bacmeister, J., Takacs, L., Liu, H. C., Gu, W., Sienkiewicz, M., Koster, R. D., Gelaro, R., Stajner, I., and Nielsen, J. E. (2008). *The GEOS-5 data assimilation system – Documentation of versions 5.0.1, 5.1.0*. Technical Report Series on Global Modeling and Data Assimilation, ed Suarez, M. J. (National Aeronautics and Space Administration, Washington, DC), 95.
- Running, S. W., and Hunt, E. J. (1993). Generalization of a forest ecosystem process model for other biomes, BIOME-BGC, and an application for global-scale models. In J. R. Ehleringer, C. Field (Eds.), *Scaling Processes Between Leaf and Landscape Levels*. Academic Press.
- Running, S. W., Loveland, T. R., and Pierce, L. L. (1994). A vegetation classification logic based on remote sensing for use in global scale biogeochemical models. *Ambio*, 23, 77-81.

- Running, S. W., Baldocchi, D. D., Turner, D. P., Gower, S. T., Bakwin, P. S., and Hibbard, K. A. (1999). A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling and EOS satellite data. *Remote Sensing of Environment*, 70(1), 108-127.
- Running, S. W., Thornton, P. E., Nemani, R. R., and Glassy, J. M. (2000). Global terrestrial gross and net primary productivity from the earth observing system. In *Methods in ecosystem science* (pp. 44-57). New York: Springer.
- Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M., Hashimoto, H. (2004). A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production. *BioScience*, 54(6), 547-560.
- Running, S. W. (2012). A measurable planetary boundary for the biosphere. *Science*, 337(6101), 1458-1459.
- Ryan, M. G. (1991). The effects of climate change on plant respiration. *Ecological Applications*, 1(2), 157-167.
- Sellers, P. J. (1987). Canopy reflectance, photosynthesis, and transpiration, II. The role of biophysics in the linearity of their interdependence. *Remote sensing of Environment*, 21(2), 143-183.
- Smith, W. K., Zhao, M., & Running, S. W. (2012). Global bioenergy capacity as constrained by observed biospheric productivity rates. *BioScience*, 62(10), 911-922.
- Tallis, H., Mooney, H., Andelman, S., Balvanera, P., Cramer, W., Karp, D., Smith, W. K., Zhao, M., and Running, S. W. (2012). A global system for monitoring ecosystem service change. *Bioscience*, 62(11), 977-986.
- Tjoelker, M. G., Oleksyn, J., and Reich, P. (2001). Modelling respiration of vegetation: evidence for a general temperature-dependent Q₁₀. *Global Change Biology*, 7(2), 223-230.
- Turner, D. P., Urbanski, S., Bremer, D., Wofsy, S. C., Meyers, T., Gower, S. T., Gregory, M. (2003). *Global Change Biology*, 9(3), 383-395.
- Turner, D. P., Ollinger, S., Smith, M. L., Krankina, O., and Gregory, M. (2004). Scaling net primary production to a MODIS footprint in support of Earth observing system product validation. *International Journal of Remote Sensing*, 25(10), 1961-1979.
- Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Running, S. W., Zhao, M., Costa, M. H., Kirschbaum, A., Hamf, J. M., Saleskag, S. R., and Ahl, D. E. (2006). Evaluation of MODIS NPP and GPP products across multiple biomes. *Remote Sensing of Environment*, 102(3), 282-292.
- Waring, R. H., and Running, S. W. (2010). *Forest ecosystems: analysis at multiple scales*. Academic Press.
- White, M. A., Thornton, P. E., Running, S. W., and Nemani, R. R. (2000). Parameterization and sensitivity analysis of the BIOME-BGC terrestrial ecosystem model: net primary production controls. *Earth interactions*, 4(3), 1-85.
- Zhao, M., Heinsch, F. A., Nemani, R. R., and Running, S. W. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment*, 95(2): 164-176.
- Zhao, M., Running, S. W., and Nemani, R. R. (2006). Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. *Journal of Geophysical Research*, 111(G1)
- Zhao, M., Running, S. W. (2010). Drought-induced reduction in global terrestrial net primary production from 2000 through 2009, *Science*, 329(5994), 940-943.