User's Guide
GPP and NPP (MOD17A2/A3) Products
NASA MODIS Land Algorithm

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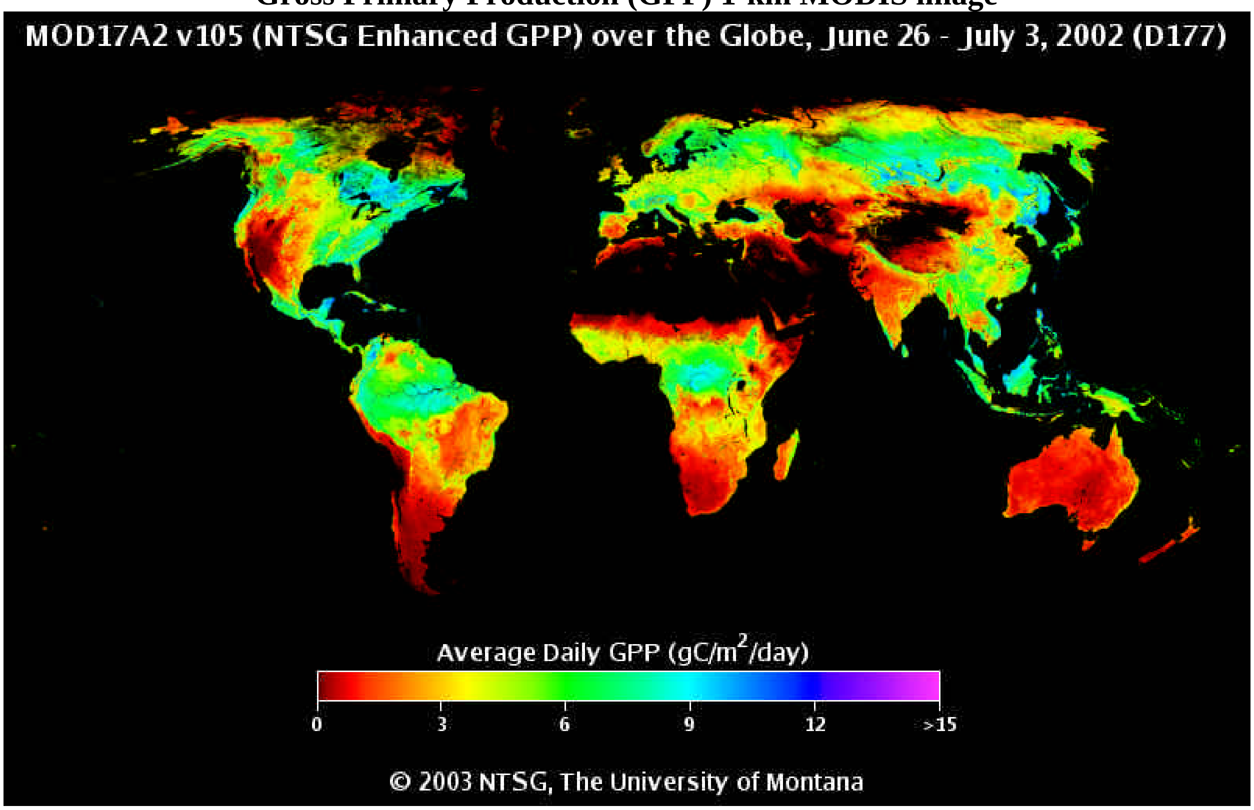
Gross Primary Production (GPP) 1-km MODIS image



Global GPP image created by Andrew Neuschwander.

Version 2.0, December 2, 2003

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Table of Contents

Table of Contents (cont.)

List of Figures

List of Figures (cont.)

List of Tables

Synopsis

Vegetative productivity is the source of all food, fiber and fuel available for human consumption and therefore defines the habitability of the earth. The rate at which light energy is converted to plant biomass is termed primary productivity. The sum total of the converted energy is called gross primary productivity (GPP). Net primary productivity (NPP) is the difference between GPP and energy lost during plant respiration (Campbell 1990).

Global productivity can be estimated by combining remote sensing with carbon cycle processing. The U.S. National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) currently "produces a regular global estimate of gross primary productivity (GPP) and annual net primary productivity (NPP) of the entire terrestrial earth surface at 1-km spatial resolution, 150 million cells, each having GPP and NPP computed individually" (Running et al. 2000; Thornton et al. 2002). The MOD17A2/A3 User's 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 are archived at a NASA DAAC (Distributed Active Archive Center). The document is intended to provide both a broad overview and sufficient detail to enable the successful use of the data in research and applications.

CHAPTER I. THE MODIS ALGORITHM

1. The Algorithm, Background and Overview

1.1. Estimating vegetative productivity from absorbed radiation

A conservative relationship between absorbed photosynthetically active radiation (APAR) and net primary productivity (NPP) was first proposed by Monteith (Monteith 1972; Monteith 1977). This original logic, known as "radiation use efficiency", suggested that the NPP of well-watered and fertilized annual crop plants was linearly related to the amount of absorbed photosynthetically active solar radiation (APAR). APAR depends upon [1] the geographic and seasonal variability of daylength and potential incident radiation, as modified by cloudcover and aerosols, and [2] the amount and geometry of displayed leaf material. Monteith's logic, therefore, combines the meteorological constraint of available sunlight at 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 the fraction of incident PAR absorbed by the surface (FPAR). 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 (APAR = PAR * FPAR). 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 Data Assimilation Office (DAO; *http://polar.gsfc.nasa.gov/index.php*) (Atlas and Lucchesi 2000) at a resolution of 1° x 1.25°. In spite of the strong theoretical and empirical relationship between remotely-sensed surface reflectance and FPAR, accurate estimates of vegetative productivity (GPP, NPP) will depend strongly on the quality of the radiation inputs.

1.2 The Biophysical Variability of e

The PAR conversion efficiency ε, varies widely with different vegetation types (Field et al. 1995, Prince and Goward 1985, 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 1998).

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 schlerophyllous shrubs absorb PAR during the non-growing season, yet sub-freezing temperatures stop photosynthesis because leaf stomata are forced to close (Waring and Running 1998). As a global generalization, we truncate GPP on days when the minimum temperature is below 0° C. Additionally, high vapor pressure deficits, > 2000Pa, 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, 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 (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 environmental variables, especially temperature, to the processes controlling GPP and those controlling autotrophic respiration have fundamentally different forms (Schwarz et al. 1997; Maier et al. 1998), 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.

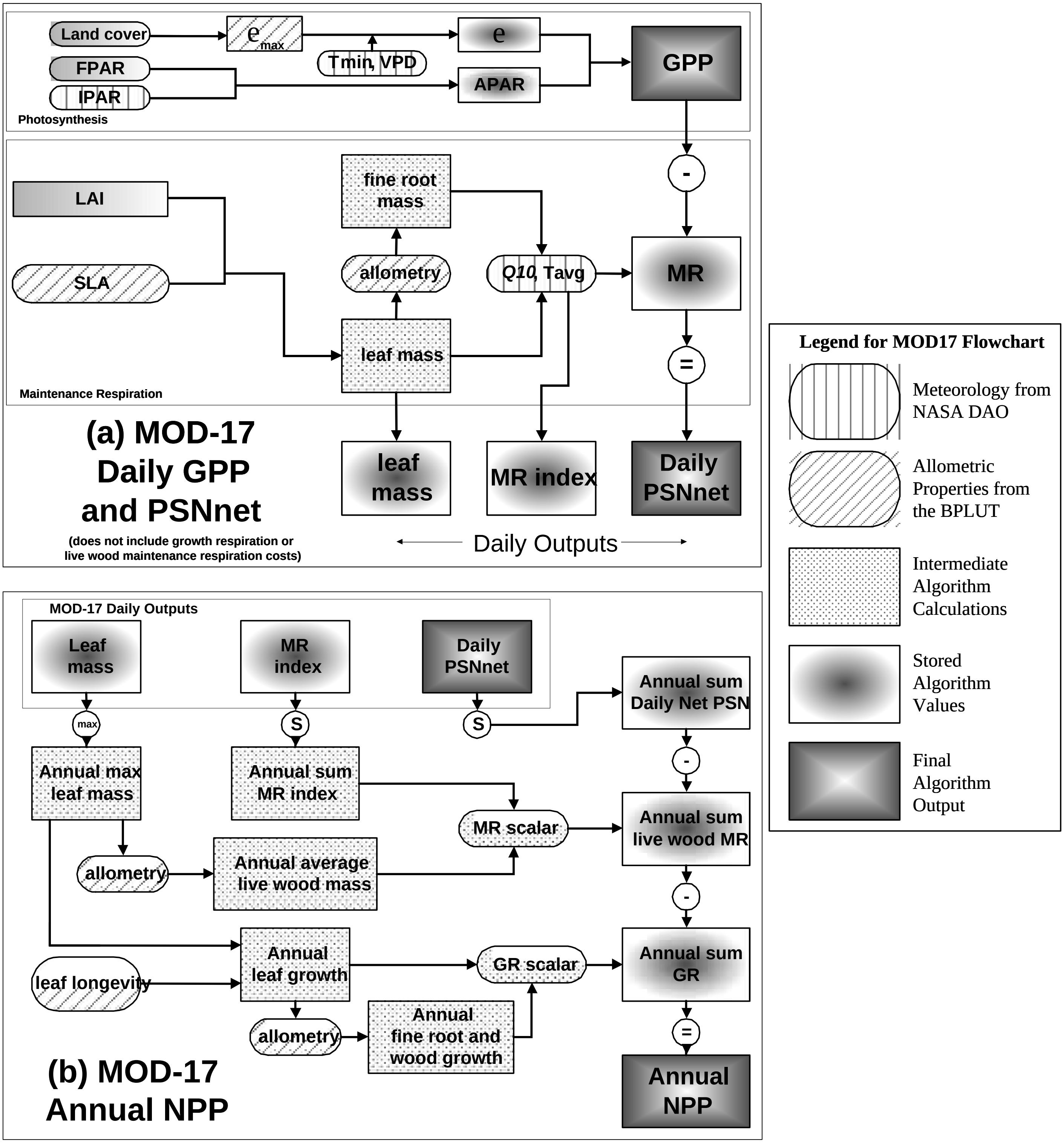


Figure 1.1. Flowcharts showing the logic behind the MOD17 Algorithm in calculating both (a) 8-day average GPP and (b) annual NPP.

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 $\varepsilon = \varepsilon_{max}$ (for optimal VPD)
TMINmin	(°C)	The daily minimum temperature at which $\varepsilon = 0.0$ (at any VPD)
VPDmax	(Pa)	The daylight average vapor pressure deficit at which $\varepsilon = \varepsilon_{max}$ (for optimal TMIN)
VPDmin	(Pa)	The daylight average vapor pressure deficit at which $\varepsilon = 0.0$ (at any TMIN)

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), 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 are derived 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; Thornton et al. 2002).

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 of which (e.g., GPP) are calculated daily, and others (e.g., NPP) on an annual basis. Calculations of daily photosynthesis (GPP) are shown in the lower half of Figure 1.1a. An 8-day estimate of FPAR from MOD15 and daily estimated PAR from DAO 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.

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

$$\varepsilon = \varepsilon_{max} * \text{TMIN\_scalar} * \text{VPD\_scalar} \quad \textbf{(1.1)}$$

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 DAO dataset, while the value of ε_{max} is obtained from the BPLUT. The resulting radiation use efficiency coefficient

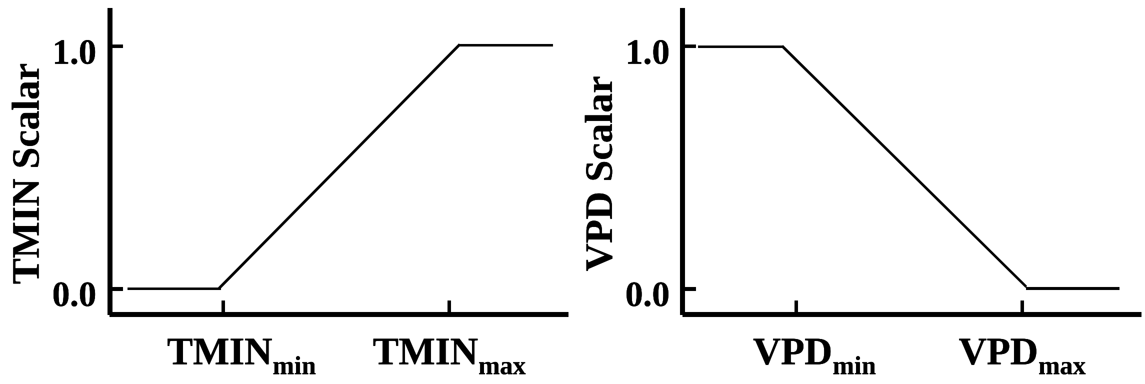


Figure 1.2. The TMIN and VPD attenuation scalars are simple linear ramp functions of daily TMIN and VPD.

Table 1.2. BPLUT parameters for daily maintenance respiration.

Parameter	**Units**	**Description**
SLA	(m^2 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	(kg C kg C^{-1} day^{-1})	Maintenance respiration per unit leaf carbon per day at 20°C
froot_mr_base	(kg C kg C^{-1} day^{-1})	Maintenance respiration per unit fine root carbon per day at 20°C
Q10_mr	None	Exponent shape parameter controlling respiration as a function of temperature

ε is combined with estimates of APAR to calculate GPP (kg C day^{-1}) as

$$GPP = \varepsilon * APAR \quad \textbf{(1.2)}$$

where APAR = IPAR * FPAR. IPAR (PAR incident on the vegetative surface) must be estimated from incident shortwave radiation (SWRad, provided in the DAO dataset) as

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

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, summarized in the lower half of Figure 2.1a, are also calculated on a daily basis. There are five parameters within the BPLUT (Table 2.2) 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

$$\text{Leaf\_Mass} = \text{LAI} / \text{SLA} \qquad \textbf{(1.4)}$$

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

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

$$\text{Fine\_Root\_Mass} = \text{Leaf\_Mass} * \text{froot\_leaf\_ratio} \qquad \textbf{(1.5)}$$

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

$$\text{Leaf\_MR} = \text{Leaf\_Mass} * \text{leaf\_mr\_base} * \text{Q10\_mr}^{[(\text{Tavg} - 20.0) / 10.0]} \qquad \textbf{(1.6)}$$

where leaf_mr_base is the maintenance respiration of leaves (kg C kg C^{-1} day^{-1}) as obtained from the BPLUT and Tavg is the average daily temperature (°C) as estimated from the DAO meteorological data.

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

$$\text{Froot\_MR} = \text{Fine\_Root\_Mass} * \text{froot\_mr\_base} * \text{Q10\_mr}^{[(\text{Tavg} - 20.0) / 10.0]} \qquad \textbf{(1.7)}$$

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

Finally, PSNnet (kg C day^{-1}) can be calculated from GPP (Equation 2.2) and maintenance respiration (Equations 2.5, 2.6) as

$$\text{PSNnet} = \text{GPP} – \text{Leaf\_MR} - \text{Froot\_MR} \qquad \textbf{(1.8)}$$

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 (Fig. 1.1b) 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	(kg C kg C^{-1} 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 process model. Leaf longevity is required to estimate annual leaf growth for evergreen forests, but it 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; Thornton et al. 2002).

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

$$\text{Livewood\_Mass} = \text{ann\_leaf\_mass\_max} * \text{livewood\_leaf\_ratio} \qquad \textbf{(1.9)}$$

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

$$\text{Livewood\_MR} = \text{Livewood\_Mass} * \text{livewood\_mr\_base} * \text{annsum\_mrindex} \qquad \textbf{(1.10)}$$

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 $Q10\_mr^{[(Tavg-20.0)/10.0]}$.

1.3d. Annual growth respiration and net primary productivity. Annual growth respiration and maintenance costs are based on their relationship to leaf growth respiration (Leaf_GR, kg C day^{-1}), which is calculated as

$$\text{Leaf\_GR} = \text{ann\_leaf\_mass\_max} * \text{ann\_turnover\_proportion} * \text{leaf\_gr\_base} \quad \textbf{(1.11)}$$

where ann_turnover_proportion (unitless) is the annual turnover proportion of leaves and leaf_gr_base is the base growth respiration (kg C kg C^{-1} day^{-1}) for leaves. Both of these terms are acquired from the BPLUT.

Growth respiration for fine roots (Froot_GR, kg C day^{-1}) is calculated as

$$\text{Froot\_GR} = \text{Leaf\_GR} * \text{froot\_leaf\_gr\_ratio} \quad \textbf{(1.12)}$$

where froot_leaf_gr_ratio is the ratio of fine root growth respiration to leaf growth respiration (unitless) as found in the BPLUT.

Next, the growth respiration of livewood (Livewood_GR, kg C day^{-1}) can be calculated as

$$\text{Livewood\_GR} = \text{Leaf\_GR} * \text{livewood\_leaf\_gr\_ratio} \quad \textbf{(1.13)}$$

where livewood_leaf_gr_ratio is the ratio of livewood leaf growth respiration (unitless) as found in the BPLUT.

And, lastly, deadwood growth respiration (Deadwood_GR, kg C day^{-1}) is calculated as

$$\text{Deadwood\_GR} = \text{Leaf\_GR} * \text{deadwood\_leaf\_gr\_ratio} \quad \textbf{(1.14)}$$

where deadwood_leaf_gr_ratio is the ratio of deadwood to leaf growth respiration (unitless) as found in the BPLUT.

As a final step, the per-pixel annual net primary productivity (NPP, kg C day^{-1}) is calculated as the sum of the cumulative daily PSNnet (annsum_daily PSNnet kg C day^{-1}) less the costs associated with annual maintenance and growth respiration, such that

$$\text{NPP} = \text{annsum\_dailyPSNnet} - \text{Livewood\_MR} - \text{Leaf\_GR} - \text{Froot\_GR} - \text{Livewood\_GR} - \text{Deadwood\_GR} \quad \textbf{(1.15)}$$

where all terms have been previously defined.

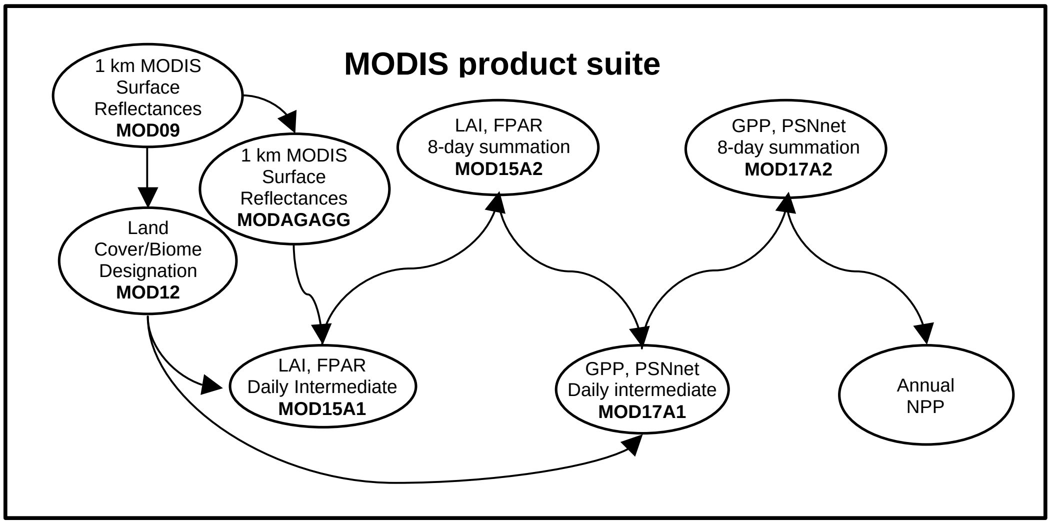


Figure 2.1. The linkages among MODIS land products.

2. Simplifying Assumptions for Global Applicability

In an ideal world, remote sensing would render an infallibly accurate depiction of surface conditions and deliver the data in a timely, cost-effective manner for every square meter of the earth's land surface. Unfortunately, such a system does not exist, and even if it did, it would be impossible to derive vegetation productivity algorithms suited for all combinations of vegetation at such a fine resolution. NASA's Earth Observing System, and more specifically, the MODIS instrument have been tasked with documenting and monitoring global biospheric health (Running et al. 2000; Thornton et al. 2002). Among other things, such a task requires timely and objective measures of vegetation productivity. This requisite necessitates several noteworthy simplifying assumptions discussed below.

2.1. 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 2.1) 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.

2.2. Leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (FPAR)

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 8-day composite product. 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

Table 2.1. The Biome Properties Look-Up Table (BPLUT) for MOD17.

	BIOME CLASSIFICATION					
PARAMETER	**ENF**	**EBF**	**DNF**	**DBF**	**MF**	**WL**
Epsilon_max	0.001008	0.001159	0.001103	0.001044	0.001116	0.000800
Daily						
Tmin_max (C)	8.31	9.09	10.44	7.94	8.50	11.39
Tmin_min (C)	-8.00	-8.00	-8.00	-8.00	-8.00	-8.00
VPD_max (Pa)	2500	3900	3100	2500	2500	3100
VPD_min (Pa)	650	1100	650	650	650	930
SLA (projected m2/kg leaf C)	21.1	23.3	31.0	26.2	21.5	33.8
Q10_mr (unitless)	2.0	2.0	2.0	2.0	2.0	2.0
Annual						
froot_leaf_ratio (kgC/kgC)	1.3	1.1	1.3	1.1	1.1	1.8
livewood_leaf_ratio (kgC/kgC)	0.081	0.162	0.152	0.203	0.132	0.107
leaf_mr_base (kgC/kgC/day, 20C)	0.00604	0.00604	0.00805	0.00778	0.00677	0.00869
froot_mr_base (kgC/kgC/day, 20C)	0.00519	0.00519	0.00519	0.00519	0.00519	0.00519
livewood_mr_base (kgC/kgC/day, 20C)	0.00322	0.00397	0.00297	0.00371	0.00372	0.00312
leaf_gr_base (kgC/kgC/day, 20C)	0.3	0.3	0.3	0.3	0.3	0.3
froot_leaf_gr_ratio (kgC/kgC)	1.3	1.1	1.3	1.1	1.1	1.8
livewood_leaf_gr_ratio (kgC/kgC)	0.16	0.20	0.15	0.19	0.19	0.15
deadwood_leaf_gr_ratio (kgC/kgC)	1.6	1.1	1.5	1.6	1.8	1.0
ann turnover prop (unitless)	0.25	0.50	1.00	1.00	0.50	0.25
Corresponding UMD Land Cover Classification (MOD12Q1)	1	2	3	4	5	8

	BIOME CLASSIFICATION				
PARAMETER	**Wgrass**	**Cshrub**	**Oshrub**	**Grass**	**Crop**
Epsilon_max	0.000768	0.000888	0.000774	0.000680	0.000680
Daily					
Tmin_max (C)	11.39	8.61	8.80	12.02	12.02
Tmin_min (C)	-8.00	-8.00	-8.00	-8.00	-8.00
VPD_max (Pa)	3100	3100	3600	3500	4100
VPD_min (Pa)	650	650	650	650	650
SLA (projected m2/kg leaf C)	33.8	12.0	19.0	40.0	36.0
Q10_mr (unitless)	2.0	2.0	2.0	2.0	2.0
Annual					
froot_leaf_ratio (kgC/kgC)	1.8	1.0	1.2	2.0	2.0
livewood_leaf_ratio (kgC/kgC)	0.051	0.079	0.040	0.000	0.000
leaf_mr_base (kgC/kgC/day, 20C)	0.00869	0.00519	0.00714	0.01280	0.00980
froot_mr_base (kgC/kgC/day, 20C)	0.00519	0.00519	0.00519	0.00719	0.00519
livewood_mr_base (kgC/kgC/day, 20C)	0.00100	0.00436	0.00218	0.00000	0.00000
leaf_gr_base (kgC/kgC/day, 20C)	0.3	0.3	0.3	0.3	0.3
froot_leaf_gr_ratio (kgC/kgC)	1.8	1.0	1.5	2.0	2.0
livewood_leaf_gr_ratio (kgC/kgC)	0.05	0.22	0.11	0.00	0.00
deadwood_leaf_gr_ratio (kgC/kgC)	0.5	0.0	0.0	0.0	0.0
ann turnover prop (unitless)	0.25	0.25	0.25	1.00	1.00
Corresponding UMD Land Cover Classification (MOD12Q1)	9	6	7	10	12

EOS biome class key:

ENF = evergreen needleleaf forest
EBF = evergreen broadleaf forest
DNF = deciduous needleleaf forest
DBF = deciduous broadleaf forest
MF = mixed forest
WL = grassy woodland
Wgrass = wooded grassland
Cshrub = closed shrubland
Oshrub = open shrubland
Grass = Grasslands
Crop = Croplands

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.

2.3. DAO daily meteorological data

The MOD17 algorithm computes productivity at a daily time step. This is made possible by the daily meteorological data, including average and minimum air temperature, incident PAR and specific humidity, provided by the Data Assimilation Office (DAO), a branch of NASA (Schubert et al. 1993). These data, produced every six hours, are derived using a global circulation model (GCM), which incorporates both ground and satellite-based observations. These data are distributed at a resolution of 1° by 1.25° (originally 1° x 1°) in contrast to the 1-km gridded MOD17 outputs. It is assumed that the coarse resolution meteorological data provide an accurate depiction of ground conditions and are homogeneous within the spatial extent of each cell. Preliminary studies done by Numerical Terradynamic Simulation Group (NTSG) suggest that the relationship between surface observations and DAO data across the U.S. appears reasonable (Fig. 2.2), but comparisons have yet to be made on a global scale.

3. 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 (Table 3.1). While, the primary product created by MOD12 is a 17-class IGBP (International Geosphere-Biosphere Programme) landcover classification map (Belward et al. 1999; Scepan 1999), the MOD17 algorithm employs Boston University's UMD classification scheme (Table 3.1). More details on these and other schemes and their quality control considerations can be found at the Land Cover Product Team website (*http://geography.bu.edu/landcover/userguidelc/index.html*).

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 all MODIS products are designed at a 1-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 (Hansen et al. 2000).

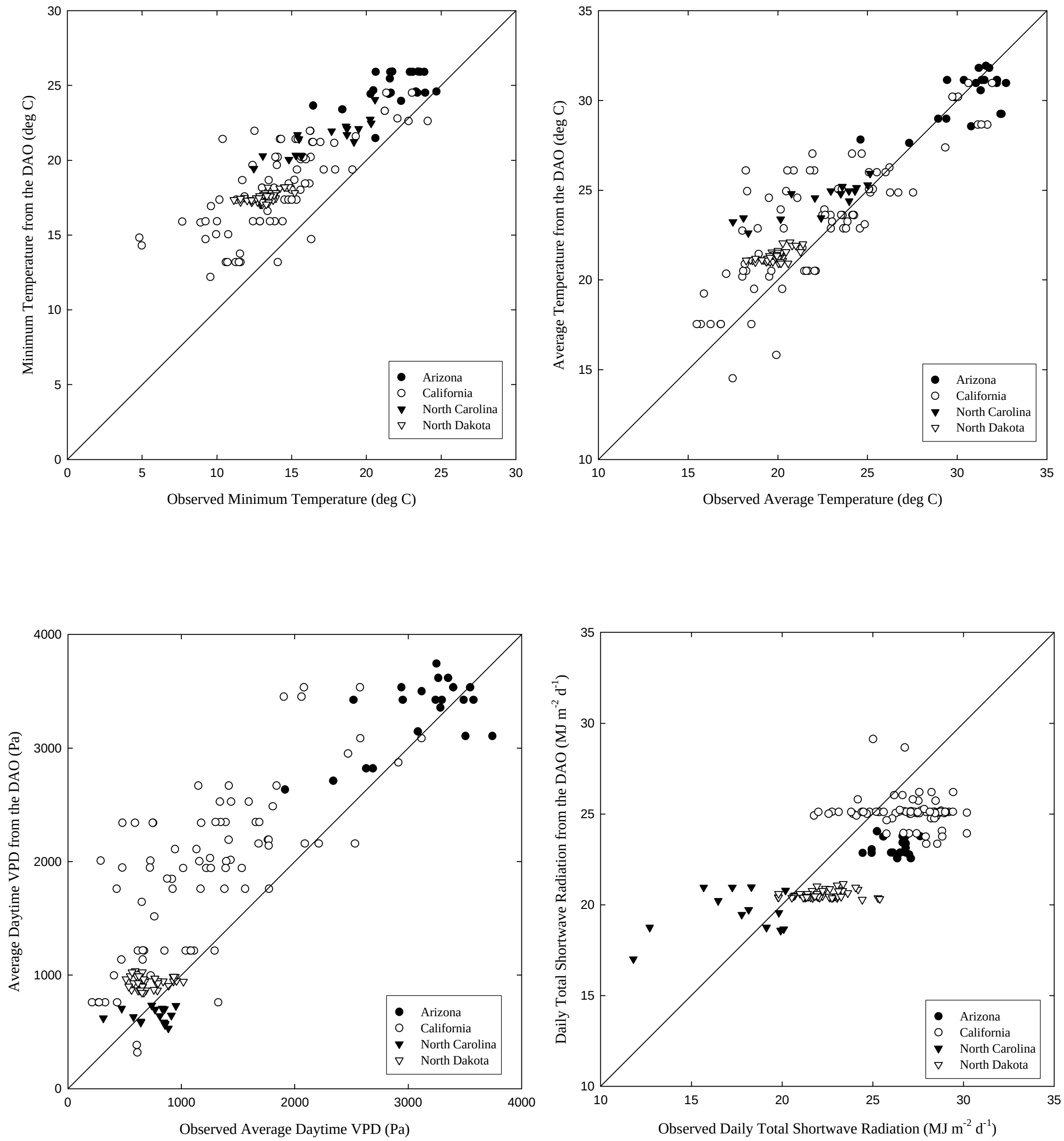


Figure 2.2. Comparisons of DAO and observed meteorological data.

Table 3.1. 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

4. Practical Considerations for Processing and Use of MODIS Data

Two considerations paramount to understanding the MODIS data stream are the unique projection and tiling system and the file format inherent to all MODIS land products.

4.1. MODIS tile projection characteristics

All MODIS land products are projected on the Integerized Sinusoidal (ISIN) 10° grid, where the globe is tiled for production and distribution purposes with 36 tiles along the east-west axis, and 18 tiles along the north-south axis, each about 1200x1200 kilometers (Fig. 4.1). MODIS is meeting the stated geolocation requirement of 0.1 pixels at 2 standard deviations for the 1 km bands (Wolfe, et al. 2002)

The Collection 4 projection ***is*** *Sinusoidal (SIN), while Collections 1-3 use a Integerized Sinusoidal Projection (ISIN). At a 1 km spatial resolution, the difference between the SIN and ISIN projections is negligible. The decision to switch from the ISIN to the SIN projection was made to make the data more compatible with current image processing software.*

For many applications it may be convenient to reproject MODIS data from the ISIN or SIN projection to a different projection that is more suited to the area of interest. Few proprietary image processing or geographic information system (GIS) software have the capability to reproject MODIS data from an ISIN projection. Fortunately, however, there are good tools, which are simple to download and are freely available. The primary tool currently used to reproject MODIS data in both formats is the MODIS Reprojection Tool (MRT). This tool, and more information can be found at *http://edcdaac.usgs.gov/tools/modis*.

4.2. File format of MOD17 end products

All NASA biophysical products are archived in the NASA HDF-EOS data format. HDF-EOS is based upon the Hierarchical Data Format pioneered by the National Center for Supercomputer Applications (NCSA) at the University of Illinois, Champaign/Urbana. The HDF-EOS format has the advantage of multiple layers of data and supporting ancillary information (such as projection characteristics, scaling factor, time and date of production etc.) in a single file. The drawback is that in order to use the actual vegetation productivity layer, one must extract this layer from the data "stack". Therefore, the MRT serves two purposes:

[1] reproject MODIS data from ISIN or SIN
[2] extract the desired data layer from the "stack"

Several tools and software systems allow the user to browse through the various data layers within a given HDF-EOS file. The growing body of HDF-EOS tools can be found at *http://hdfeos.gsfc.nasa.gov/hdfeos/index.html*. In addition, the Earth Observing System (EOS) Core System (ECS) Project Office developed the HDF-EOS to GeoTIFF (HEG).
The HDF-EOS to GeoTIFF (HEG) tool provides conversion for HDF-EOS formatted files (granules), converting HDF-EOS swath and grid data to HDF-EOS Grid, GeoTIFF, or a generic binary format. The tool can be used to re-project data from its original format to other standard projections, as well as to subset data and to mosaic adjacent granules together. The HEG packages are available for Sun and SGI systems in 'tar' format, and a User's Guide in Microsoft Word is available. Download and installation instructions can be found at *http://eosweb.larc.nasa.gov/PRODOCS/misr/geotiff_tool.html*.

Remember, potential byte-order problems can be avoided by unpacking the HDF files (via the MRT or other means) on the same computer with which they will be doing their analysis.

4.2a. Local (Science Dataset SDS) Attributes. A complete, updated description of each MODIS land product is found in the MODIS File Specification documents for MOD17A1, MOD17A2, and MOD17A3 (*ftp://modular.gsfc.nasa.gov/pub/LatestFilespecs/*). With each SDS or HDF-EOS gridfield, a series of local SDS attributes are included:

[1] Scale factor and offset (if appropriate)
[2] Data range {minimum,maximum}
[3] Fill value
[4] Longname

4.2b. Global Attributes. All EOS Core System (ECS) data products are assigned a unique Earth Science Data Type (ESDT), and are provided to users with several types of quality metadata. Level 3 and 4 data products are gridded using the Integerized Sinusoidal (ISINUS) or Sinusoidal (SIN) rectangular map projection, and supplied to users with several types of metadata. Two broad types of metadata are defined, collection level, and granule level, with the granule level metadata specific to a given granule or tile. All ECS metadata entries are formally introduced to the system and are registered within the ESDT definition. For complete details on ECS metadata issues, interested readers are encouraged to visit URL *http://observer.gsfc.nasa.gov/*. A fairly complete ECS related glossary relevant to metadata may be found at: *http://ecsinfo.gsfc.nasa.gov/sec2/glossary.html*.

At the tile (or granule) level, the standard ECS metadata are organized into three different sections, each appearing in a given HDF-EOS file as a global character attribute (Table 4.1). A granule is the smallest unit of data that is produced, inventoried, and archived within the EOSDIS. Within each of these large metadata blocks, data are organized using the Object Data Language (ODL) conventions established by NASA, with the data itself formatted as a series of name-value pairs or Parameter Value Language (PVL). An example of PVL syntax is the "GROUP… END_GROUP" and OBJECT… END_OBJECT" form commonly found in both the MCF files and each granule or tile HDF-EOS file. ODL enables the internal software used in MODIS production to access data defined within the Metadata Control File (MCF), with a unique MCF file defined for each ESDT that is archived, such as MOD17A2, or MOD17A3.

Users interested in quickly viewing the metadata contents of a HDF-EOS file may wish to use the commonly available HDF utility called **ncdump**. The ncdump utility for most computer platforms may be obtained from the National Center for Supercomputer Applications (NCSA) HDF web site (*http://hdf.ncsa.uiuc.edu/hdftools.html*) as well as from common NASA HDF-EOS tool URL sites. To produce a listing at the console of Science Data Set (SDS) properties as well as ECS metadata, enter a command such as:

"ncdump –h MOD17A2.A2002353.h08v05.003.2003008095623.hdf"

Other interactive (graphical user interface based) software tools users may employ to view the original ECS metadata information in a HDF-EOS tile are HDFLook on Unix/Linux, and the Java-based WebWinds tool available on most platforms. Additional information on these tools can be found in Section 4.4.

Principal Investigators who wish to define additional attributes specific to their data product may also use the Product Specific Attribute (PSA) mechanism, wherein a limited number of attributes not covered in the standard metadata may be included in a granule. Note that the size of a global file attribute in HDF v4.x (and therefore, in an HDF-EOS file) is limited to 64Kb. The ECS tile level metadata sections are summarized in Table 4.1. Note that although the examples below refer to the MOD17A2 (8-day photosynthesis) ESDT, these metadata also apply to the MOD17A3 annual NPP product.

4.2b.i. Core and Archive Metadata: *What's The Difference?* The ECS *Core metadata* (CoreMetadata.0) are granule level metadata that describe a number of useful tile level attributes for the granules held in a common Collection, such as the current Collection 4. These metadata are also known as *INVENTORY* metadata, reflecting the fact they constitute a baseline resource

Table 4.1. ECS Metadata Summary for PSN, PSNnet and NPP Data Products.

Block	**Organization**	**Contents**
StructMetadata.0	Object Data Language (ODL)	Geospatial data, tile origin coordinates, map projection attributes
CoreMetadata.0	Object Data Language (ODL)	Inventory attributes
ArchiveMetadata.0	Object Data Language (ODL)	Archive metadata attributes

describing the inventory of data available. INVENTORY (or Core) metadata includes all granule-level metadata that will reside in ECS inventory tables and will thus be searchable.

Archive metadata (stored in each granule in the ArchiveMetadata.0 block), on the other hand, contain metadata fields that the producer wants to accompany the granule when it is delivered to end-users, but need not be searchable by the system. Both the Core and Archive metadata elements are defined in the Metadata Control File (MCF) that accompany each process-generation executable (PGE) in the system.

4.2b.ii. StructMetadata Attributes. For gridded Level 3/4 products such as the PSN, NPP products, a GridStructure object is defined – no swatch structure is defined. The StructMetadata.0 block contains the physical (e.g. non-science) attributes of the dataset. These are the minimum attributes that a software reader utility would need to correctly read and interpret the data at a physical level These include the grid name (MOD_Grid_MOD17A2), the data set dimensions (1200x1200), the grid upper left origin coordinates, the General Cartographic Transform Package (GCTP) map projection conversion parameters, and a list of the science data set (SDS) names.

An abbreviated list of StructMetadata attributes is:

```
GridName MOD_Grid_MOD17A2
XDim1200  YDim1200
UpperLeftPointMtrs(-8895604.158132,5559752.598833)
LowerRightMtrs(-7783653.638366,4447802.079066)
ProjectionGCTP_ISINUS
ProjParams (6371007.181000,0,0,0,0,0,0,0,86400,0,1,0,0)
SphereCode -1
PixelRegistration HDFE_CENTER
DimensionName YDim  Size 1200
DimensionName XDim  Size 1200
DataFieldName Gpp_1km
DataType DFNT_INT16
DimList  YDim,XDim
DataFieldName PsnNet_1km
DataType DFNT_INT16
DimList YDim,XDim
DataFieldName Psn_QC_1km
DataType DFNT_UINT8
DimList YDim,XDim
```

ECS MODIS data are generally produced and organized at a high level in terms of collections. A collection may be considered a generation of data, sharing the common property of having been produced with a latest "milestone" set of processing algorithms. Within a given collection, considerable effort is made to re-process all ESDT (products), usually for entire period when raw Level 0/1A satellite data are available (the period of record), into consistent structured collections. Since Terra launched in December 1999, there have currently been four (4) collections produced (Collection 4 is currently being re-processed as of March, 2003), with each collection taking into account the latest algorithm improvements. Each subsequent collection is therefore expected to represent incrementally higher quality science data than the previous. Scientists using Terra MODIS data are therefore encouraged to base their science research and applications on the most recent collection of data available. Recall that the

collection identifier is also contained in each production tile (individual files) name, as in the following example tile name shown for MOD13A2 where the collection identifier, "**003**" is shown highlighted:

MOD13A2.A2002353.h08v05.**003**.2003008095623.hdf

A simplified list of CoreMetadata.0 attributes (for the MOD17A2 ESDT) are shown below. The names are typically self descriptive. Note that Product Specific Attributes (PSA), if supplied by the Principle Investigator, are contained within the ADDITIONALATTRIBUTE objects. The spatial extent of the tile is described by the GRINGPOINT (latitude and longitude) attributes, where these describe the four corner coordinates (N,E,S,W) of the tile.

ADDITIONALATTRIBUTENAME
ADDITIONALATTRIBUTESCONTAINER
ASSOCIATEDINSTRUMENTSHORTNAME
ASSOCIATEDPLATFORMINSTRUMENTSENSORCONTAINER
ASSOCIATEDPLATFORMSHORTNAME
ASSOCIATEDSENSORSHORTNAME
AUTOMATICQUALITYFLAG
AUTOMATICQUALITYFLAGEXPLANATION
DAYNIGHTFLAG
EXCLUSIONGRINGFLAG
GPOLYGONCONTAINER
GRINGPOINTLATITUDE
GRINGPOINTLONGITUDE
GRINGPOINTSEQUENCENO
INPUTPOINTER
LOCALGRANULEID
LOCALVERSIONID
MEASUREDPARAMETERCONTAINER
PARAMETERNAME
PARAMETERVALUE
PGEVERSION
PRODUCTIONDATETIME
QAPERCENTCLOUDCOVER
QAPERCENTINTERPOLATEDDATA
QAPERCENTMISSINGDATA
QAPERCENTOUTOFBOUNDSDATA
RANGEBEGINNINGDATE
RANGEBEGINNINGTIME
RANGEENDINGDATE
RANGEENDINGTIME
REPROCESSINGACTUAL
REPROCESSINGPLANNED
SCIENCEQUALITYFLAG
SCIENCEQUALITYFLAGEXPLANATION
SHORTNAME
VERSIONID

Users may find the following distinction helpful to understand the difference between the GRINGPOINT coordinates in the CoreMetadata.0 and the NORTH, SOUTH, EAST, WEST BOUND coordinates in the ArchiveMetadata.0 block. In the ArchiveMetadata block, the

NORTH, SOUTH, EAST, and WEST BOUND coordinates represent a minimum bounding rectangle (MBR) defined by the tile, rather than the typically trapezoidal shaped polygon represented by the GRINGPOINT coordinates.

4.2b.iii. ArchiveMetadata Attributes. The following Archive metadata attributes are designed to assist end-users in using and effectively interpreting the Terra MODIS (PSN, NPP) data. These attributes are not considered essential as “searchable” metadata in the overall ECS metadata, partially because some of this information is overlapped by almost equivalent elements in the CoreMetadata.0 attributes (which as INVENTORY metadata, are searchable).

ALGORITHMPACKAGEACCEPTANCEDATE
ALGORITHMPACKAGEMATURITYCODE
ALGORITHMPACKAGENAME
ALGORITHMPACKAGEVERSION
CHARACTERISTICBINANGULARSIZE
CHARACTERISTICBINSIZE
DATACOLUMNS
DATAROWS
DESCRREVISION
GEOANYABNORMAL
GEOESTMAXRMSERROR
GLOBALGRIDCOLUMNS
GLOBALGRIDROWS
GRANULEBEGINNINGDATETIME
GRANULEDAYNIGHTFLAG
GRANULEENDINGDATETIME
INSTRUMENTNAME
LOCALINPUTGRANULEID
LONGNAME
MAXIMUMOBSERVATIONS
NADIRDATARESOLUTION
NUMBEROFGRANULES
PLATFORMSHORTNAME
PROCESSINGCENTER
PROCESSINGDATETIME
PROCESSINGENVIRONMENT
SPSOPARAMETERS

NORTHBOUNDINGCOORDINATE
EASTBOUNDINGCOORDINATE
SOUTHBOUNDINGCOORDINATE
WESTBOUNDINGCOORDINATE

4.2b.iv. Other Helpful ECS Metadata References. A number of detailed ECS related web pages and Adobe Postscript documents may be found at *http://observer.gsfc.nasa.gov/*, including the document “ECS_ProvidersGuideToMetadata.pdf”. Although document describes the Terra MODIS metadata scheme from a “providers” standpoint, it is quite useful for interested readers who want more in-depth coverage on this topic.

4.3. Data set characteristics

As indicated in Figure 1.1 and Table 4.2, the MODIS vegetation productivity data stream consists of three biophysical products:

[1] 8-day summation GPP MOD17A2 (Equation 1.2)
[2] 8-day summation PSNnet MOD17A2 (Equation 1.8)
[3] annual NPP MOD17A3 (Equation 1.15).

To properly visualize and interpret any of these products, it is necessary to convert them from scaled digital images to a biophysical quantity. This can be accomplished using the equation:

$$\text{Biophysical\_pixel} = \text{scale\_factor} * \text{digital\_value}. \qquad \textbf{(4.1)}$$

where Biophysical_pixel is sequestered carbon (kg C m^{-2}), scale_factor is the gain for the MODIS productivity products, and digital_value is the numeric value of a file pixel. For example, if we obtain a mid-summer digital_value of 421 for Gpp_1km from an HDF file, an 8-day summation of Gpp_1km would be

$$\text{Biophysical\_pixel} = \text{scale\_factor} * \text{digital\_value} = 0.0001 * 421 = 0.0421 \text{ kg C m}^{-2}.$$

In order to obtain a **daily** estimate of Gpp_1km, we must divide this number by 8, so that we get

$$0.0421 \text{ kg C m}^{-2} / 8 = 0.00526 \text{ kg C m}^{-2} \text{ d}^{-1}.$$

The information contained in Table 4.2 can also be found within an HDF-EOS data set and can be viewed using the various tools found at *http://hdfeos.gsfc.nasa.gov/hdfeos/index.html*.

🗲 *Remember, the result is an 8-day summation. In order to obtain daily estimates of Gpp_1km or PsnNet_1km, it is necessary to divide your Biophysical_ pixel value by 8.*

4.4. Links to MODIS-friendly tools.

4.4a. HDFLook: HDF and HDF-EOS viewer. This product is available for Solaris, Alpha VMS, HP-UX, IRIX, AIX, and Linux. It is a handy little tool available at: *http://www-loa.univ-lille1.fr/Hdflook/*.

Table 4.2. Summary of output variables from the MODIS vegetation productivity algorithm.

Summary of MOD17 output variables						
Variable	*Data Type*	*Units*	*Fill Value*	*Scale Factor*	*Valid Range*	*Product*
Gpp_1km	Int16	Kg C m^{-2}	32766	0.0001	0 - 30000	MOD17A2
PsnNet_1km	Int16	Kg C m^{-2}	32766	0.0001	-30000 - 30000	MOD17A2
Npp_1km	Int16	Kg C m^{-2}	32766	0.0001	-30000 - 30000	MOD17A3
Psn_QC_1km	Uint8	N/A	255	N/A	0 - 254	MOD17A2
Npp_QC _1km	Uint8	N/A	255	N/A	0 - 254	MOD17A3

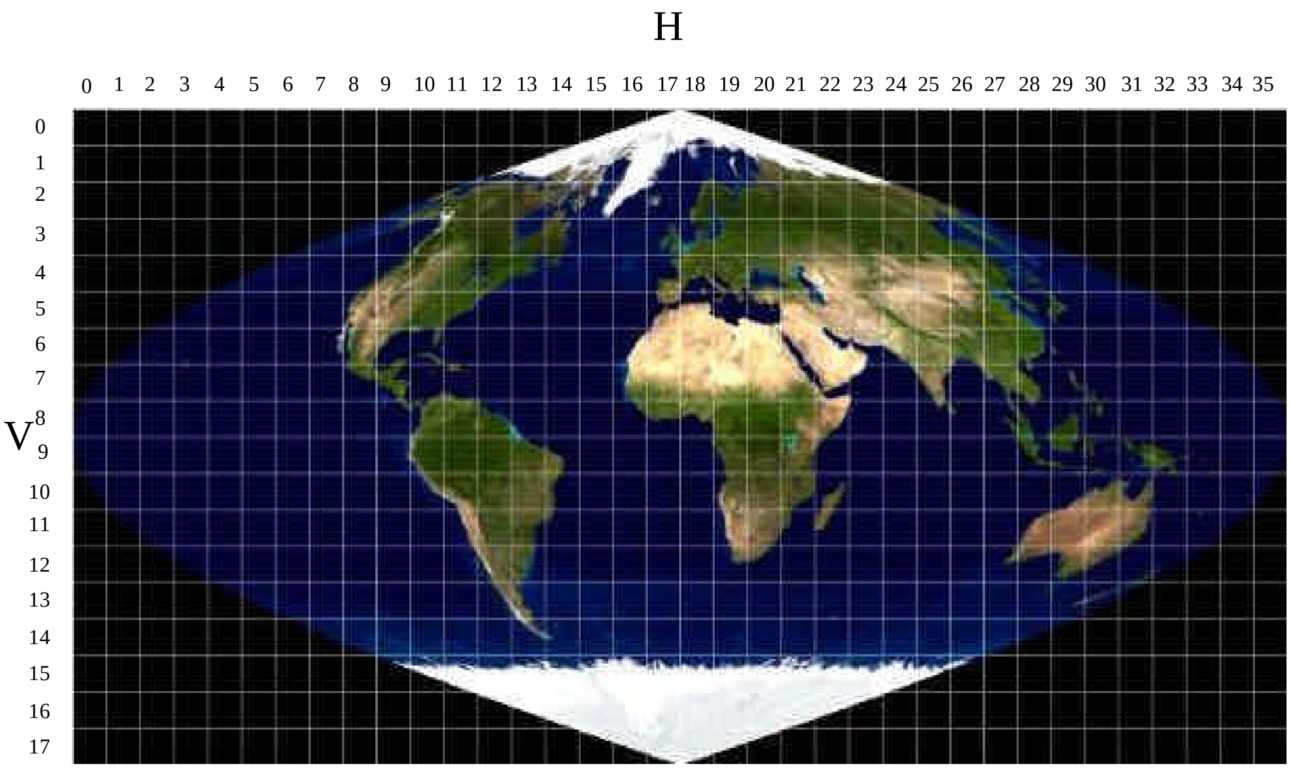


Figure 4.1. MODIS tiling system. Any location on the earth can be spatially referenced using the horizontal (H) and vertical (V) designators. Each tile is 1200 x 1200 kilometers.

4.4b. Msphinx: This free utility can read HDF and HDFEOS, and it has some visualization and other capabilities. Supported platforms include; HP, DEC, Silicon Graphics, IBM, Sun, and Linux. For more information, go to: *http://www-loa.univ-lille1.fr/Msphinx/*.

4.4c. Webwinds: Webwinds is written in Java, enabling it to run on any platform that supports Java. It is a science data visualization system, capable of reading several data formats. For more information please see the Webwinds home page at: *http://www.openchannelsoftware.com/projects/WebWinds*.

4.4d. LDOPE Tools: LDOPE tools were created to assist in quality assessment of MODIS Land products. Look at the overview of this toolset at: *http://edcdaac.usgs.gov/tools/ldope*.

There are several additional tools available, some free and others not, which support the HDF-EOS data format in which MODIS data are stored. For a larger listing, see the N.C.S.A.'s (National Center for Super Computing Applications) tool page at *http://hdf.ncsa.uiuc.edu/tools.html#util*.

5. Data Collection History

As with any new product, there have been modifications and improvements to the MODIS algorithm and outputs. In fact, there have been three such collections (Collections 2, 3 and 4) that may currently be in use. It is important for the user to know which collection they have, and, furthermore, what assumptions were made in the calculation of that collection. It is also wise to periodically check the EDC website for any updates on the data. The MOD17 product, at the end of the processing line because of its reliance on other MODIS products (Fig. 2.1), is one of the last products to be updated.

Collection 3. If your data were downloaded prior to December 13, 2002, the algorithm uses Collection 3 inputs of Land Cover and LAI/FPAR, and an *older, less restrictive* BPLUT (To avoid potential confusion, this version of the BPLUT will not appear in the User's Guide). The dataset using the older BPLUT is no longer available from the EDC.

If your data were downloaded after December 13, 2002 and before January 15, 2003, then you have the most complete version of Collection 3 data. The primary modification is a change in the VPD constraints on ε_{max} in Equation 1.1. This product continues to rely upon Collection 3 inputs of Land Cover (MOD12Q1) and LAI/FPAR (MOD15A2).

Collection 4. Distribution of Collection 4 data began on **January 15, 2003**. Collection 4 will continue to use the improved algorithm of Collection 3, but will employ Collection 4 inputs from both the Land Cover and LAI/FPAR algorithms, providing the most up-to-date calculations available.

Collection 4.5. While not available through the EOS Data Gateway as a standard product, Collection 4.5 represents an improved MOD17A2/A3 dataset. This dataset includes a revised BPLUT (Table 3.1) based on the most current research, and is described in Chapter II of this document. This dataset includes temporal interpolation of cloud-contaminated MOD15A2 LAI/FPAR data and spatial smoothing of the DAO meteorology. This dataset is available upon request from NTSG (http://*www.ntsg.umt.edu*). It can be differentiated from the standard product by looking at the "Product version number" (Figure 1.1, Chapter 3). The standard product version number will always begin with a "0" (e.g., 004 for Collection 4) as in

MOD17A2.A2003177.h10v04.**004**.2003201102319.hdf

, while any product created at NTSG will begin with a "1" (e.g., 105 for Collection 4.5) as in

MOD17A2.A2003177.h10v04.**105**.2003201102319.hdf.

For further information about Collection 4.5, including naming conventions, granules, imagery, and analysis please visit *http://images.ntsg.umt.edu*.

Users are strongly encouraged to obtain and use Collection 4.5 of the MOD17A2/A3 datasets when available.

6. Quality Assurance

Quality assurance (QA) measures are produced at both the file (e.g. 10-deg tile level) and at the pixel level. At the tile level, these appear as a set of EOSDIS core system (ECS) metadata fields, described later in this document. At the pixel level, quality assurance information is represented by a separate data layer in the HDFEOS file, whose pixel values correspond to specific quality scoring schemes that vary by product Earth Science Data Type (ESDT). The QC organization of MOD17A2 and MOD17A3 files generated from Collection 4 and higher is summarized in Tables 6.1 and 6.2. Significant changes include the new 3-bit scheme of the SCF bits in MOD17A2, and overall change in the QC of the MOD17A3.

In general, two broad types of quality assurance activities are performed at the SCF and by the Land Data Operations Processing Environment (LDOPE) group at Goddard Space Flight Center:

[1] routine QA
[2] problem-triggered QA

The primary quality assurance activity routinely conducted at the SCF is the post-processing assignment of the tile level SCIENCEQUALITYFLAG and accompanying SCIENCEQUALITYFLAGEXPLANATION. Due to the volume of data, this activity is performed on only a small percentage of product tiles. Valid components for this field include:

[1] PASSED
[2] FAILED
[3] SUSPECT, BEING INVESTIGATED
[4] NOT BEING INVESTIGATED

Routine QA involves periodic sampling of the product tiles using visual and statistical methods. Problem triggered QA follows from a report of an inconsistency or other problem in the data, which has been discovered by the Land Data Operational Product Evaluation (LDOPE) front line QA personnel, the SCF staff, or users. In this case, an effort is usually made to duplicate the problem under controlled conditions to resolve it.

During the design phase, the MODIS team chose to provide a Quality Assurance measure for each pixel. The quality assurance "flags" make it possible for the user to match data sets to their applications. The user is encouraged to make use of the quality assurance information associated with each pixel because it permits quick, objective, and repeatable screening to filter out undesirable pixels. The QA flags that users will find in the MOD17A2 products are summarized in Table 6.1. Each flag is divided into a series of bitfields which can be parsed to allow separate interpretation of each field for maximum control over the data set. The EDC DAAC (Earth Resources Observation Systems Data Center Distributed Active Archive Center) is currently working on tools that will enable the user to automatically parse and process each bitfield. The process of parsing bitfields may seem confusing at first. As a general rule, if the user does not wish to examine every bitfield independently, a threshold value of zero should produce the best quality pixels for scientific analysis, although this may reduce the number of pixels available for evaluation (Fig. 6.1). There are two steps to interpreting MOD17A2 QA values:

[1] Convert the file pixel QA number to its binary equivalent.
[2] Alter the binary equivalent to become 8 digits long.
    For example, if the binary equivalent is 100, you must add zeroes to the left-hand side *until there are a total of* ***8 binary digits***, since the MOD17A2 QA value is an 8-bit unsigned integer. So, 100 becomes 00000100.
[3] Parse individual bit fields from the 8-bit integer (Figure 6.1) and interpret their meaning per Table 6.1. Therefore, in this example, the third bit = 1, indicating that dead detectors caused >50% adjacent detector retrieval.
    For example, QA = 4 has a binary equivalent = 100.

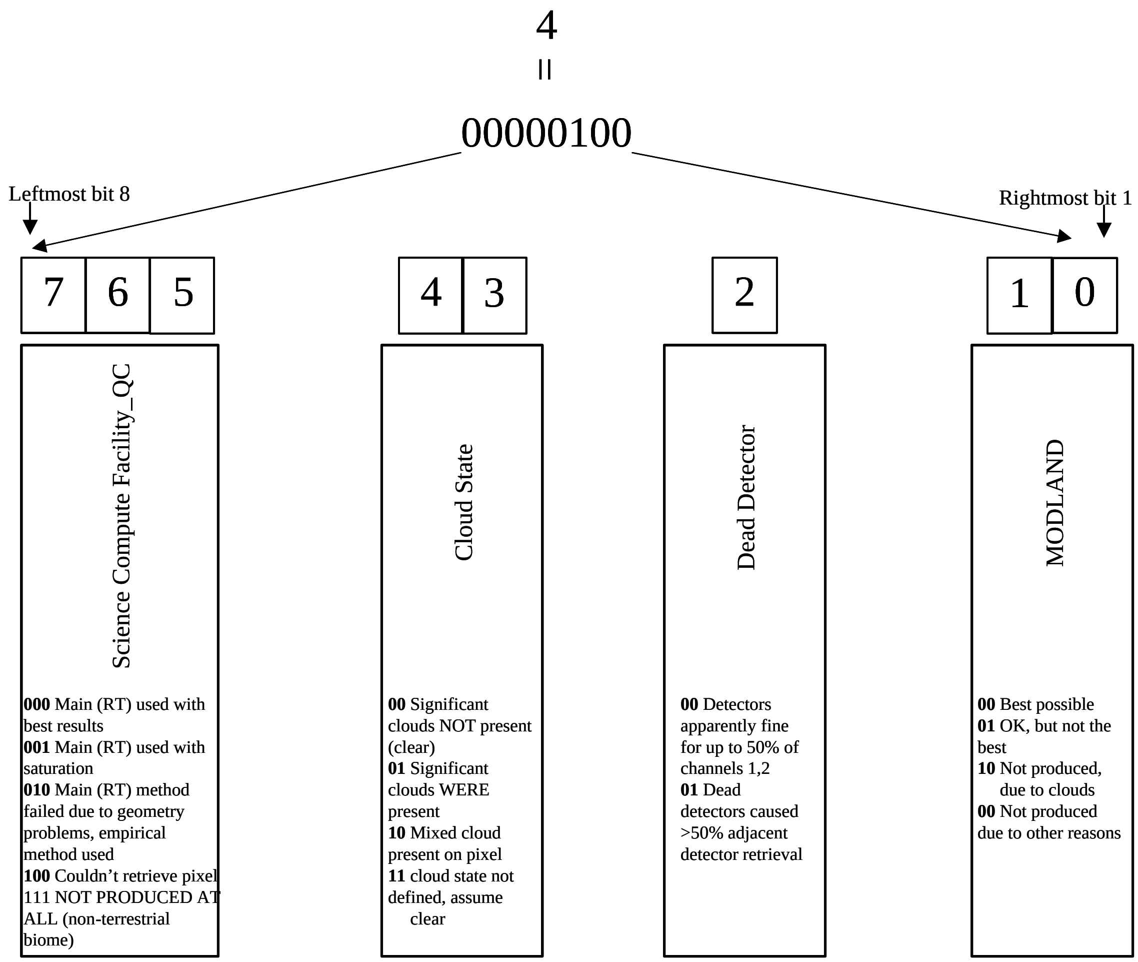


Figure 6.1. A diagram for a hypothetical MOD17A2 quality assurance value of 4.

6.1 GPP and NPP Quality Assurance Variable Scheme

The definitions of the bitfields within a given 8-bit GPP QA variable (denoted as Psn_1km_QC) are shown in Tables 6.1 and 6.2. Recall that the quality of the precedent input data product (FPAR, LAI 8-day composite) exerts a very direct influence on the quality of the GPP variable, and for this reason, we "inherit" the FPAR, LAI QA scoring for a given pixel and pass this through as the GPP quality variable. At this time, the quality bits for MOD17A3 (Table 6.3) are taken from the last full 8-day period of MOD15A2 and therefore caution should be used in interpreting these QA values.

6.2. Identifying non-terrestrial fill-values in the GPP/NPP data products

We recognize that many users will want to use GPP and NPP data products in combination with a geographical information system (GIS) and remote sensing analysis software. To facilitate production of single layer MODIS data product maps, we now classify non-terrestrial (e.g. non-modeled) pixels with special identification codes to allow for quick masking and exclusion from quantitative ecological analysis. A dual encoding scheme is followed whereby pixels whose values lie within the valid range for the biophysical variable may

Table 6.1. GPP 8-bit Quality Assurance Variable bit-field definitions (Coll. 3).

Variable	**Bitfield**	**Binary, Decimal Values**	**Description of bitfield(s)**
Psn_1km_QC	MODLAND Bits 0,1	00=0 01=1 10=2 11=3	0=Highest overall quality 1=Good quality 2=Not produced, cloud 3=Not able to produce
	ALGOR_PATH Bits 2,2	00=0 01=1	0=Empirical FPAR method used 1=FPAR R-T Main method used
	DEAD-DETECTOR, Bits 3,3	00=0 01=1	0=Detectors acceptable for up to 50% of channel 1,2 1=Dead detectors affected >50% of adjacent detectors retrieval
	CLOUDSTATE Bits 4,5	00=0 01=1 10=2 11=3	0=Cloud free 1=Significant cloud covered pixel 2=Mixed clouds present 3=Not set, assume clear
	SCF_QC, Bits 6,7 (NTSG) **S**cience **C**ompute **F**acility **Q**uality **C**ontrol	00=0 01=1 10=2 11=3	0=Best model result 1=Good quality, not the best 2=Use with caution, see other QA 3=Could not retrieve with either method.

be interpreted as biophysically relevant, while non-modeled pixels are given a special higher number integer code at the high end of the numeric integer range for the GPP and NPP variables. Table 6.4 describes these non-terrestrial land cover type codes, which range from 32761 to 32767. Recall that valid GPP or NPP biophysical values are restricted to values less than or equal to 30,000. This value separation may thus be used to quickly separate subpopulations of pixels into two classes:

[1] valid, modeled pixels (≤ 30000), and
[2] non-modeled pixels (> 30000).

Table 6.2. GPP 8-bit Quality Assurance Variable bit-field definitions (Coll. 4).

Variable	**Bitfield**	**Binary, Decimal Values**	**Description of bitfield(s)**
Psn_1km_QC	MODLAND_QC Bits 0,1	00=0 01=1 10=2 11=3	0=Best Possible 1=OK, but not the best 2=Not produced, due to cloud 3=Not produced, due to other reasons
	DEADDETECTOR Bits 2,2	00=0 01=1	0=Detectors acceptable for up to 50% of channel 1,2 1=Dead detectors caused >50% adjacent detector retrieval
	CLOUDSTATE, Bits 3,4	00=0 01=1 10=2 11=3	0=Significant clouds NOT present (clear) 1=Significant clouds WERE present 2=Mixed cloud present 3=cloud state not defined, assumed clear
	SCF_QC, Bits 5,7 (NTSG) **S**cience **C**ompute **F**acility **Q**uality **C**ontrol	000=0 001=1 010=2 011=3 100=4 111=7	0=Main (RT) method used with best possible results 1=Main (RT) method used with saturation 2=Main (RT) method failed due to geometry problems, empirical method used 3=Main (RT) method failed due to problems other than geometry, empirical method used 4=Couldn't retrieve pixel 7=NOT PRODUCED AT ALL (Non-terrestrial biome)

Table 6.3. NPP 8-bit Quality Assurance Variable bit-field definitions (Collection 4).

Variable	**Bitfield**	**Binary, Decimal Values**	**Description of bitfield(s)**
Npp_QC_1km	MODLAND_QC Bits 0,1	00=0 01=1 10=2 11=3	Highest overall quality Good quality Not produced, due to cloud Not produced due to other reasons
	NOT-YET-ASSIGNED Bits 2,4		
	SCF_QC, Bits 5,7 (NTSG) **S**cience **C**ompute **F**acility **Q**uality **C**ontrol	000=0 001=1 010=2 011=3 100=4 111=7	0=Pixel produced, best quality 1=Pixel produced, good quality – saturation in FPAR/LAI algorithm 2=Pixel produced, poor quality due to geometry problems 3=Pixel produced, poor quality due to problems other than geometry 4=Couldn't retrieve pixel 7 = NOT PRODUCED AT ALL (non-terrestrial biome)

Table 6.4. GPP 8-day summation and annual NPP non-terrestrial fill-value code definitions.

Code	Definition
32767	Fill value: conventional HDF-EOS fill value assigned to non-modeled pixels not falling into other categories below.
32766	Perennial salt or inland fresh water body cover type
32765	Barren, sparsely vegetated (rock, tundra, desert) cover type
32764	Perennial snow or ice cover type
32763	Permanent wetlands/inundated marshland type
32762	Urban/built-up cover type
32761	Unclassified pixel

7. Missing Data

There are several reasons for missing data in the MOD17A2 product stream (identified as fill values; Code 32767); sensor malfunction and cloud cover appear to be the primary causes. The MODIS satellite has been very stable, and there has been only one period of time during which the sensor malfunctioned. As a result, there were no MODIS products produced for the 8-day summation days 169 and 177 in 2001. Reconstruction of the data is possible, but it is not done at the EDC. Cloudiness and darkness also deleteriously affect MODIS measurements in the visible portion of the electromagnetic spectrum. There is nothing to be done regarding darkness, which fortunately is an issue primarily at the poles, where it is dark during the winter. Several methods for dealing with missing data resulting from cloud cover are discussed in Section 9.1 (Figure 9.1). If there is at least 1 day of quality LAI/FPAR data taken during any given 8-day period, that data is used in the MOD17 Algorithm and then converted into an 8-day summation, but if no LAI/FPAR data are available, then the MOD17 pixel will not be calculated.

All pixels without a GPP calculation will have a value greater than 30,000, regardless of the reason for the missing values.

8. Usefulness of Data for Answering Research Questions

One of the most important questions to ask before beginning a project is whether MODIS data are applicable to your research. This really depends upon the questions you are asking and the scale of that research. Spatially, MODIS has a much coarser resolution than some other satellite sensors (1-km x 1-km). Given the assumptions associated with the data, a pixel-to-pixel comparison is not possible. On the other hand, MODIS data are well-suited to large regional or global analyses. Temporally, MODIS is much better than many satellite sensors, with its daily overpasses and 8-day compositing of the data, which can be used to look at annual productivity and interannual variability of both GPP and NPP. There is no other satellite that can provide a global, 8-day look at vegetative productivity and carbon balance on an annual basis. In addition, these data are available in near-real time, which will allow users to make comparisons with their own research data during the growing season, often within weeks of the actual data collection. As mentioned previously, periodic reprocessing of the data will allow for interpolation of missing data, resulting in a more complete, and more accurate product.

9. Considerations for MOD17A2 Product Improvement

Based on studies conducted at NTSG, several areas of research have been identified as possible improvements for future implementations for the MOD17 algorithm and output, including:

[1] filling model values for cloudy pixels
[2] changing the method of data compositing
[3] landcover

9.1. Filling model values for cloudy pixels

Under cloudy conditions, MOD17A2 GPP has two sources of contamination:

[1] MOD15A2 products
[2] DAO meteorological data.

Accurate retrieval of LAI and FPAR is not possible under cloudy conditions because the reflectances are distorted, resulting in poor QA values and inaccurate calculations of GPP for the contaminated pixels. DAO data are affected by cloud contamination because of the resolution difference as compared to MODIS (1° x 1.25° vs. 1-km x 1-km). As a result, DAO data cannot

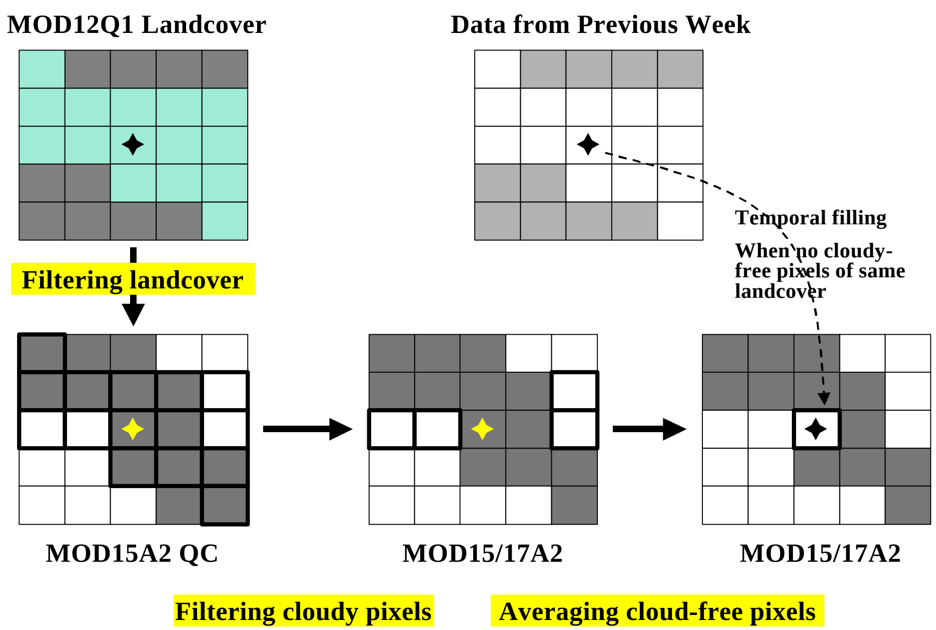


Figure 9.1. A schematic diagram illustrating the process of spatial and temporal interpolation using information from land cover and QA flags. In this example, the landcover map has only two values (dark and dashed pixels). In the bottom windows, dark pixels are cloudy pixels, and white pixels are those with the best QA conditions. The thick-bordered pixels are the pixels selected after filtering. In temporal filling, data from the previous week is used to fill MOD15 or MOD17A2.

capture the effect of clouds on the *local* meteorology of any given pixel as DAO data is averaged across the spatial domain of the data. There is nothing to be done at this point to account for cloudiness in the DAO data. However, three interpolation methods for filling the GPP or LAI/FPAR of cloudy pixels are suggested:

[1] fill the GPP of a cloudy pixel with GPP values from surrounding cloud-free pixels

[2] fill the FPAR of a cloudy pixel with FPAR values from surrounding cloud-free pixels and then recompute the GPP of the cloudy pixel using the filled FPAR

[3] fill the FPAR and LAI of a cloudy pixel with FPAR and LAI values from surrounding cloud-free pixels and recalculate the MOD17A2 algorithm.

The process of spatial and temporal interpolation is illustrated in Figure 9.1. When the central pixel of a 5×5 moving window is cloudy, nearby cloud-free pixels with the same landcover are used to interpolate the value of the central pixel. If there is no cloud-free pixel with a same landcover within the moving window, the central pixel inherits the value from the preceding week.

9.2. Data compositing

Currently, the MOD17A2 output is an 8-day summation product. However, in cloudy areas such as the tropics, this scheme is not always sufficient, as there are times during the year for which there are no cloud-free 8-day periods. As a result, researchers at NTSG are looking into a 16-day summation, which might be more useful for exploring interannual differences in GPP. This conversion will only occur if it provides an improved data stream. For those areas of the earth's land surface which are reasonably cloud-free, an 8-day summation may be continued.

9.3. Land cover

The land cover classification scheme ingested by the MOD17 Algorithm is at a 1-km resolution as are all MODIS products. There are areas of the world, however, for which improved, finer-resolution land cover data sets are available. Given the importance of accurate land cover for the MOD17 algorithm, research is needed to determine if such data sets would improve the MOD17 end products. For example, consideration is being given to using LandSat-derived land cover with 15-m resolution in place of the MOD12Q1 Land Cover product in some areas (Fig. 9.5). In this way, there would be a multi-resolution product that could increase the accuracy of the MOD17 Algorithm. LandSat land cover data could provide enhanced spatial resolution, while MODIS data (LAI/FPAR) provide the temporal resolution needed for the goals set by the MODIS Science Team. LandSat-derived land cover hasn't been used often for productivity analysis in the past because of the long return-time (16-days) and cloudiness associated with these products, but combining that land cover with the daily overpass of the MODIS data could improve the MOD17A2 product. As with all MODIS products, MOD17 would continue to be produced at a 1-km resolution.

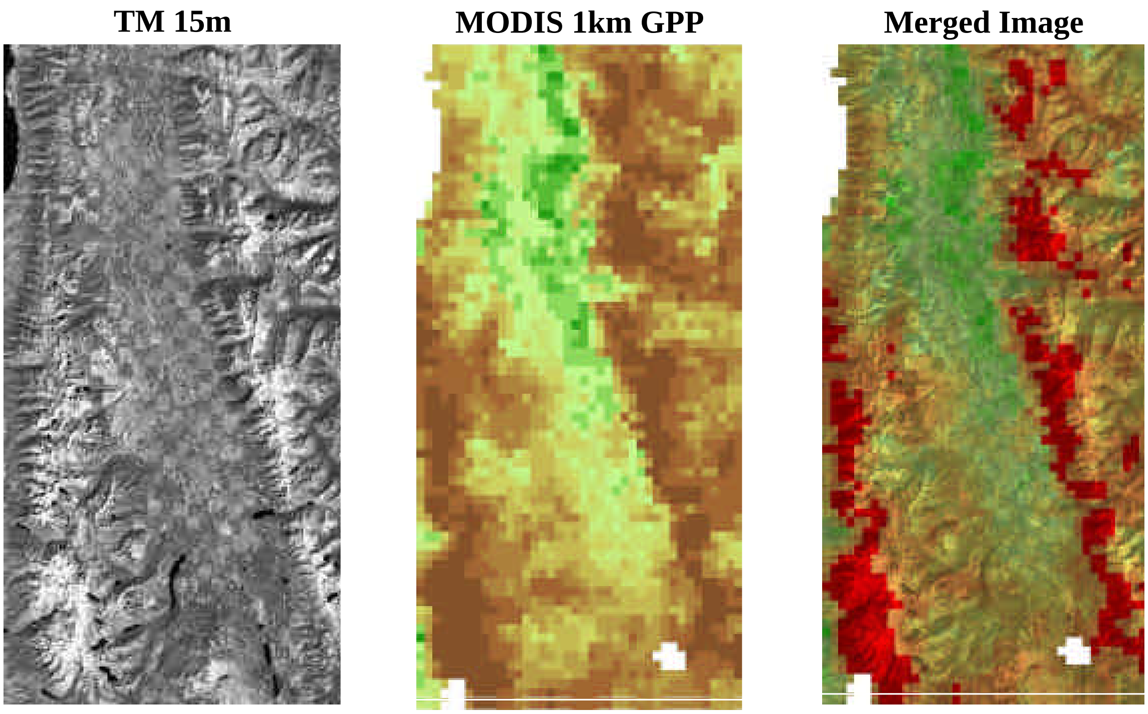


Figure 9.5. Merging MODIS productivity data with high-resolution LandSat (TM) Data.

CHAPTER II. PROPOSED IMPROVEMENTS TO THE COLLECTION 4 ALGORITHM

1. Introduction

MODIS is the primary global monitoring sensor on the two NASA EOS satellites and features improved geolocation, atmospheric correction and cloud screening provided by the MODIS science team. MOD17 is a near real-time, continuous, consistent, operational data set of global terrestrial gross primary productivity (GPP), and net primary productivity (NPP) at a 1-km^2 spatial scale, at both 8-day (MOD17A2) and annual (MOD17A3) time scales. Current satellite data for MOD17 comes from the TERRA, EOS-AM platform, which was launched on December 19, 1999. MOD17 began to provide 8-day estimates of GPP in December 2000. There are currently almost 3 years of MODIS data available.

The MOD17 algorithm is based on the idea of the conservation ratio between APAR and NPP, proposed by Monteith (1972), and the limitations of suboptimal environmental conditions on the related conversion efficiency for different biome types. Detailed structure, and processes of the algorithm can be found in Chapter I.

The objective of this Chapter is to provide users with a brief outline of the maturation of MOD17 products from Collection 4 to Collection 4.5 (available upon request from NTSG), and information on how Collection 4.5 improves the quality of MOD17 products. First, we provide a retrospective view of the Collection 4 MOD17 algorithms and its problems; second, we show how we have resolved these issues and improved MOD17. Finally, some results from Collection 4.5 are provided.

2. Problems with Collection 4 MOD17

To investigate the problems with the MOD17 algorithm, it is necessary to understand how MOD17 operates (Fig. 2.1, Chapter I). For a given pixel, MOD17 requires two upstream MODIS data inputs: MOD12Q1 and MOD15A2. The algorithm reads MOD12Q1 to obtain land cover type to match the corresponding parameters in the Biome Parameter Look-Up Table (BPLUT) (Table 2.1, Chapter I). The LAI/FPAR algorithm (MOD15A2) contains an 8-day MVC (Maximum Value Composite) Fraction of Photosynthetic Active Radiation absorbed by the green vegetation canopy (FPAR) and a corresponding Leaf Area Index (LAI). The MOD17 algorithm assumes that there is no variation of FPAR and LAI within a given 8-day period. Outputs from MOD12Q1 and MOD15A2 provide real-time ground vegetation conditions. The MOD17 algorithm also requires input of climate data to derive GPP and respiration. These data are obtained from the DAO (Data Assimilation Office) (Atlas et al., 2000) modeled daily meteorological obersvations as a 1° x 1.25° scale. At the end of each year, MOD17A3 (annual NPP) is calculated from the 8-day MOD17A2, i.e., NPP is the summation of 8-day PsnNet minus growth respiration.

There are two main problems with the Collection 4 MOD17 data set. The first is that, in some cases, 8-day MVC MOD15A2 is still contaminated by clouds or other noise. 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 (Fig. 2.1). To distinguish between good quality and contaminated data, MOD15A2 contains Quality Control (QC) fields, which allow 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 PsnNet, and consequently, unreliable annual NPP. The second problem arises from the use of DAO meteorological data in the algorithm. Currently, the DAO data version used by MOD17 is GEOS402, which has a spatial resolution of 1° x 1.25°. All 1-km^2 MODIS pixels located within the same "large" DAO cell will use the same meteorological data without spatial variation. In other words, each 1 km^2 pixel retains the characteristics of the nearest neighbor DAO cell. As a result, a DAO cell boundary line may appear in 1-km MOD17 images due to the relatively steep gradients between DAO cells (Fig. 2.2). 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 relatively abrupt climatic gradient zones, it may introduce inaccurate climatic predictions for some productivity calculations.

3. Improvements from Collection 4 to Collection 4.5

We solved the first 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 does not meet the quality screening criteria, its value is determined through linear interpolation between the previous period's value and that of the next good period. Fig. 2.1 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. As depicted in Fig. 2.1, 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 still depend on QC labeling as 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. Changes in 8-day PsnNet, however, will depend on the changes in both FPAR and LAI because improved MOD15A2 leads to increases in not only GPP but also respiration (Equation 1.2, Chapter I). We found that in most regions, PsnNet increased in Collection 4.5 relative to Collection 4. But for some small portions of the globe, PsnNet may not change or may even be reduced as shown in Fig. 2.2.

For the second problem, arising from coarse spatial resolution daily DAO data, we use spatial interpolation to enhance meteorological inputs. The four DAO cells nearest to a given 1-km MODIS pixel are used in the interpolation algorithm. There are two reasons for choosing four DAO cells per 1-km MODIS pixel:

[1] this will not slow down the computational efficiency of the MOD17 datastream, which is a global product, and

[2] it is more reasonable to assume no elevation variation within four DAO cells than any greater number of DAO cells.

We first attempted to use linear spatial interpolation, similar to the inverse distance weighting (IDW) function commonly found in most GIS software. However, it failed because DAO boundary lines remained. Instead we used non-linear interpolation. 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

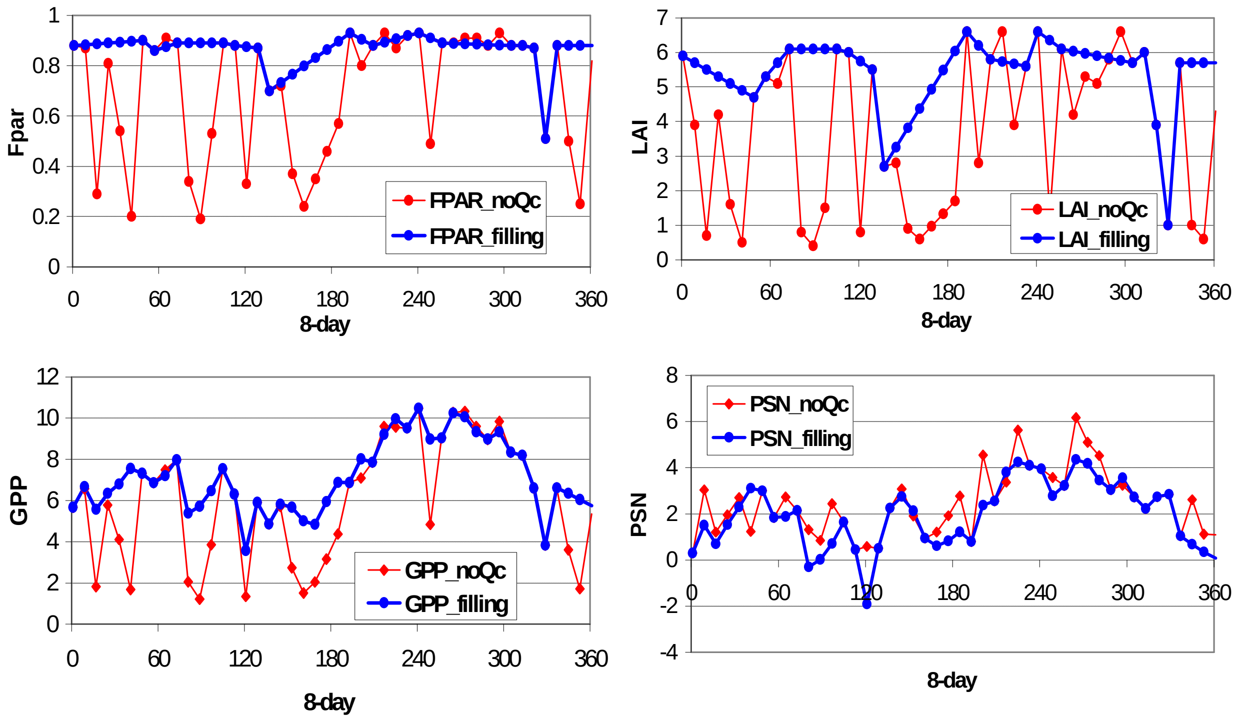


Figure 2.1. Comparison of temporal profiles of 2001 Collection 4 MOD15A2 with original values (FPAR_noQc, LAI_noQc) and temporally linearly-filled FPAR and LAI (FPAR_filling, LAI_filling), and of temporal profiles of MOD17A2 with original MOD15A2 inputs (GPP_noQc, PSN_noQc), and MOD17A2 with filled MOD15A2 (GPP_filling, PSN_filling). The pixel is located in the Amazon rainforest (lat = -1.0, lon = -60) with the MODIS land cover Evergreen Broadleaf Forest (EBF).

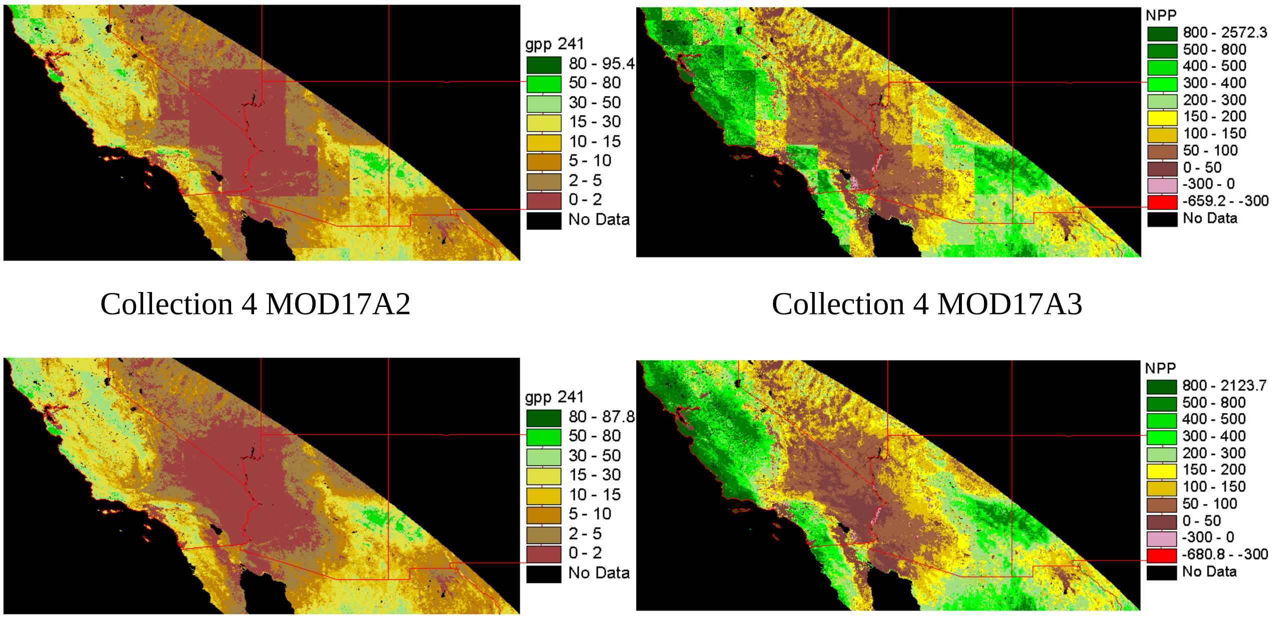
eliminate DAO cell boundary lines in a MOD17 image, and thus we utilize a modified cosine function of the form:

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

where D_i is the non-linear distance between the 1-km MODIS pixel and any one of four surrounding DAO cells; d_i is the great-circle distance between the 1-km pixel and the same DAO cell; and $d_{\max}$ is the great-circle distance between the two farthest DAO 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,



Collection 4 MOD17A2 Collection 4 MOD17A3

Collection 4.5 MOD17A2 Collection 4.5 MOD17A3

Figure 2.2. Comparison of Collection 4 and Collection 4.5 MOD17A2 GPP (composite period 241) and MOD17A3 NPP for 2001.

Tavg, VPD, SWrad) is

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

Theoretically, this DAO 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 DAO boundary to the other, as seen in Collection 4. Fig. 2.2 shows how this method works for MOD17A2/A3. The degree to which this interpolated DAO will improve the accuracy of meteorological inputs, however, is largely dependent on the accuracy of DAO 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, Fig. 3.1) to compare changes in Root Mean Squared Error (RMSE) and Correlation (COR) between the original and enhanced DAO data.

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 (Fig. 3.2). Clearly, the nonlinear spatial interpolation significantly improves DAO inputs for most stations, although for a few stations interpolated DAO accuracy may be reduced due to the inaccuracy of DAO in these regions and local conditions as noted above.

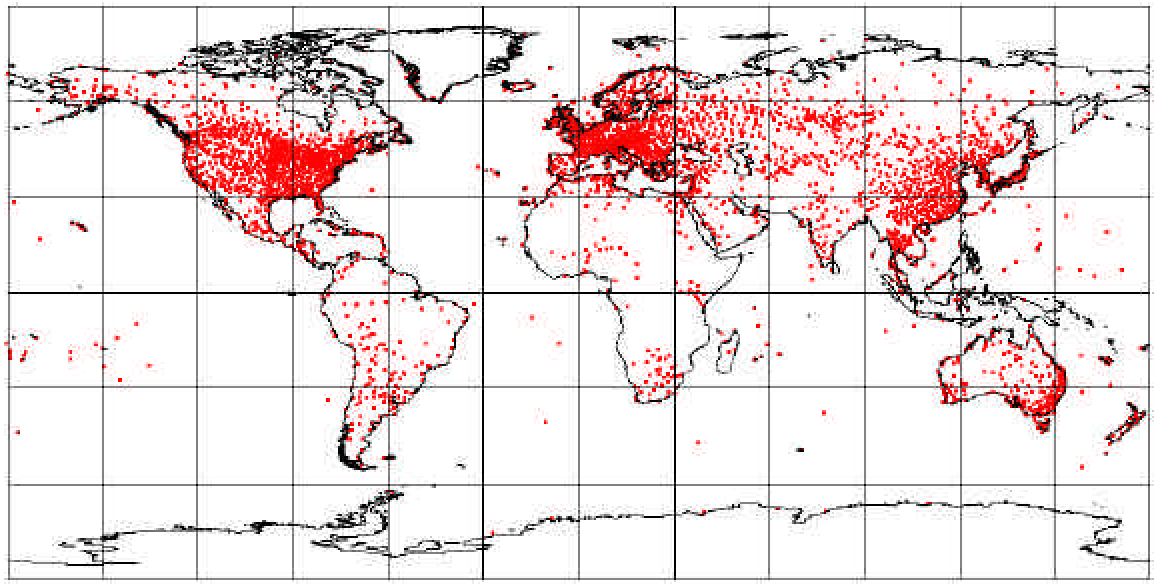


Figure 3.1. Distribution of more than 5,000 WMO stations for 2001 and 2002.

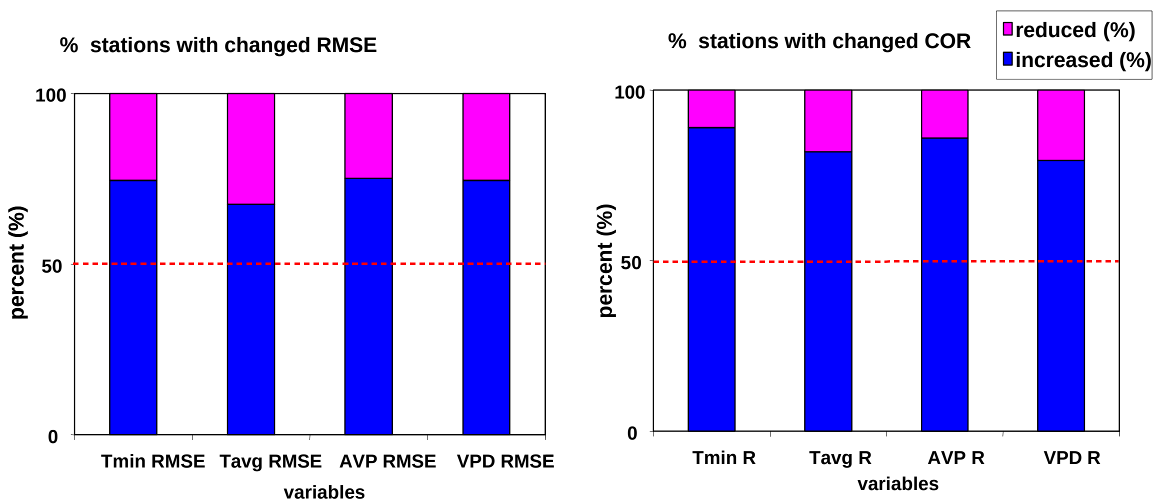


Figure 3.2. Percent of WMO stations with changes in RMSE and COR between spatially interpolated and non-interpolated DAO. For most stations, DAO accuracies are improved (reduced RMSE and increased COR) as a result of spatial interpolation.

4. Addition of annual GPP and QC to Collection 4.5 MOD17A3

In an effort to make the MOD17A3 product more complete, we have added annual GPP (summation of GPP) and a meaningful QC flag for NPP values. Currently, Collection 4 MOD17A3 has two layers in an HDFEOS file: NPP and NPP_QC (although this NPP_QC is meaningless). We therefore define the MOD17A3 QC for a given pixel as

$$QC = (Periods_{missingandbad}/Periods_{total})*100 \qquad \textbf{(4.1)}$$

where $Periods_{missingandbad}$ is the number of times linearly interpolated and $Periods_{total}$ is the total number of 8-day composite periods during the growing season. The pixel with more periods of filled MOD15A2 has a less reliable annual total for both GPP and NPP.

5. Final BPLUT applied to Collection 4.5 MOD17

The standard Collection 4 MOD17A2/A3 product is calculated using a BPLUT that was calibrated to the GEOS3.0 DAO data set and Collection 3 MOD15A2, two primary inputs to the MOD17 algorithm. The latest DAO (GEOS402) and MOD15A2 (Collection 4) have been updated and improved. Given these enhanced inputs, the BPLUT (Table 2.1, Chapter I) has been updated to improve global MOD17 outputs. This BPLUT for Collection 4.5 is based on recent work by Nemani et al. (2003), observed GPP data from 13 flux towers in 2001 (Heinsch et al., in prep), Ecosystem Model-Data Intercomparison (EMDI) NPP data (Olson et al., 2001), a recent book summarizing global NPP (Roy et al., 2001), and additional publications (White et al., 2000; Poorter et al., 2001; and Hoffmann et al., 2003).

6. Results

Improved MOD15A2 and improved DAO inputs together will enhance the MOD17 products. For example, even for North Dakota grasslands, which have a lower frequency of cloud cover and smoother climatic gradients, r^2 from Collection 4 to Collection 4.5, increased from 0.54 to 0.77 in 2001 and from 0.50 to 0.57 in 2002 for the relationship between clipped herbaceous biomass in July and integrated MOD17 PsnNet from Composite Period 1 through 193 (Reeves, et al., in prep), indicating Collection 4.5 significantly improves NPP compared to Collection 4.

Several of the corrections discussed in this Chapter cannot be performed in a forward-processing mode. Therefore, at the end of each year the data from that year will be reprocessed to include the corrections, such as linear interpolation of the MOD15A2 input data. While we feel that Collection 4.5 data are the most accurate data, users should balance their research needs with data availability to determine the product that fits their needs. The standard Collection 4.0 product will continue to be available in near real-time. Currently, Collection 4.5 data are available for 2001-2002. Additional data will be released as they become available.

The global Collection 4.5 image gallery can be found at http://www.ntsg.umt.edu. Data from Collection 4.5(2001-2002) are available upon request from NTSG.

CHAPTER III. ORDERING MOD17A2 DATA

1. Naming Conventions

In order to efficiently take advantage of the Earth Observing System Data Gateway (EDG) it is useful to understand the naming convention for the MODIS granule ID. The granule names are a combination of several pieces of key information, which will help you to discern if the granule in question is what you desire.

From Figure 1, we see that the local granule ID (see the EDG web user's guide for a definition; *http://edcimswww.cr.usgs.gov/pub/imswelcome/*) contains much information about the data stored therein. The product short name tells us that we are looking at MODIS GPP data from the **Terra** Satellite.

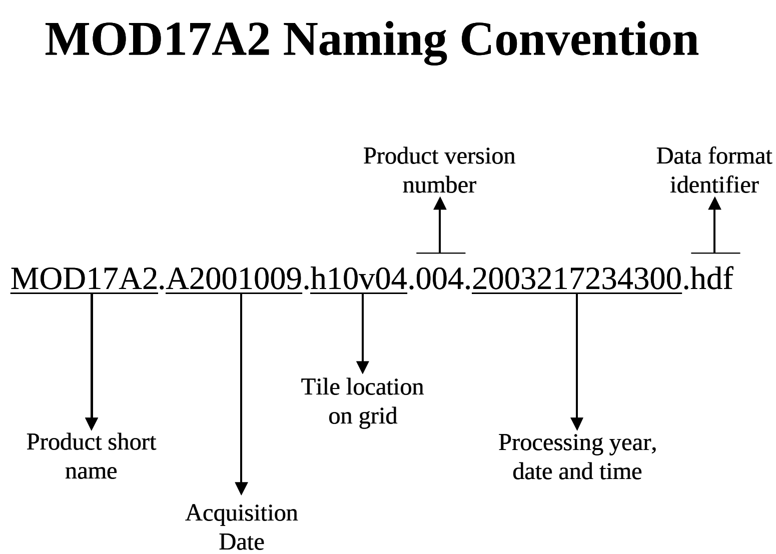


Figure 1.1. The MOD17A2 Standard Product naming convention.

The acquisition date is simply the year and yearday, indicating when the data was collected. The next field indicates the horizontal and vertical positions associated with the data granule (these numbers are related to the map projection of the data; see Fig 5.1). The product version number shows which version of the production software was used to generate the data. The processing information tells you the year, date and time when the processing was run on the data present in the granule. The format identifier simply tells you what type of file format the data is stored in.

2. Logging into the EDG

When you first bring up the EDG web site (*http://edcimswww.cr.usgs.gov/pub/imswelcome/*) in your browser you will be greeted by a page similar to that in Figure 2.1. You can either enter as a guest or as a registered user. If you wish to become a registered user you may click on the appropriate link. If you do not wish to become

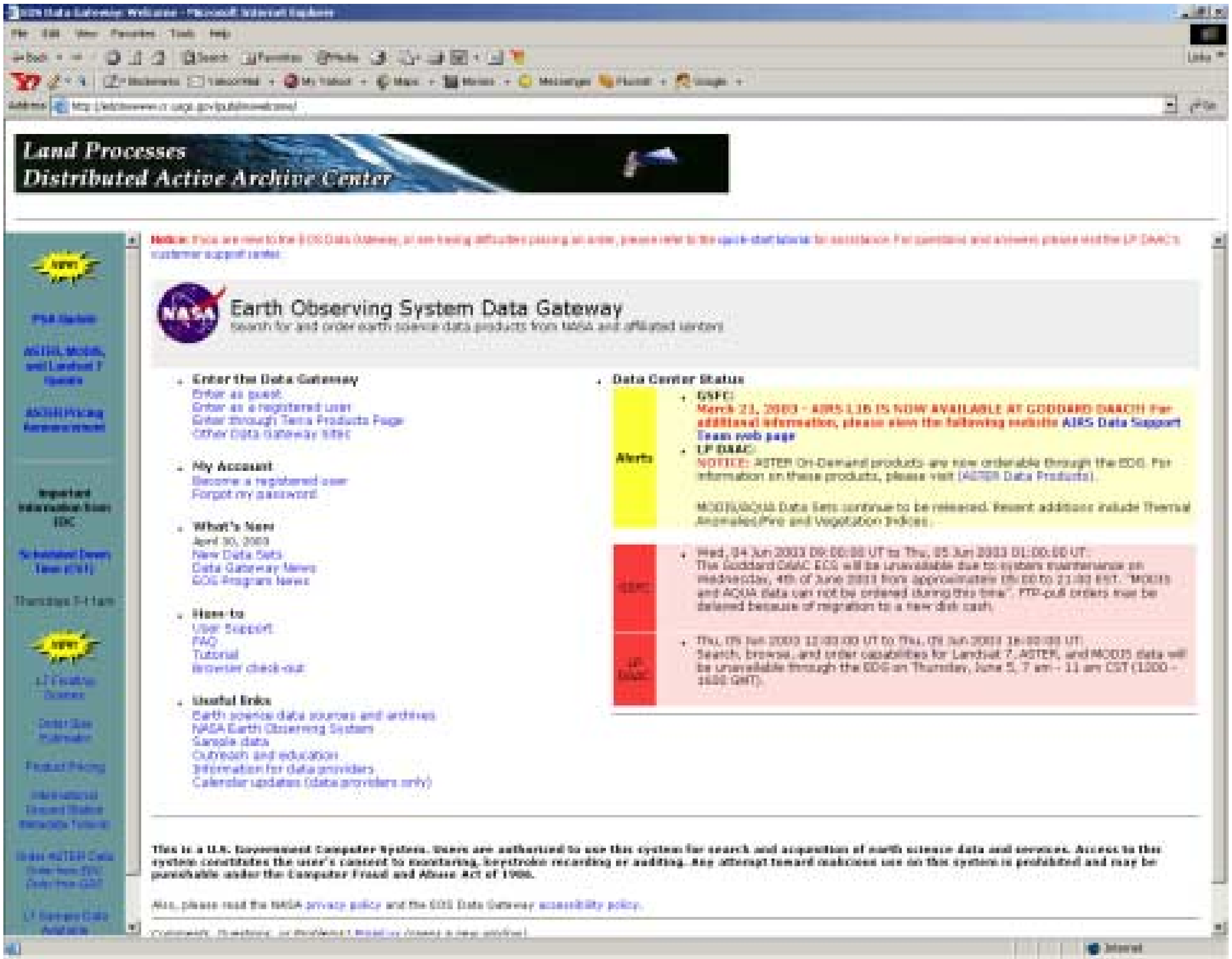


Figure 2.1. The EDG home page.

a registered user, you are still able to order data as a guest, although you will not be able to save any searches or user information.

3. Searching the Data

3.1. EDG search page

The search page (Fig. 3.1) consists of several fields, in which you enter the information on which you want to search. Since the EDG has an extensive online help system and several tutorials, here we will only cover what you need to know to order MOD17A2 data.

First you will have to specify which data set you wish to search for. In this case you will want to enter '**MOD17A2**' in the field labeled 'Method 1: Data Set Lookup'. Then just click on the button labeled **GO**. The screen will change slightly to display the results of the data set search. You should see something like 'MODIS/TERRA NET PHOTOSYNTHESIS 8-DAY L4 GLOBAL 1KM ISIN GRID V003'. You want to select the most recent version of the data unless

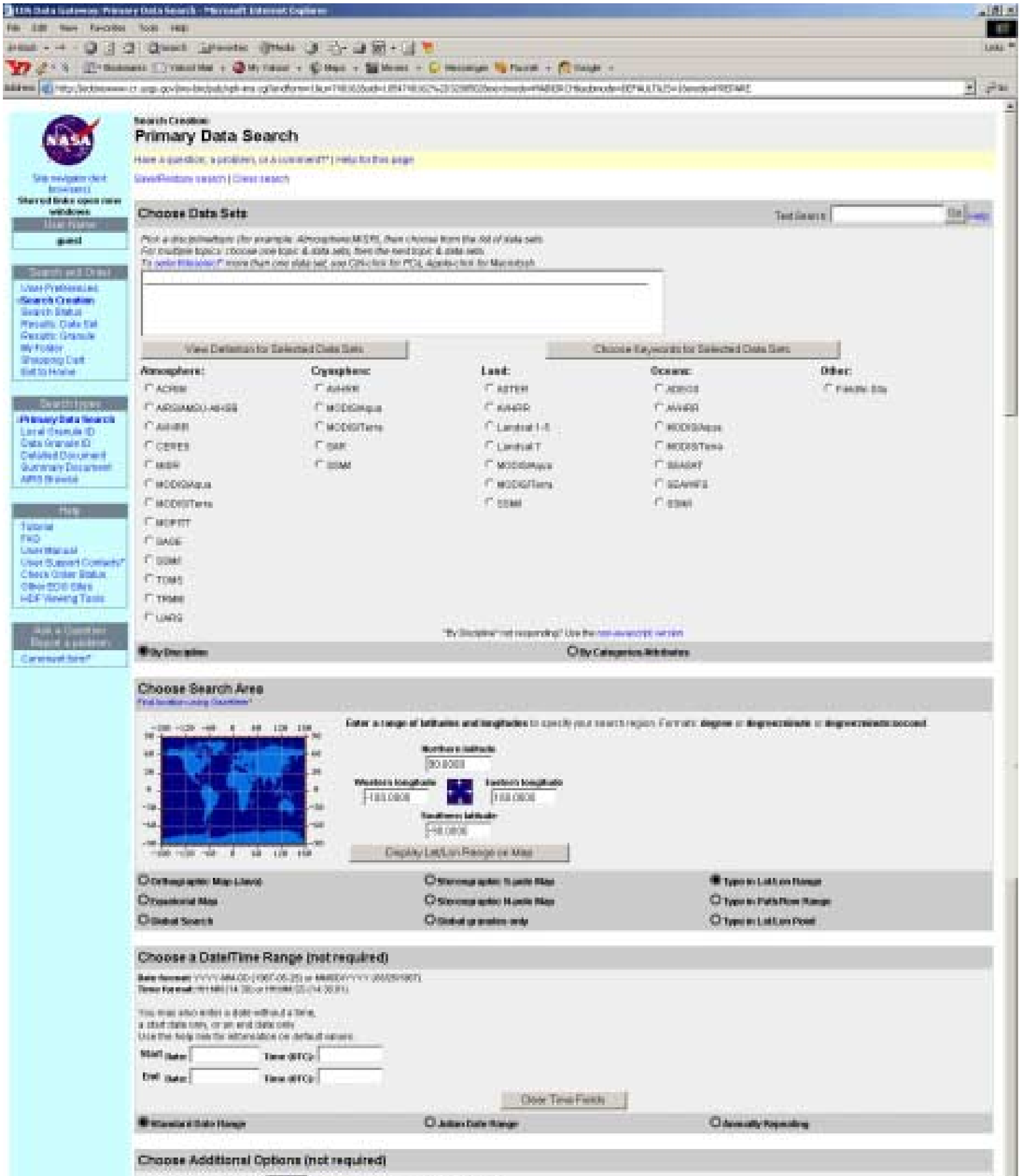


Figure 3.1. The EDG search page.

your research restricts you to an older version. Be sure to document which version you are using. In this case it is version 3 (V003).

Next you must choose your search area. You can do this in several ways, by typing in latitude and longitude, choosing a global search, or by selecting the area you wish to search from

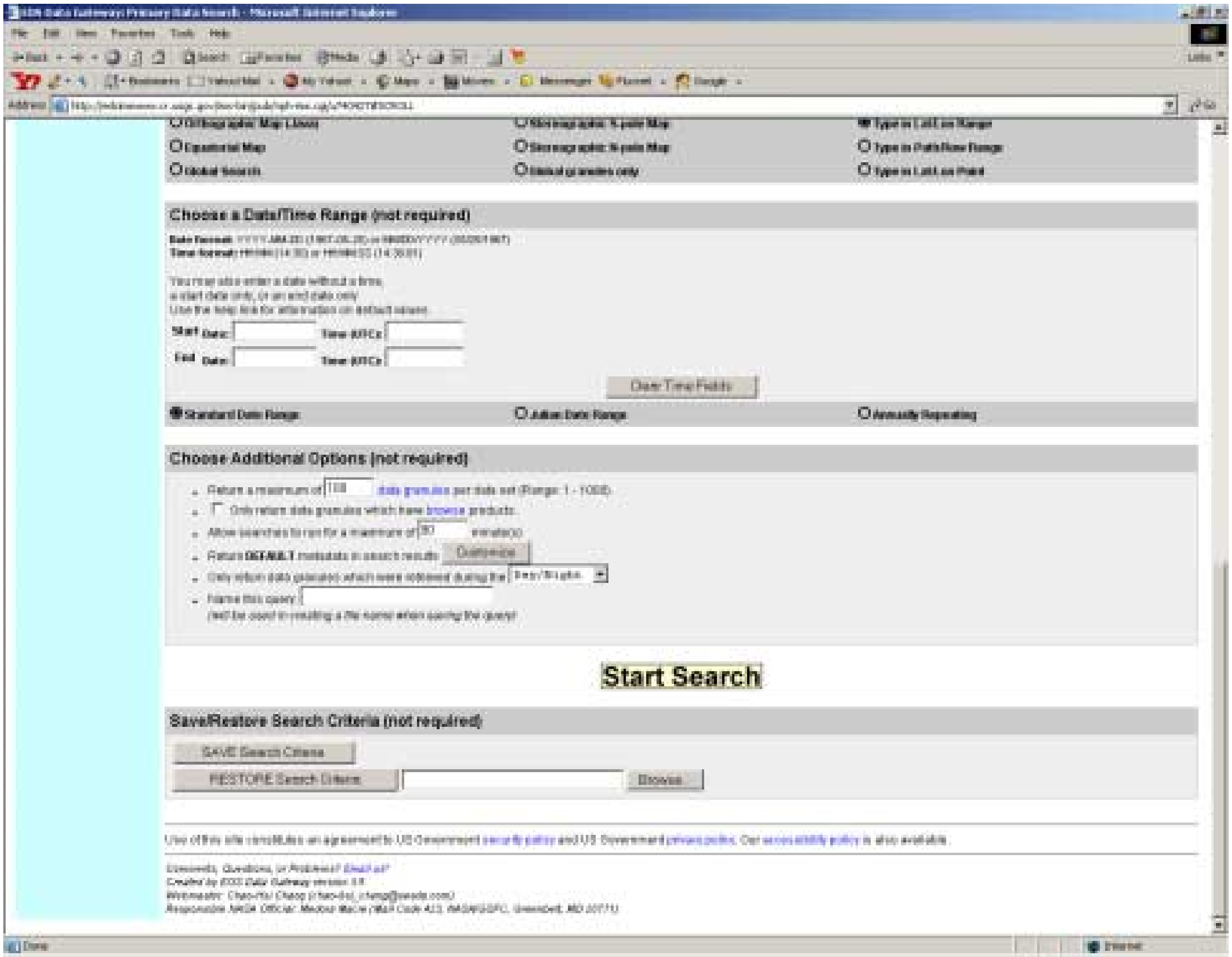


Figure 3.2. Choosing the time range.

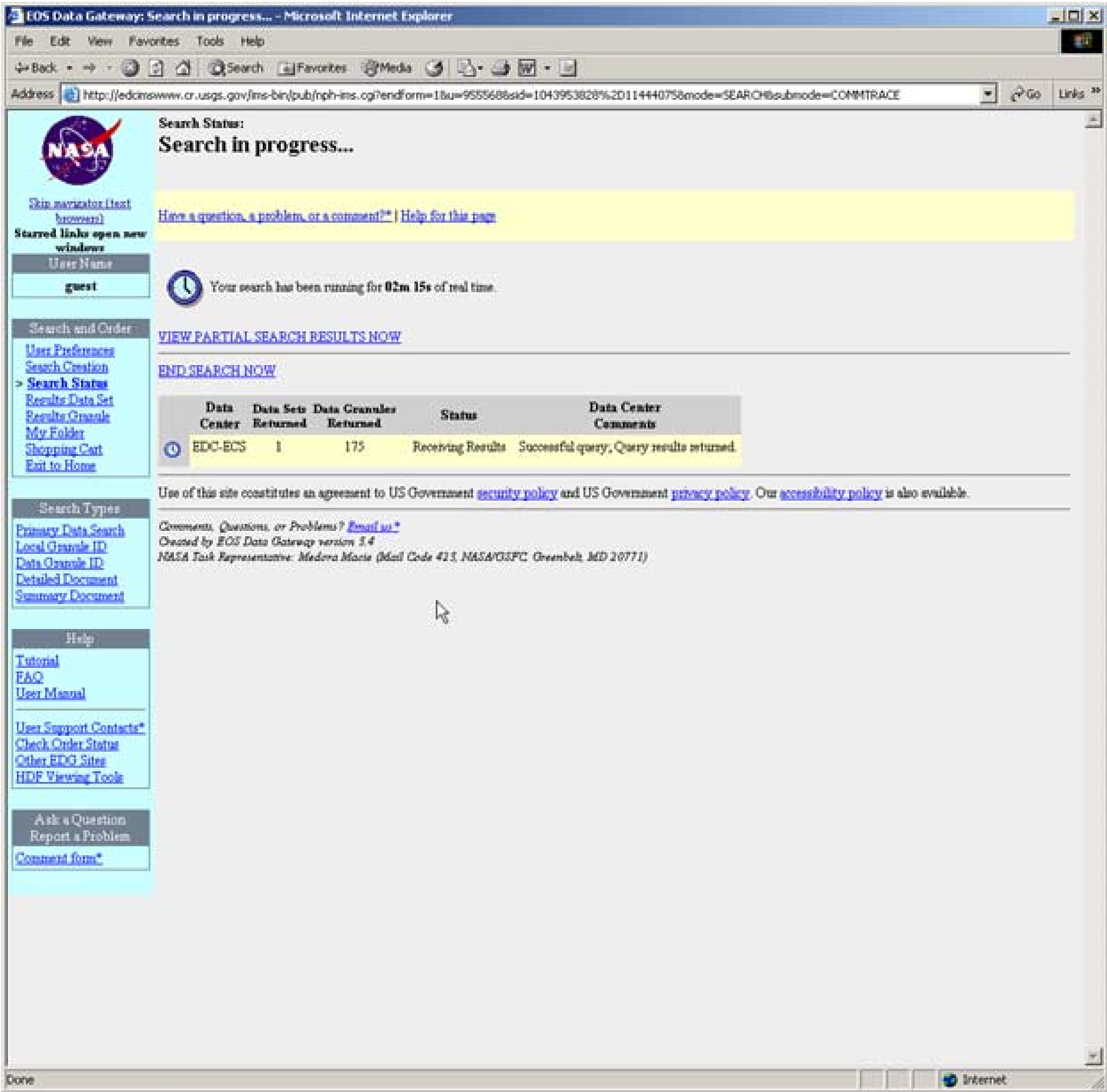
a java applet (you must have a java enabled browser for this approach). This is fairly straightforward.

Next you need to choose the time range of your search. To do this you may enter the date in normal or standard date range (YYYY-MM-DD), Julian date range (YYYY-DDD) or you can do an annually repeating time range (Fig. 3.1 and Fig. 3.2). After indicating the time range you must make sure that you have allowed the search engine to return the proper number of results. This is done by entering the number of granules to return in the field entitled, 'Return a Maximum of <blank> data granules'. The maximum number of granules that can be returned, at the time of this writing, are **1000** (Fig. 3.2).

Not much more is required to get MOD17A2 data; just click on the start button and you're in business!

3.2 Search In Progress page

This page shows you the results of the search as it is happening. If there are any errors this page will indicate them with '**Error**' in the status field. The status field will also tell you



the back button on the browser and correct the issue.

Figure 3.3. The "Search in progress" page.

when your search is successful and the other fields will give you more information, including number of granules returned (Fig. 3.3). Some errors on this page will be in the form of server errors, caused by neglecting to fill in a required field on the search page. If this happens just hit

3.3. Granule listing page

The granule-listing page lists the granules that were returned as a result of your search. This page also gives you the choice of adding the granules to your shopping cart. Using this page, you may select some or all of the granules by clicking the checkboxes in the desired granules row (Fig. 3.4). Once you have selected your granules, you must add them to your cart.

3.4. Disclaimer page

After your data are found, the EDG will display a disclaimer (Fig. 3.5). This page is displayed because of the current state of the MODIS data stream. MODIS data are still being evaluated and validated. If you wish to continue, click the '**Accept**' button at the bottom of the page.

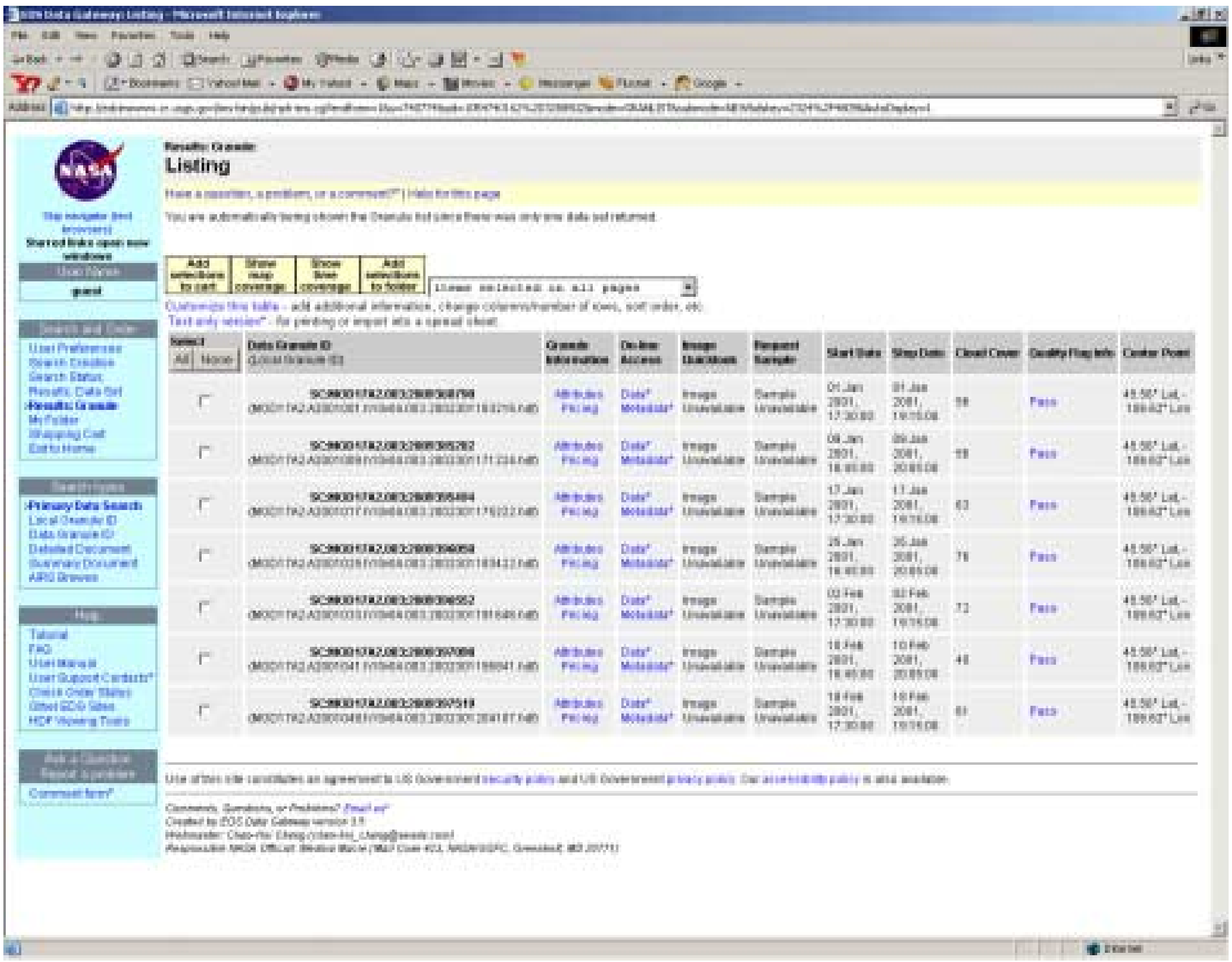


Figure 3.4. The page listing the granules you have requested.

Figure 3.5. The disclaimer.

4. Ordering the Data

4.1 Ordering options page

The ordering options page is very similar to the granule-listing page. You are shown your granules (10 at a time) and you may choose the ordering options for them one at a time or all at once. For our purposes just click on **Choose Options** (Fig. 4.1). This will take you to the second part of the ordering options page.

4.2. Ordering options page (part II)

The second half of the ordering options page allows you to select the method of data transfer (Fig. 4.2). For our purposes select **FtpPull**. Then mark the selection box, which states you wish to use this option for all the granules of this data set (Fig. 4.2). Then press the **OK** button.

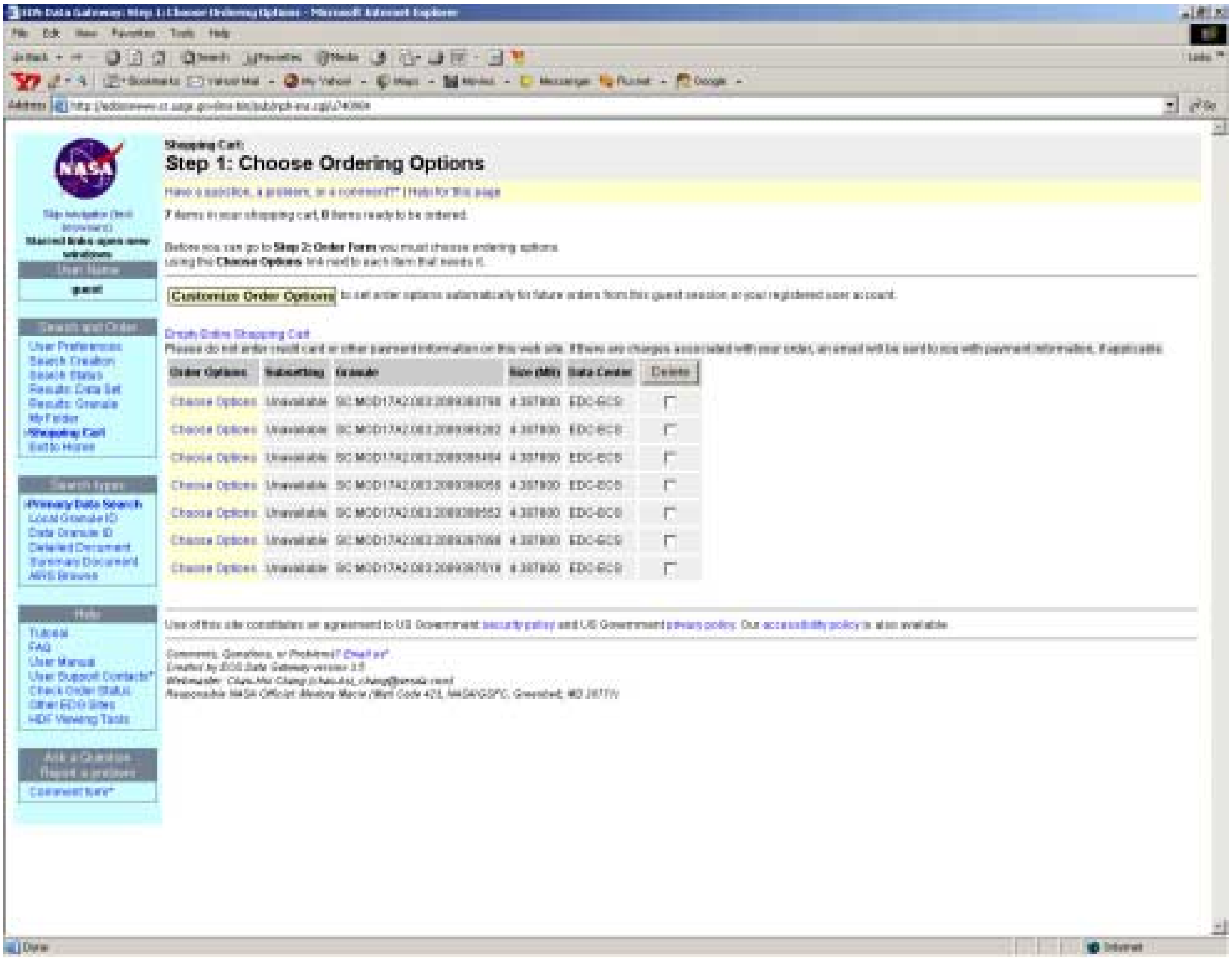


Figure 4.1. Choosing ordering options.

This will take you, once again, back to the Ordering Options page. You will notice a change, however (Fig. 4.3). The words '**FtpPull**' and '**Change Options**' will appear next to each row displayed on the page. This is telling you that these granules are ready to be ordered. ***Be careful here!*** If you are ordering more than one data set (say MOD17A2 and MOD17A3) not all of your granules are ready. The display shows 10 granules at a time. Read the page carefully to find on which page the second data set starts and click on that button (the numbered buttons on the bottom of the page (1-10....). Fore each extra data set, repeat the steps for data retrieval that were covered previously and then you proceed to the next section.

To move forward in the ordering process press the '**Go to Step 2: Order Form**' button.

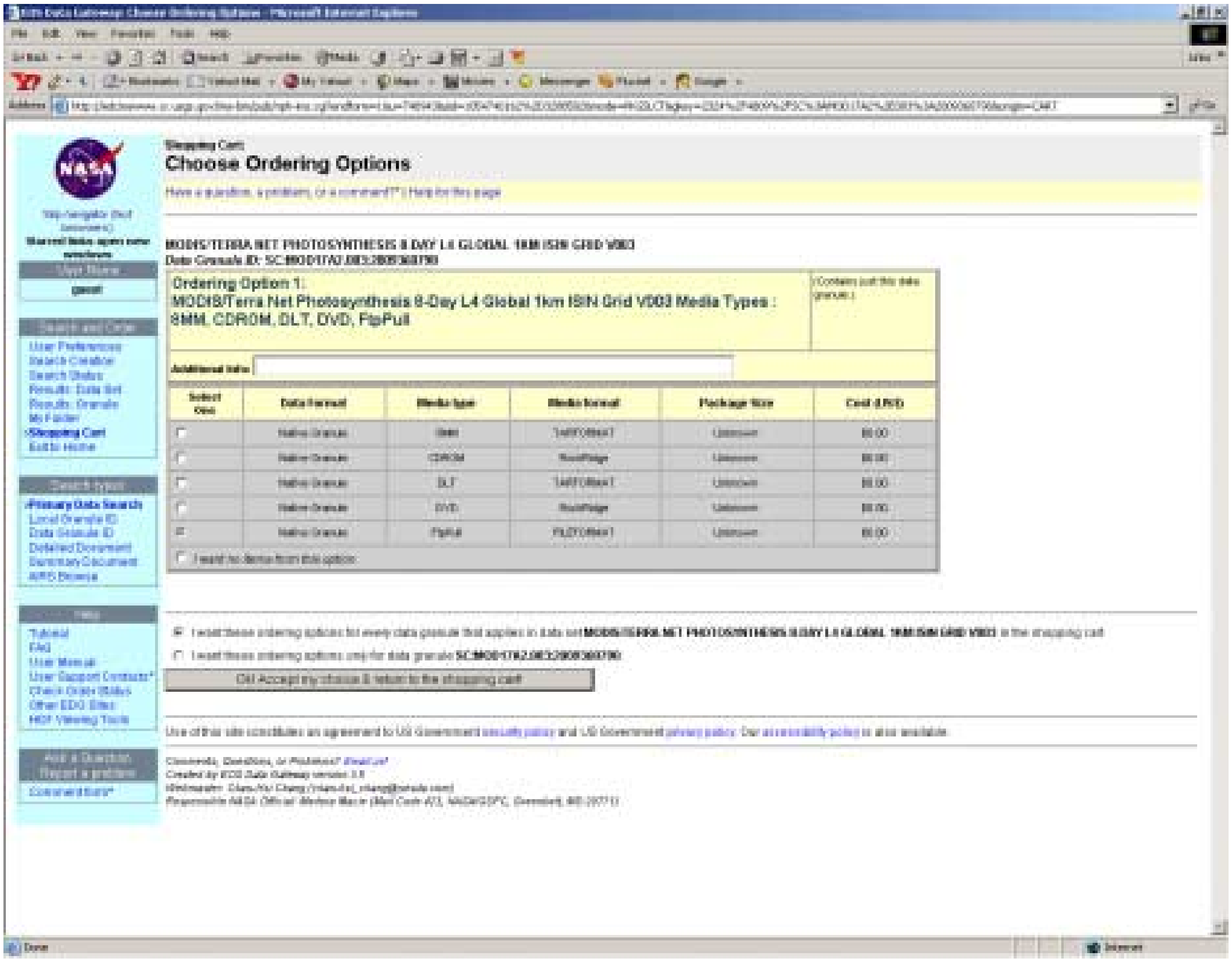


Figure 4.2. Choosing ordering options, part II.

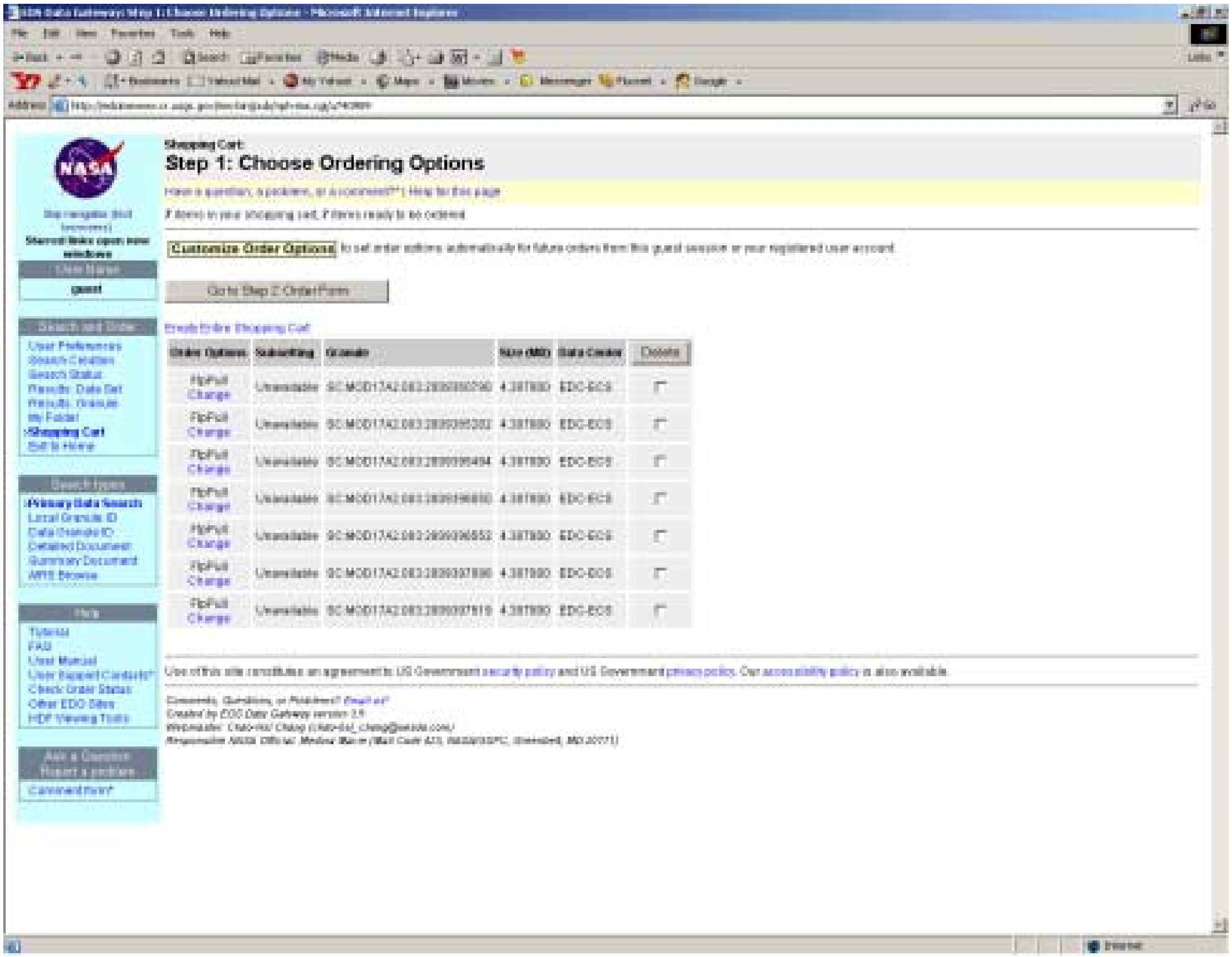


Figure 4.3. Choosing ordering options, the "Ready" page.

4.3. Order form

In this step you will fill out the order form telling the specific D.A.A.C. (Distributed Active Archive Center) how to get in touch with you via e-mail regarding your request and data availability. If you have any questions concerning this form read the online tutorial, or contact the EDG's help desk. When you are done click on the button, which will take you to step 3 of the ordering process (Fig. 4.4).

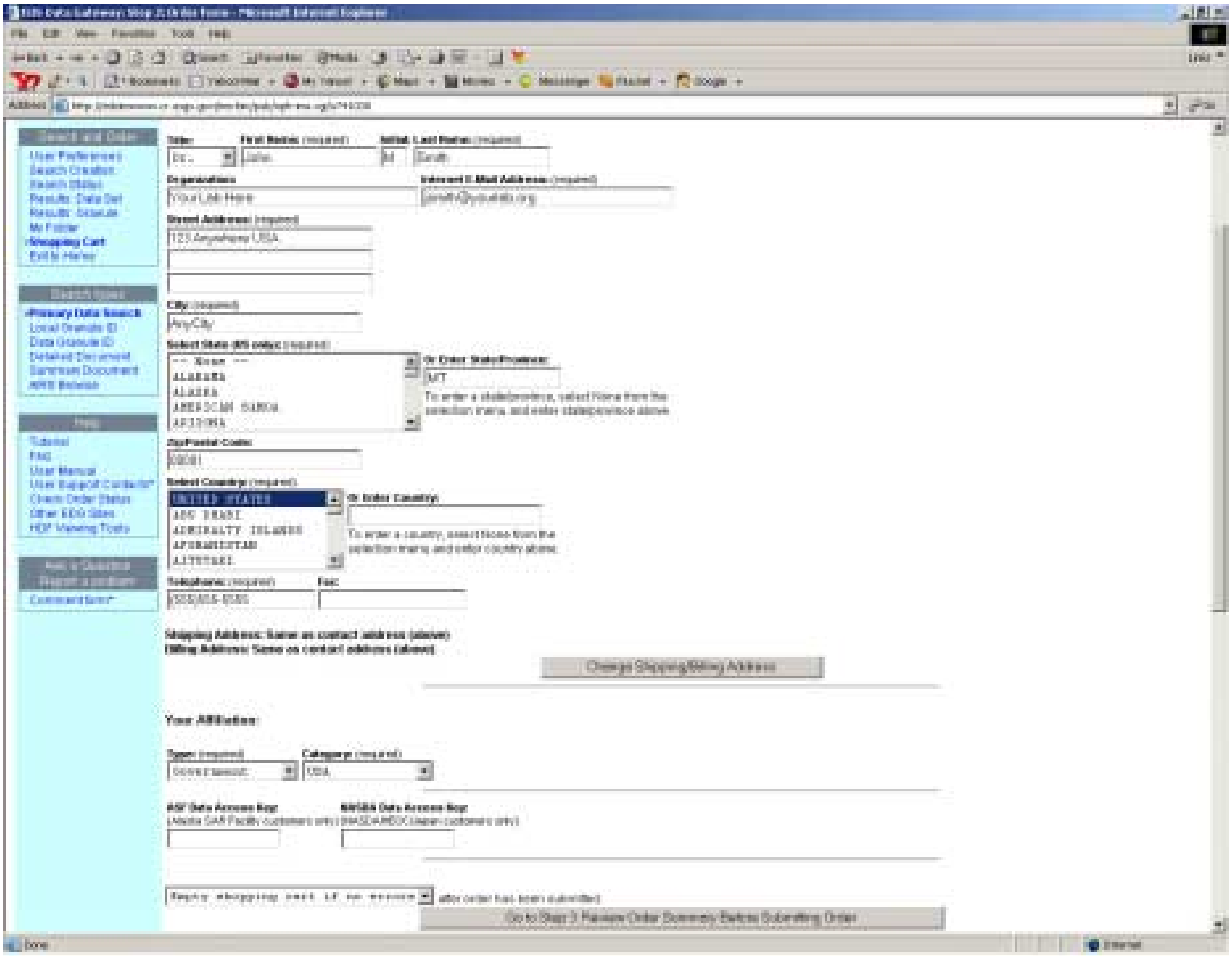


Figure 4.4. The order form.

4.4. Reviewing your order (Step 3)

This step gives you a summary of what you have accomplished thus far. Since MODIS data are available at no cost to the public, the total cost should amount to US $0.00. If everything is satisfactory just click the button that allows you to continue on to the next step, '**Submit Order**' (Fig. 4.5).

4.5. Submitting the order

Once you have submitted the order, you will see a screen similar to the search in progress page. This will notify you if any errors occurred while contacting the data center which houses the data you requested. Once this step is complete, you will see a page stating that your order was submitted, with a comprehensive listing of what you ordered.

You will receive e-mail notification of your request at the address you provided in the order page. You will also receive a notification via e-mail when your order is being filled. This last notification is important because it tells you from where you need to get your data (ftp address, directory where the data are stored, file names). If you have any other questions, please utilize the materials at the EDG's web site (*http://edcimswww.cr.usgs.gov/pub/imswelcome/*).

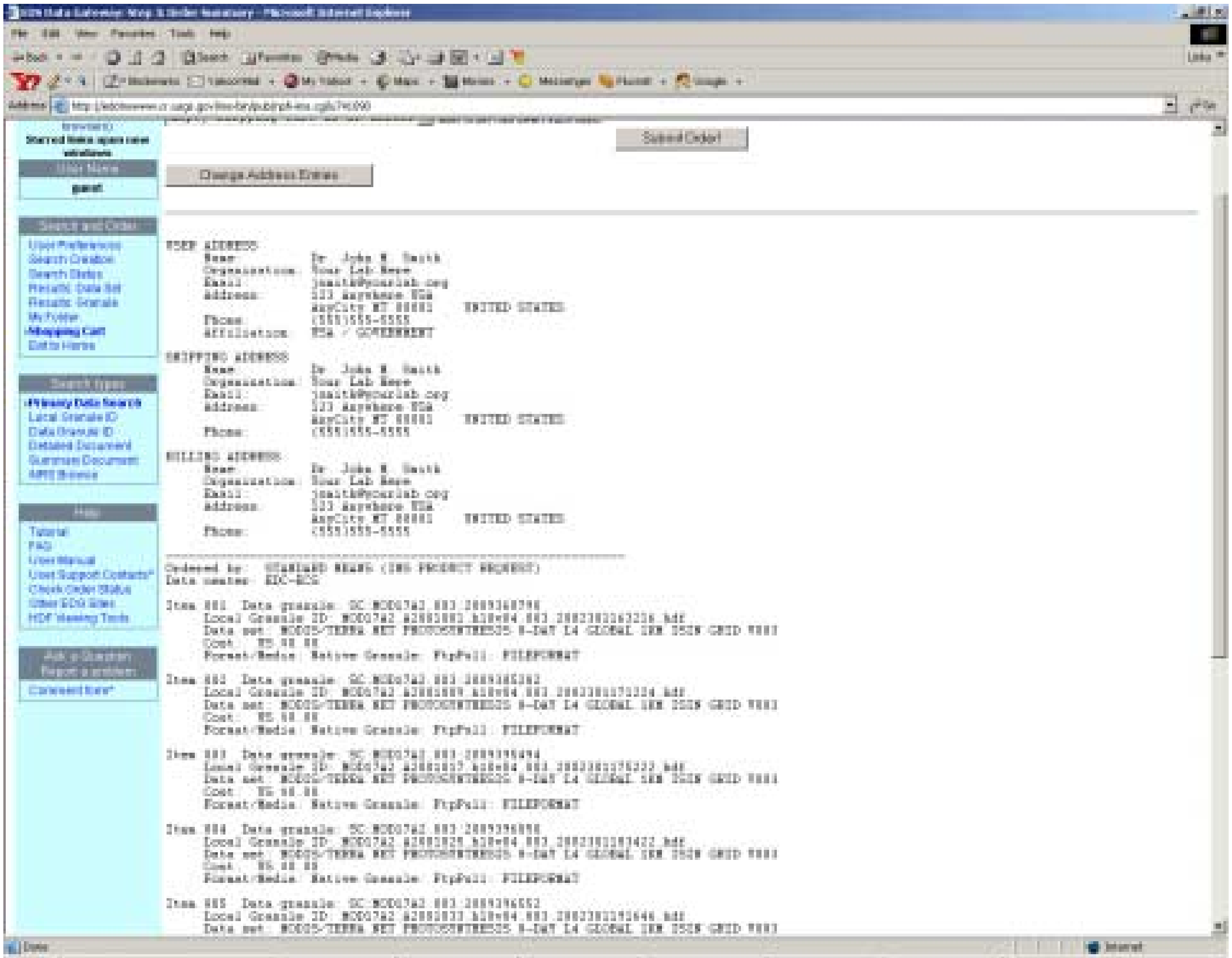


Figure 4.5. Verifying and submitting the order.

5. The DataPool:

The DataPool was developed as an alternative distribution point for EOS data. The DataPool is a large disk cache where EOS data are temporarily stored after they are inserted at the DAAC. What is stored in this area depends upon usage. The primary benefit of using the DataPool is that data can be more quickly retrieved. For more information please see *http://lpdaac2.usgs.gov/datapool/datapool.asp*.

Please see the DataPool located at the DAAC you are using for specific access instructions as they may differ among DAAC's. (Please note: The above URL will take you to the Land Processes DAAC DataPool page.)

MODIS FAQ's

There are many MODIS related FAQ's available on the internet. Perhaps the most comprehensive of these is located at: *http://daac.gsfc.nasa.gov/MODIS/FAQ/*.

MOD17A2/A3 FAQ

1. How much do MODIS data cost?

Nothing. MODIS data are free.

2. What units are my data in?

The MOD17A2/A3 data are in units of kg C m^{-2} day. However, you must apply a scale factor of 0.0001 to each pixel to obtain these units.

3. What is the difference between PSN_1km and GPP?

There is no difference.

4. What is the difference between Gpp_1km and PSNnet_1km?

PSNnet_1km is equal to Gpp_1km MINUS the maintenance respiration from leaves and fine roots. In other words, Gpp_1km should always be ≥ PSNnet_1km at any given pixel.

5. What criteria do you use to create quality assurance (QA) for the annual net primary productivity (NPP) product?

The QA values are inherited from the final 8-day composite period in any given year from the MOD15 LAI/FPAR input data.

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