



Linking *In Situ* Measurements, Remote Sensing, and Models to Validate MODIS Products Related to the Terrestrial Carbon Cycle

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Synopsis

The overall goal of BigFoot is to provide validation of MODLand (MODIS Land Science Team) science products, including land cover, leaf area index (LAI), fraction absorbed photosynthetic active radiation (f_{APAR}), and net primary production (NPP). To do so, we use ground measurements, remote sensing data, and ecosystem process models at sites representing different biomes. BigFoot sites are 5 x 5 km in size and surround the relatively small footprint (≈ 1 km²) of CO₂ flux towers. At each site we make multi-year in situ measurements of ecosystem structure and functional characteristics that are related to the terrestrial carbon cycle. Our sampling design allows us to explicitly examine scales of fine-grained spatial pattern in these properties, and provides for a field-based ecological characterization of the flux tower footprint. Multi-year measurements ensure that inter-annual validity of MODLand products can be assessed.

For each measurement year we derive land cover, f_{APAR} , and LAI surfaces by linking our in situ measurements to Landsat ETM+ data. These BigFoot surfaces are developed using logic that preserves functionally important fine-grained information. Errors in these surfaces are quantified and the surfaces summarized to provide a characterization of vegetation patterns in the greater flux tower footprint. Using these land cover and LAI surfaces and derived climate surfaces, we model NPP over the 5 x 5 km BigFoot footprint. Two independent ecosystem process models are used: Biome-BGC and IBIS. The ability of the models to capture

environmental and ecological controls on water and carbon cycles is assessed with the following comparisons: modeled NPP against in situ measurements of NPP, modeled GPP to tower-based calculations of GPP, and modeled daily water vapor and CO₂ fluxes to tower estimates. We validate MODLand land cover, LAI, f_{APAR} , and NPP surfaces by comparing them to BigFoot surfaces derived using field measurement data. A series of exercises that isolate important scaling factors is conducted, so that their effects on NPP model estimates can be better understood. This involves rerunning the models after converting site-specific land cover classes into broad, globally applicable classes, successive coarsening of land cover and LAI surface grain size, and generalizing the light use efficiency factor (ϵ) to coincide with the more generalized land cover classes.

There are nine BigFoot study sites that span eight major biomes, from desert to tundra, to tropical forest. At these sites, in addition to validation of MODIS products, we quantify carbon content and NPP, examine how these variables vary spatially and temporally, and how NPP is related to climatic variables. Collectively, the standardized NPP data from the contrasting biomes elucidates biophysical controls on NPP, and their sensitivity to changing climate and land use. Our standardized data also allow for direct testing of whether light use efficiency (LUE) differs among plant functional types, or seasonally for a given type.

A global terrestrial observation system is needed to assist in the validation of global products such as land cover and NPP from MODIS and other sensor and modeling programs. A key component of such a system is the eddy flux tower network, FLUXNET; however, flux sensors measure net ecosystem productivity (NEP), not NPP. BigFoot is learning how NEP and NPP are related, and through modeling, how to integrate a wide range of carbon cycle observations. Another key component of an observing system is the use of remote sensing and models to scale tower fluxes and field measurements. Although this may be relatively common at a given site, no other project is doing so with standardized methods across so many biomes. As such, BigFoot is a pathfinding activity that will contribute to the development of useful scaling principles. The project can also serve as a nucleus for the global terrestrial observing system that is needed to validate global, generalized products used to monitor the health of the terrestrial biosphere.

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Introduction

Accurate assessments of regional- and global-scale changes in the terrestrial biosphere are essential if human impacts on biosphere-atmosphere function are to be understood. There are a myriad of ecosystem attributes to be monitored, but quantifying human impacts necessarily includes an evaluation of vegetation cover and net primary productivity (NPP), as these determine amounts of fuel, fiber, and food for human consumption (Running et al. 1999). A global terrestrial observing system is needed that integrates field-based measurements, flux towers, remote sensing, and ecosystem modeling (Baldocchi et al. 1996, Running et al. 1999, Canadell et al. 1999).

Ecosystem process models that simulate carbon, water, and energy exchange between terrestrial ecosystems and the atmosphere require leaf area index (LAI) and vegetation cover as primary drivers (Landsberg and Gower 1997, Waring and Running 1998), and these must be derived by remote sensing. MODIS (Moderate Resolution Imaging Spectrometer) is the primary high temporal frequency mapping sensor onboard NASA's Earth Observing System (EOS) satellite Terra, launched in December 1999. MODIS is poised to become the most important global mapping sensor ever, as it views the entire Earth's surface every 1-2 days acquiring data in 36 spectral bands at spatial resolutions of 250 to 1000m.

Validation of the global data products derived from MODIS and related sensors is essential to both assess product accuracy and to provide feedback to algorithm developers so the algorithms can be improved. Faced with the challenge of validating global remotely sensed products, NASA formed the EOS Validation Program to assist MODIS (and other) Science and Instrument Teams with product validation. For the Land Science Team (MODLand), research at intensive study sites forms the backbone of the validation plan. These have evolved into what constitutes the [MODLand core validation sites network](#). The sites associated with our current project, BigFoot, are important sites within that network. Each BigFoot site is centered on an eddy flux tower that measures continuous water, energy, and carbon fluxes that can potentially be used to validate MODIS products. However, with their relatively small footprint on the order of ≈ 1 km², nearly equivalent to a single MODIS resolution cell (that in most cases will not perfectly align with the footprint), it is important that the spatial context of flux towers be known.

BigFoot is designed to provide that context using a combination of in situ ecological data, Landsat ETM+ data, and ecosystem models (Cohen and Justice 1999). Moreover, BigFoot maps land cover, LAI, fraction absorbed photosynthetic active radiation (f_{APAR}), and NPP over a 5 x 5 km area around an eddy flux tower at ETM+ resolution. This means we fully characterizes 25 MODIS cells around a given tower site, and are able to test a number of scaling factors that should reveal possible causes of MODIS mapping errors (thereby providing feedback to algorithm developers). Finally, BigFoot takes important steps to enhance the goals of GTOS (the [Global Terrestrial Observing System](#)).



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Objectives

- 1** Make multi-year *in situ* measurements of carbon-related ecosystem properties at BigFoot sites. Our sampling design will enable scales of fine-grained spatial pattern in these properties to be explicitly examined, and provide for a field-based ecological characterization of the flux tower footprint. Multi-year measurements will ensure that the temporal validity of MODLand products can be accurately assessed.
- 2** Develop multi-year site-specific land cover, LAI, and f_{APAR} surfaces by linking *in situ* measurements and observations to Landsat ETM+ data. Errors in these surfaces will be quantified and the surfaces summarized to provide a map-based characterization of the greater flux towers footprint.
- 3** Model NPP over the 5 x 5 km BigFoot footprint at each site in multiple years using land cover and LAI surfaces derived from Obj. 2 and derived climate surfaces. Two independent ecosystem process models will be used and their performance assessed by comparisons of modeled NPP against *in situ* measurements of NPP from Obj 1. Modeled GPP and water vapor will compared to tower-based calculations of these variables.
- 4** Validate MODLand land cover, LAI, f_{APAR} , and NPP surfaces and examine the contribution of several scaling factors to differences between MODLand and BigFoot surfaces. Validation will involve direct comparisons of MODLand surfaces to BigFoot field data and derived surfaces. Scaling factors examined will include land cover class, grain size, and generalization of light use efficiency factors (ϵ) to coincide with the generalized land cover labels. Effects of these scaling factors on LUE and model-based NPP estimates will be determined by developing new NPP surfaces, using as inputs, the scaling factors at each degree and type of generalization. We will also determine the temporal sensitivity of the MODLand NPP product using multi-year field measurements, tower measurements, and BigFoot NPP surfaces.

Facilitate achievement of the GTOS goal to develop a network of sites that will serve as long-term global NPP monitoring sites. We want BigFoot activities to both serve as a nucleus for this network and to help define a practical scaling logic relevant to these sites that incorporates field measurements, remote sensing, and ecological modeling.

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Background and Context

The origins of BigFoot are traceable to 1992 when S. Running of MODLand contacted the Long-Term Ecological Research (LTER) community to assist with validation of anticipated MODIS products. The first proposal, funded by NASA's Terrestrial Ecology Program (TEP) in 1994, involved prototype scaling exercises using existing data at 14 (mostly LTER) sites. In 1996, the 20+ person team held an LTER-funded workshop to share results and strategies for future direction. Workshop proceedings were published in a special issue of Remote Sensing of Environment in October 1999, edited by Cohen and Justice. In 1998, the largely amorphous project was rescoped, and with renewed TEP support became what we now call BigFoot. What defines the project is its focus on using remote sensing and ecosystem process models to scale ecological field measurements within a greater eddy flux tower footprint. Doing this across a range of biomes using standardized measurements and an innovative sampling design affords us a unique opportunity to examine ecosystem function at the local level in a global context.

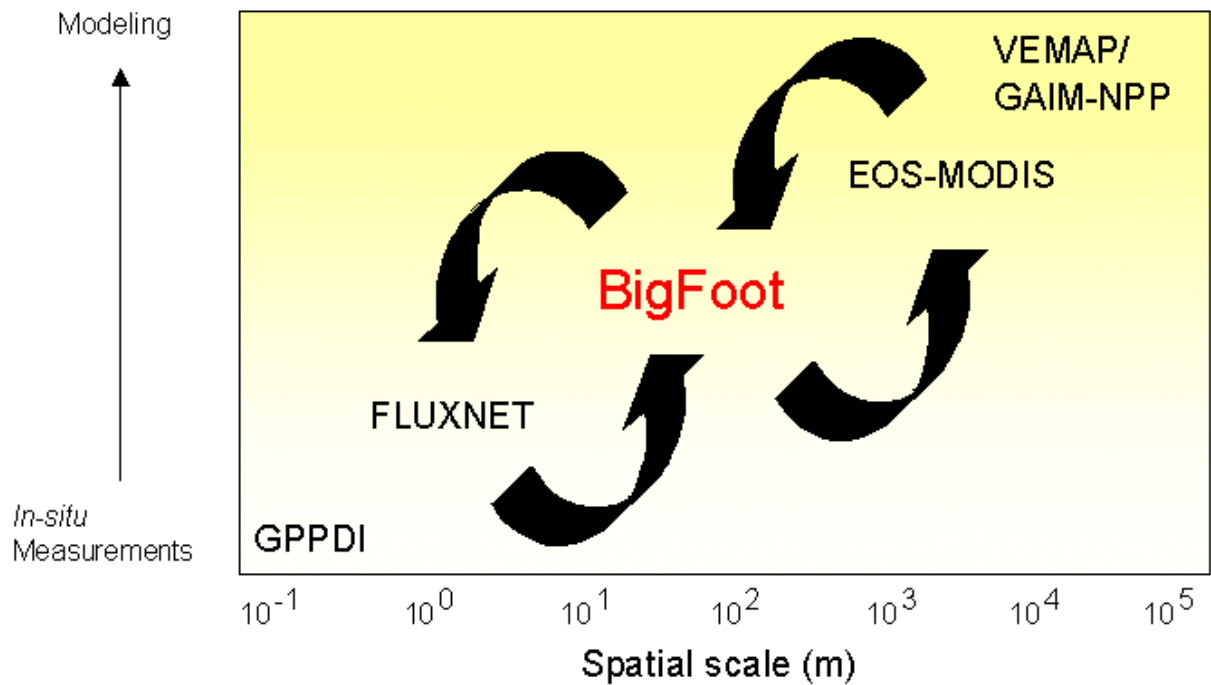
Originally, BigFoot included four sites, with the first field season being in 1999 at two of these sites (see group 1 in field activity schedule below). Each site represents a distinct and globally important biome. The NOBS site (or Northern Old Black Spuce site from BOREAS) is a boreal needleleaf evergreen forest. HARV, (the Harvard Forest LTER site) is a temperate mixed forest. The agricultural cropland site, AGRO (a.k.a. Bondville) is primarily corn and soybeans. KONZ (the Konza Prairie LTER site) is a tallgrass prairie. The project focused on validation of MODIS land cover, LAI, and NPP products.

Group	Name	Location	Biome	1999	2000	2001	2002	2003
1	AGRO	Tolono, IL, USA USA (aka Bondville)	crop (corn & soybean)	cover, NPP LAI/fAPAR	cover, NPP LAI/fAPAR	cover, NPP LAI/fAPAR	none	none
	KONZ	Manhattan, KS, USA (Konza LTER)	tallgrass prairie		cover, NPP LAI/fAPAR	NPP LAI/fAPAR	none	none
	HARV	Petersham, MA, USA (Harvard Forest LTER)	temperate mixed forest		cover, NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR
	NOBS	Thompson, MB, Canada (BOREAS site)	boreal forest	cover, NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR
2	TUND	Barrow, AK, USA	arctic tundra			reconnais- sance	cover, NPP LAI/fAPAR	NPP LAI/fAPAR
	TAPA	Tapajos (near Santarem), Brazil (LBA site)	tropical broadleaf evergreen forest			reconnais- sance	cover, NPP LAI/fAPAR	NPP LAI/fAPAR
	SEVI	Belen, NM, USA (Sevilleta LTER)	desert			reconnais- sance	cover, NPP LAI/fAPAR	NPP LAI/fAPAR
3	CHEQ	Park Falls, WI, USA (Tall Tower site)	temperate mixed forest	cover, NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR		
	METL	Sisters, OR, USA (OTTER site)	temperate needleleaf forest		cover, NPP LAI/fAPAR	NPP LAI/fAPAR	NPP LAI/fAPAR	

- Original BigFoot project; funded to Cohen et al. by TEP.
- Current BigFoot project; funded to Cohen et al. by TEP.
- Current BigFoot project; funded to Gower by NSF.
- Current BigFoot project; funded to Gower by EOS Validation.
- Current BigFoot project; funded to Law et al. by EPA.
- No BigFoot activity

The overall goal of BigFoot is to continue with MODIS land cover, LAI, and NPP product validation at the four existing sites, but now we have expanded our focus to include validation of f_{APAR} and our biome coverage to include five new sites for a more globally comprehensive assessment of MODIS product validity (see field activity schedule above). The new sites include a desert grassland (SEVI, the Sevilleta LTER), an tundra near the Arctic coastal plain (TUND, near Barrow, AK), and a tropical broadleaf evergreen forest in the Amazon Basin (TAPA, the Tapajos Primary Forest site of LBA). In addition, we offer two sites at no additional cost to NASA (Group 3); these sites include a second temperate mixed forest (CHEQ, Chequamegon National Forest in Wisconsin), and a temperate needleleaf evergreen forest near Metolius, Oregon (METL). The Group 3 sites are fully funded by either the NASA EOS Validation Program (CHEQ to Gower) or the Environmental Protection Agency (METL to B. Law, Turner, Cohen et al.). Continued work at NOBS beyond 2000 is funded by the National Science Foundation to Gower. Another important goal of BigFoot is to explicitly assess if MODLand products can detect the effects of inter-annual variation in climate on vegetation cover, LAI, f_{APAR} , and NPP. Also, we examine how LUE varies within and among sites and vegetation types and propose to actively facilitate further formation and definition of GTOS in support of MODIS validation.

In addition to BigFoot, there are several other initiatives addressing the development of a global terrestrial monitoring and validation program. These include the Global Primary Production Data Initiative (GPPDI), the worldwide CO₂ flux network (FLUXNET), the MODLand Science Team and associated validation program, the Vegetation/Ecosystem Modeling and Analysis Project (VEMAP), and the Global Analysis, Integration, and Modeling (GAIM) NPP model intercomparison activity. These all recognize the need to consider several key elements in the formation of a global terrestrial monitoring system, including: *in situ* vegetation measurements, eddy flux tower measurements, vegetation surfaces derived from remote sensing, and biogeochemical process models, all used over time. However, these programs exist either as stand alone efforts (e.g., FLUXNET, MODIS-NPP modeling) or incorporate only one or two of the key elements of a comprehensive observation and validation program (e.g., GPPDI, VEMAP). In contrast, BigFoot integrates all of the aforementioned key elements at a spatial scale that serves as a rigorous validation of global sensor and terrestrial modeling products (as shown in the figure below).



Specifically, BigFoot:

- Uses field measurements and Landsat ETM+ data to parameterize ecosystem process models at a local scale (i.e., within the 5 x 5 km BigFoot footprint) so that we can understand the environmental and ecological controls on carbon exchange between terrestrial ecosystems and the atmosphere at that scale.
- Assesses how accurately process models capture the environmental controls on CO₂ and H₂O exchange between terrestrial ecosystems and the atmosphere.
- Statistically compares the land cover, LAI, f_{APAR} , and NPP surfaces we generate against field measurements to help establish the accuracy of those surfaces, so that they can be legitimately compared against co-located sections of globally-derived, generalized surfaces (such as those of MODLand).
- Compares BigFoot modeled GPP (gross primary production) against calculations of GPP from flux tower data—a strong first step towards effective integration of process models and flux measurements.
- Provides both field-based and map-based characterizations of flux tower footprints.

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Site Selection Logic

As the cost for a full BigFoot characterization of a given site is not trivial, careful selection of sites is an imperative. The BigFoot concept requires continuous eddy flux measurements of H₂O and CO₂ exchange between terrestrial ecosystems and the atmosphere. Although the number of flux towers is growing, there are still only around 100 globally (Running et al. 1999). Biomes that cover a larger fraction of the land surface, or that are expected to experience the greatest change because of warming or land use patterns, were considered high priority sites. In addition, we selected biomes that cover a broad range in LAI and NPP to provide a robust data base for the validation of MODLand products and the examination of climatic influences on NPP.

Our boreal forest site (NOBS) represents the biosphere's second largest biome. Boreal forests have low NPP, and are interesting from the point of view that the large amount of soil carbon they contain is believed to be susceptible to release if warming occurs (Goulden et al. 1998). Our agricultural cropland site (AGRO) has high NPP, and both it and our tallgrass prairie site (KONZ) are subject to intensive land use change and management practices (e.g., cropping, burning and grazing). The BigFoot temperate mixed forest site (HARV) represents a large, historically highly disturbed biome that is purported to be a current carbon sink (Goulden et al. 1998). The desert grassland (SEVI) serves as a low anchor for LAI and NPP. The arctic tundra site (TUND) also has relatively low LAI and NPP, but it is an expected carbon source with warming. The tropical broadleaf evergreen forest in the Amazon (TAPA) has high LAI and NPP and represents the largest terrestrial biome. This biome is experiencing rapid deforestation and changes in land use. The second temperate mixed forest site (CHEQ) serves as a replicate to determine if there is variability among widely dispersed sites within the same general biome. The temperate needleleaf site (METL) is representative of xeric continental conifer forest. The five newest sites all have substantial ongoing measurement and modeling activities that complement our original efforts.

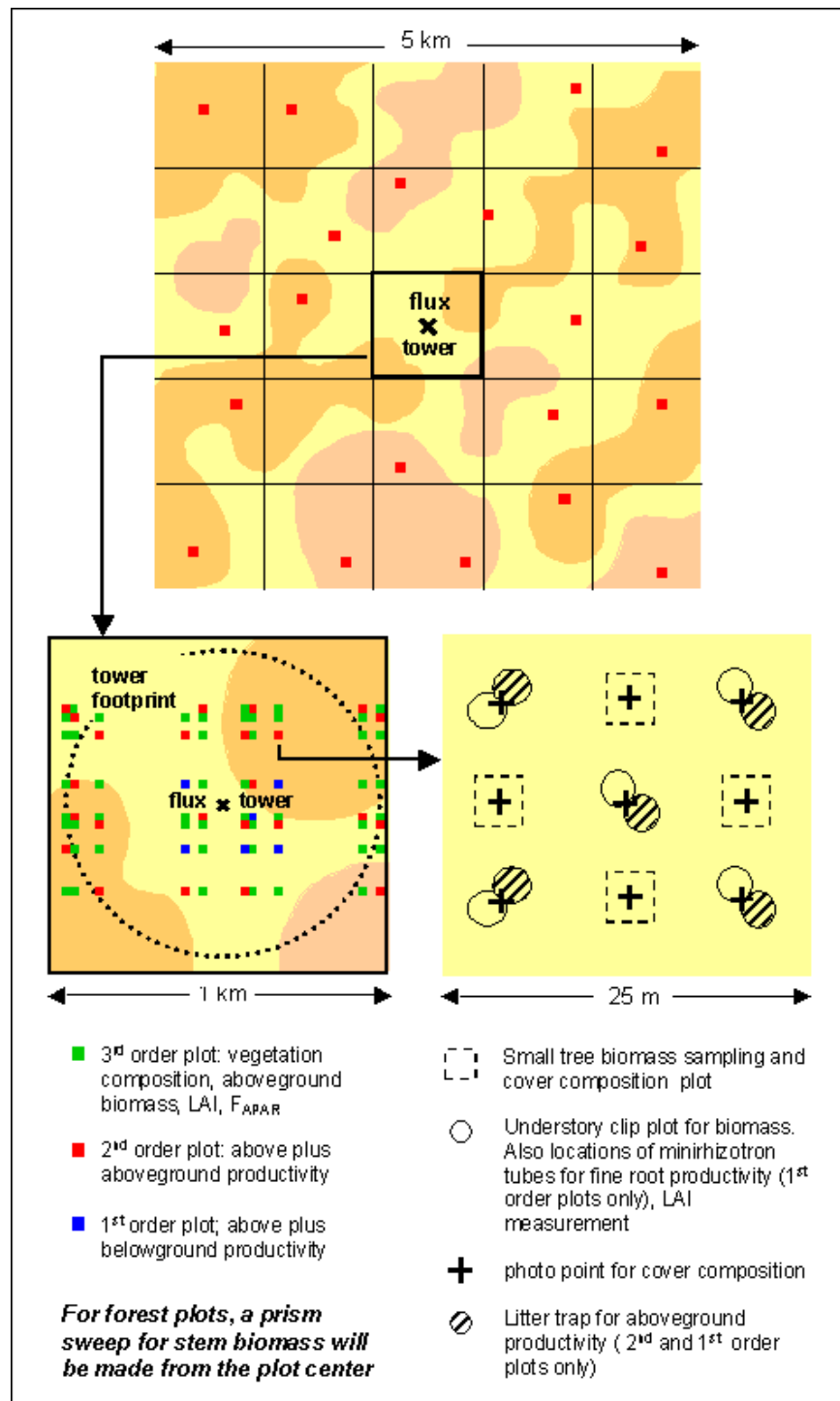
At AGRO, we are extending our field sampling for an additional year ([see field activity schedule](#)) so that we can assess MODLand product temporal validity at this site (recall there were no MODIS data in 1999). BigFoot originally made measurements in both 2000 and 2001 at KONZ and HARV, and is continuing sampling at HARV in 2002 and in 2003. The continued work (with a less intensive field effort) at NOBS is funded by NSF. We continue working at HARV and NOBS throughout BigFoot because these two sites have long-term flux observations and are in biomes that are important to monitor under conditions of land use and global change (i.e., HARV is a purported carbon sink due to a recovery phase following widespread disturbances that took place over 100 years ago and NOBS has large carbon stores and is sensitive to climate change). Field measurements accompanying the flux data at these sites provide continued mutual corroborative support and help us understand the ecological changes that accompany the interactions of land use, climate, and carbon cycle changes. No additional field measurements are made at AGRO or KONZ beyond 2001, but using the developed remote sensing and modeling algorithms from the earlier years, we continue to monitor these sites. Sampling at the CHEQ site is 100% consistent with the BigFoot design, but at METL there will be less dense sampling than at other sites. However, the data collected and the collection protocols at METL are consistent with BigFoot.

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Sampling Design and Implementation

The BigFoot sample design calls for 100 ground validation measurements of land cover, LAI, f_{APAR} , and NPP at each site (see Figure 2, below). Plot size is 25 x 25 m, chosen to roughly correspond to the pixel size of ETM+ data and neatly nesting at various increments up to 1 km. Between 60 and 80 plots will be concentrated within a 1 km cell centered on the site's eddy flux tower, with the balance of the 100 plots located outside the tower cell, but within the 5 x 5 km BigFoot footprint. This density of plots within the tower footprint ensures adequate characterization of the vegetation properties within that footprint, a critical accomplishment if flux data are to be properly interpreted and used to assess scaled carbon and water flux estimates from biogeochemical models. The 20-40 plots outside of the tower footprint (i.e., within the 24 external cells) are apportioned within basic land cover strata to enable independent validation of BigFoot surface products over the full BigFoot footprint.



To facilitate a geospatial understanding of the ecology of the tower footprint, the plot design is a nested spatial series (see sampling design diagram above). This permits explicit examination of spatial covariation among field-measured ecosystem properties using

variograms and cross-variograms (Cressie 1993). Further, the nested cyclical design provides a distribution of plots that is efficient at maximizing the number of plots at each lag (i.e., separation distance) in increments of 25 m up to nearly 1 km, an important consideration if the data are to be used for geostatistical analyses (Figure 4a-b). This also facilitates an examination of the effects of observation grain size on MODIS NPP estimates, an essential element of the BigFoot validation protocol. In high spatial frequency (e.g., heterogeneous) landscapes, functionally-important, but small vegetation patches cannot be detected above a certain grain size of observation. The use of geostatistical techniques will play an important role in increasing our understanding of the effect of image pixel resolution on coupled remote sensing–modeling characterizations within a biome (Milne and Cohen 1999). Moreover, we can assess if there is a fundamental grain size above which functionally-important vegetation patches can not be resolved and modeling errors accelerate, and, how the fundamental grain size varies among biomes.

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Methodology

- Objective 1: *In situ* measurements of land cover, LAI, f_{APAR} , and NPP
- Objective 2: Development of land cover and LAI surfaces
- Objective 3: Modeling NPP over the 5 x 5 km BigFoot footprint
- Objective 4: Validation of MODIS land cover, LAI, f_{APAR} , and NPP products
- Objective 5: Facilitating the continued development of GTOS

Objective 1: *In situ* measurements of land cover, LAI, f_{APAR} , and NPP.

The plots have already been established at the original four BigFoot sites. For newer sites, we have established the plots using two Ashtech GG-24 Surveyor units. Plots are surveyed to within 50 cm horizontal root mean square error and plot centers are marked with a stake. Vegetation cover, LAI, f_{APAR} , and NPP is measured at several subplots within each plot for at least two years (see sampling design diagram and field activity schedule). LAI is measured using standard direct and optical methods at each site (Gower et al. 1999). Direct measurement approaches include periodic area harvest for non-forest sites and application of allometric equations to tree diameter data for forest sites. LAI and f_{APAR} are also estimated indirectly using the Li-Cor LAI-2000 Plant Canopy Analyzers (Fassnacht et al. 1994, Chen et al. 1997, Gower et al. 1997, Gower et al. 1999). Therefore, the number of LAI/ f_{APAR} measurement campaigns must vary among sites, as phenology of LAI development varies among biomes, among ecosystems within each biome, and between years for a given ecosystem. Consequently, we measure LAI and f_{APAR} three times each year at the forest sites and four to six times at other sites.

f_{APAR} is estimated two ways: from the DIFFN variable provided by the Li-Cor LAI-2000 Plant Canopy Analyzer (Gower et al. 1999) and from a continuous PAR tram system. We designed and successfully deployed a PAR tram at NOBS in 2000. The PAR tram measures incident and reflected PAR both above and below the canopy at small increments along a 30 m track. We will be installing a tram at AGRO, SEVI, TAPA, HARV, NOBS, and METL in 2002 for several reasons. First, the fraction of direct to diffuse PAR influences LUE (Gower et al. 1999) and this relationship varies with canopy structure. Furthermore, the continuous measurements provide more complete characterization of daily and seasonal patterns of f_{APAR} .

NPP (the sum of the annual biomass production of each tissue for all vegetation strata) is measured for a minimum of two years (see field activity schedule) at approximately 50 plots at all five newer sites. NPP is defined as equal to $\text{NPPW} + \text{NPPF} + \text{NPPCR} + \text{NPPFR} + \text{NPPU} + \text{NPPGC}$, where W = aboveground wood (e.g., stem + branches), F = foliage, CR = coarse roots, FR = fine roots,

U = understory, and GC = ground cover (e.g., mosses and sphagnum). This equation is appropriate for any terrestrial ecosystem, but the field methods used to estimate each component vary among ecosystems (Gower et al. 1999). Aboveground woody biomass (e.g., stem and branch) and coarse root biomass is also estimated from allometric equations that correlate component biomass to stem diameter at breast height (1.3 m). Woody biomass increment is determined from radial growth, measured using increment cores. As tropical trees do not produce reliable annual growth rings, we are using rust-resistant dendrometer bands (Walker and Whiteaker 1988) to measure annual diameter growth. The number of tree species and size classes will be determined during the 2001 reconnaissance trip. Numerous abiotic and biotic factors have been shown to influence the allometric coefficients for new foliage biomass; therefore we are estimating new foliage production from annual leaf litterfall detritus production for forests where site- and species-specific allometric equations are not available (Gower et al. 1999). This approach assumes the canopy biomass is in steady state. Total foliage biomass and leaf area equations are from the literature. Where appropriate, biomass and leaf area data for harvested trees of the same species, but different sites, are composited and a generalized regression equation is used. NPPA of the shrub and herbaceous layers is quantified using clip plots. We also use clip plots throughout the growing season to quantify biomass production at the non-forest sites. NPPA of bryophytes, lichens, etc. are estimated using crank wires and ingrowth mesh plots (Gower et al. 1997, Bisbee et al. 2000). Fine root net primary production and mortality is estimated using minirhizotrons (Steele et al. 1997). Measurements on NPPB are restricted to the two dominant vegetation types within a site because of the large costs associated with obtaining and processing these data. Minirhizotrons are installed in each ecosystem and fine root growth is measured for two years. In the forest ecosystems, coarse root NPP is estimated from allometric equations.

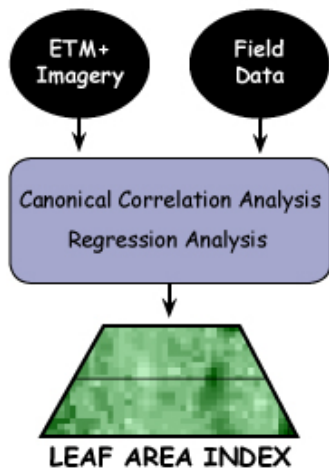
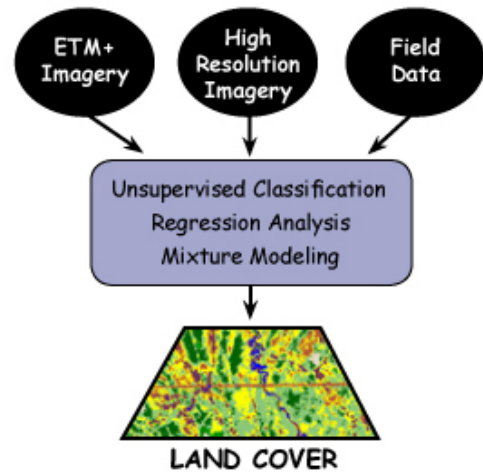
Gower has experience in measuring components of the carbon budgets in grasslands and agriculture crops (Brye et al. 2000), tropical forests (Gower 1987, Gower and Vitousek 1989) and are adapting relative methodology to the new ecosystems.

Objective 2: Development of land cover and LAI surfaces.

To develop land cover, LAI, and f_{APAR} surfaces at any given site we are applying both general and specific sets of methods. Landsat ETM+ serves as the backbone of our remote sensing analyses. Each ETM+ image is radiometrically normalized and georeferenced. A 7 x 7 km area is extracted, linear statistical transformations and mapping decisions are developed and applied, and an error characterization performed. Multiple dates of Level 1G imagery from a given year are used and radiometric normalization commence by applying to each image the COST atmospheric correction algorithm of Chavez (1996), which converts digital counts to reflectance. The COST model is based on a simple but effective use of the dark object subtraction technique that accounts for both additive scattering and multiplicative transmittance effects. COST uses the cosine of the solar zenith angle to approximate atmospheric transmittance and has been shown to be as accurate as models that use *in situ* (i.e., surface-based) atmospheric measurements and more rigorous radiative transfer code (Chavez 1996). For single-year, multi-image normalization at a given site, the image closest in date to maximum LAI is chosen as a reference and all other dates relatively normalized to it using a technique that locates the “ridge” of the two dimensional histogram formed by plotting a given ETM+ band from a subject date against that same band from the reference date. This method (conceived by R. Kennedy and W. Cohen) has been used quite effectively by Song et al. (in press). The ridge is located statistically (with the assistance of visual image inspection) and defines those pixels that have not undergone surface change. This results in a more robust relative normalization control set than is commonly obtained by selecting just a handful of pixels from the bright and dark ends of the brightness range of a given image (e.g., Hall et al. 1991). The ridge for each band of a given image pair (subject and reference) is subject to a regression analysis to calculate the normalization coefficients, which are then applied to the subject image to complete the normalization. This is done for each subject image from a given year for a given site.

Georeferencing is accomplished using the best source of reference data available. For the seven sites in the USA, the positional accuracy of the Level 1G-processed image is assessed by direct comparison with USGS digital orthophoto quadrangles (DOQs) in a 9 x 9 km area centered on the site. We found that for our original BigFoot sites, which are relatively small and free of significant topography, a small (<200 m) systematic shift in the *x* and *y* directions has been sufficient to provide a high-quality georeferencing of ETM+ to DOQs. After shifting the image into position, it is resampled to 25 m using the cubic convolution algorithm, and then clipped to a 7 x 7 km area centered on the site. The 7 x 7 km area provides a buffer that allows for subsequent alignment with a 5 x 5 km area of MODIS products. For the non-USA sites the same process is used, but IKONOS 1 m images that have been georeferenced with GPS are used instead of DOQs. This has worked well for NOBS and we expect similar results using the image being purchased via the Science Data Purchase Program for TAPA. Georeferencing in this way is done for the reference radiometric normalization image, and all images from other dates within the same year are shifted to match the reference image.

We continue mapping at all original four BigFoot sites in addition the five newer BigFoot sites. Land cover mapping relies on a combination of unsupervised classification, regression analysis, mixture modeling, and other techniques applied to the multi-date image set within a given year. Unsupervised classification is used to first stratify the scene into a single vegetation and several non-vegetation classes (e.g., water, barren, urban/built), but the process after that point is specific to the site. For example, at AGRO, we use a supervised classification to separate corn and soybean, which tend to be spectrally distinct, especially when seasonal development is captured via multi-date imagery. For forested sites, we also use an unsupervised classification to separate a forest class from non-forest classes. Then within the forested class, regression analysis is used to model percent tree cover and, if relevant, percent conifer versus hardwood. At HARV, because we use leaf-off and leaf-on imagery, we are able to identify conifer in the understory. The new sites each present a unique challenge, and our methods are tailored to the specific data sets available and information required for ecological modeling. Our work in the area of forest characterization under high LAI and biomass conditions, such as at TAPA, and in agricultural systems is current and extensive (e.g., Cohen et al. 1990, Cohen et al. in press, Lefsky et al. in press, Oetter et al. in press). For sites where low temporal frequency change is the norm, such as at the forested sites, subsequent years of land cover mapping rely on change detection. First, we determine if changes have occurred, then we label those areas that changed but carry the original label forward for those areas that have not changed. We used this procedure effectively in the Greater Yellowstone Ecosystem, which is a mix of forest, range, agriculture, and urban land use.



To map LAI and f_{APAR} , our primary concern is characterizing the seasonal maximum, which we do using regression analysis. Again, here we take advantage of seasonal development of spectral properties in relationship to maximum LAI. For this we rely on canonical correlation analysis (CCA, Seal 1964), which is an optimal alignment of the seasonal spectral data with an axis of LAI/ f_{APAR} from low to high. An additional advantage of CCA is that it accommodates linear calibration, a technique that minimizes (the often significant) bias in regression model predictions when the true response variable (i.e., spectral data) is used as the independent variable in the model (Curran and Hay 1986, Snedecor and Cochran 1989). Unlike regression analysis, there can only be one independent variable in linear calibration. A vegetation index such as NDVI from a single date could be used, but the first CCA axis is superior as it weights all bands from all dates according to their contributions in predicting maximum LAI/ f_{APAR} . We have used this method effectively at BigFoot sites and in other, independent in-progress studies. The combination of CCA and linear calibration is also used in the land cover mapping for BigFoot whenever we rely on regression modeling to provide

unbiased continuous estimates of vegetation properties (e.g., percent forest cover).

Characterization of errors in our land cover, LAI, and f_{APAR} surfaces is critical if they are to serve as validation for MODIS. To this end, we use our reference data (field data and other ancillary information such as aerial photos) in combination with a method called cross-validation, which is similar to bootstrapping and jackknifing (Efron and Gong 1983). We have the option of collecting more reference data and will do so where feasible, but reference data are expensive to collect and process. Having data from 100 plots, we could set some proportion aside explicitly for accuracy assessment, but as the primary consideration is the development of maps of the highest possible quality, we choose to use all data to develop the maps. Cross-validation is a statistical solution to this problem (Neter et al. 1999), in that 100 separate models are developed, each time with data from 99 plots. Each model is tested on the plot that was left out, providing a nearly unbiased estimator of prediction error (Efron and Gong 1983).

Objective 3: Modeling NPP over the 5 x 5 km BigFoot footprint.

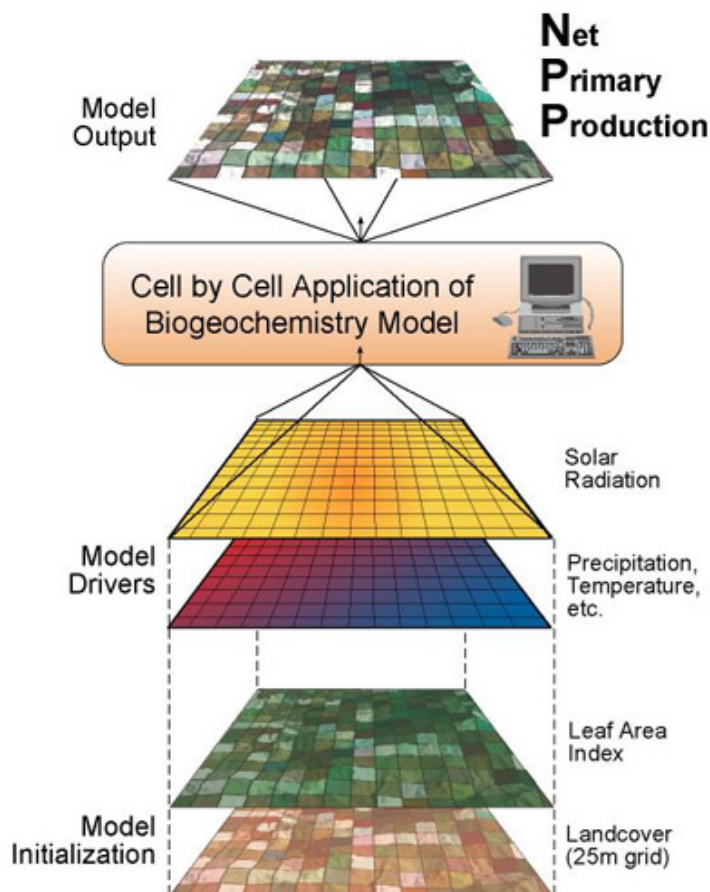
A description of the BigFoot scaling approach for NPP and its rationale are found in Reich et al. (1999). Briefly, we use ecosystem process models as our principal scaling tool. Inputs include the land cover and LAI surfaces previously described, soil data if available, and climatic variables. Model parameterization is cover-type specific (e.g. White et al. 2000). To derive an NPP surface for a given year, the model is run in each of 1600, 25 x 25 m grid cells with daily or annual outputs, which are temporally aggregated and the surfaces saved as needed. The daily climate drivers are derived from half-hourly observations at the flux towers and extrapolated to each cell if needed to account for the effects of elevation, slope and aspect (e.g., at KONZ, steep south facing slopes receive over 20% more solar radiation than the north facing slopes). Daily GPPs, at either the flux tower or spatially aggregated in the vicinity of the tower, are compared against flux tower-based GPPs. The NPP products for specific grid cells are compared with our field-measured NPP values.

In BigFoot, we use two different ecosystem models to compare water and carbon fluxes from the flux tower, and to estimate NPP for the 5 x 5 km MODLand footprint. The two models are Biome-BGC (Running and Hunt 1993) and IBIS (Foley et al. 1996, Kucharik et al. 2000). We selected Biome-BGC because it was developed specifically for application in a spatially-distributed mode in combination with satellite data (e.g., Hunt et al. 1996). Biome-BGC was also used in the development of the light use efficiency factors for the MODIS GPP algorithm, hence it is helpful in interpreting differences between the MODLand products and the BigFoot products. In addition to providing an independent assessment of NPP, IBIS was selected for several reasons. First, IBIS is an integrated ecosystem model that simulates carbon and water fluxes for terrestrial ecosystems and the output has been validated for a variety of ecosystems (Kucharik et al. 2000). The model employs multiple time steps, including an hourly time step, which allows for tighter comparisons to hourly flux estimates from the towers. For Biome-BGC comparisons, tower GPP estimates are aggregated to the daily time step. IBIS also does a complete carbon budget, so that outputs are checked directly against tower NEE. Soil respiration measurements are being made at several of our sites which provide additional information of heterotrophic respiration. Gower is already using IBIS at NOBS and CHEQ. Jon Foley, the author of IBIS, is a BigFoot collaborator, and he is using IBIS to simulate carbon and water exchange within LBA. In BigFoot we originally used PnET (Reich et al. 1999) in addition to Biome-BGC, but we have decided not to continue use of this model because it is too similar to Biome-BGC.

For 2002 and 2003 at AGRO and KONZ we will rely on new ETM+ imagery with existing algorithms to map land cover, LAI, and f_{APAR} . These are used with tower meteorological data to model GPP only, as there will be no new NPP measurements for these sites during those years (see field activity schedule).

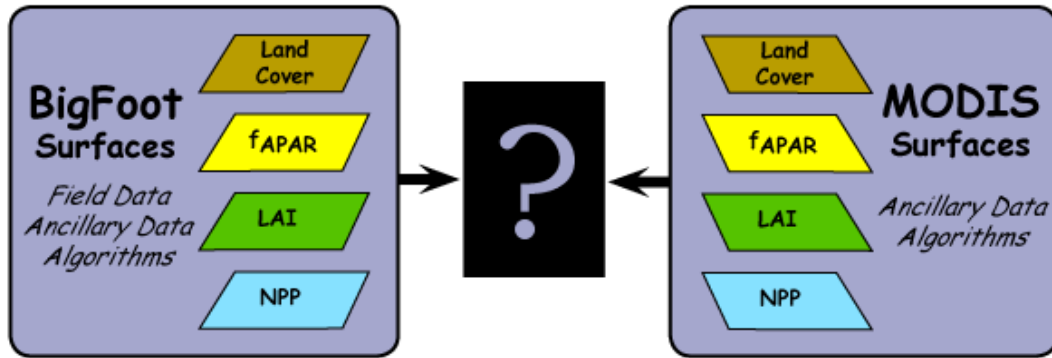
For the purposes of assessing LUE algorithms, such as that used by MODLand, BigFoot will produce daily 1 km resolution data layers for PAR (photosynthetic active radiation), f_{APAR} , APAR (absorbed PAR), and ϵ_g (GPP efficiency factor). In each case, these data layers are initially derived at the 25 m resolution and aggregated to 1 km. PAR comes from the tower meteorological observations and DEM-based interpolations. For f_{APAR} , we map its distribution with ETM+ imagery for multiple dates across the growing season (described earlier). Continuous measurements of transmittance and reflectance at the flux tower help with the interpolation between the dates for which clear-sky ETM+ imagery is available. We then create a daily ϵ_g surface by dividing model-based daily GPP (checked against tower based GPP) by the daily APAR ($PAR * f_{APAR}$) just described. Thus, we produce a continuous record of spatially and temporally varying PAR, f_{APAR} , and APAR which can be aggregated to the 1 km grid cells and 8-day averages needed for direct comparisons with the components of the MODLAND NPP algorithm. These data could also be used with other LUE algorithms.

We can also gain insights into the daily unstressed or maximum GPP efficiency (ϵ_g^*) which is used in the MODLand NPP algorithm. Looked at for all days across the growing season, the scatter plot of APAR against GPP at the daily time scale indicates the variability in ϵ_g for that vegetation type. GPP in this case could be taken directly from the tower data so that model accuracy is not an issue. The slope of the line demarking the upper limit of the scatter is the maximum GPP efficiency at the time scale relevant to the satellite-based LUE algorithms. By examining the relationship of departures from this line on any given day, and environmental factors such as maximum air temperature and daily average VPD, we evaluate the scalars for stress effects typically used in operational LUE algorithms (e.g., Goetz et al. 1999). Ultimately, these observations could become the basis for a new biome-specific parameterization scheme for ϵ_g^* and the stress factor scalars. This scheme can be tested for eventual wider



application using the MODLand land cover, PAR, and f_{APAR} products. Whether for validation or parameterization, better understanding of how ϵ_g varies across biomes and varies over the growing season within a biome is needed (Goetz and Prince 1999).

Objective 4: Validation of MODLand land cover, LAI, f_{APAR} , and NPP products.

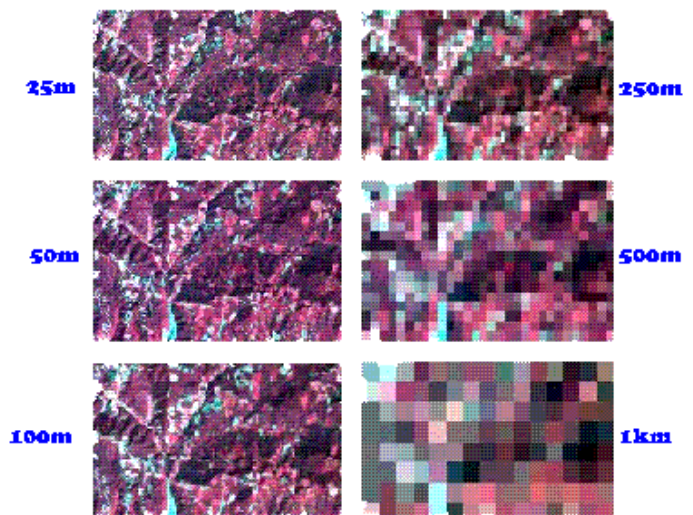


There are several ways in which we validate MODLand products. The simplest and most straight-forward is direct map-to-map comparisons, and we do this for each land cover, LAI, f_{APAR} , and NPP BigFoot surface created. Within one 1 km² MODIS cell, there are 1600, 625 m² cells, so for each cell the frequency distributions of fine-grain BigFoot values can be contrasted against the single cell value of a MODIS product. This is particularly informative for land cover, and at the very least we would expect the MODLand cover class call for a given cell to be the same as the mode of the fine-grained distribution. For the numerical surfaces (e.g., LAI) we calculate the mean of the fine-grained values and compare this against the value in the cell of the coincident MODLand product. Summarizing the data across a single site, we evaluate the 25 MODLand cells in relation to the BigFoot aggregated 1 km fine-grained modes and means. These same data can be compared across sites. The MODLand GPP product is produced each 8 days, so for the purposes of comparison an 8-day 1 km BigFoot GPP product will be created.

The most basic level of confirmatory validation is that the slope of the BigFoot vs. MODLand trends across sites for the numerical products is positive and close to 1.0. The next level is that the absolute values match, and then that there is good correspondance among cells of a given site. Undoubtedly, there will be discrepancies. The MODLand surfaces can be compared directly to the field data, but this is probably only valid in the central, flux tower cell where the density of ground plots is high. However, the accuracies of BigFoot maps (characterized from comparisons with the field data) serve as confidence estimates for the quality of BigFoot surfaces as validation media.

To the degree that there are errors in our surfaces, some of the differences observed between BigFoot and MODLand surfaces will be unexplainable. Given our protocols and our ability to tailor a mapping process to a given site, however, the quality of our maps should be high enough (e.g., Figure 8d) to provide strong insights into the discrepancies between the BigFoot and MODLand NPP products. As such, we conduct several scaling exercises that involve generalization of the BigFoot surfaces. These include translation of BigFoot classes into MODLand classes, as was demonstrated by Thomlinson et al. (1999). Another is to successively coarsen the grain size of the BigFoot input images up to 1 km (e.g., Milne and Cohen 1999). With each kind and level of generalization we rerun the process models and evaluate the change in NPP output (Reich et al. 1999). If, for example, use of the 17+ classes of IGBP land cover, provides significantly better NPP estimates than use of 6 + classes of the current MODLand NPP product, a perhaps simple but effective means of improving the MODLand product will be at hand. If 250 m surfaces are required to, on average, preserve biome-specific vegetation patterns, then more reliance on the MODIS 250 m bands may be in order (Turner et al. 2000).

Spatial Resolution and Information Content



Other factors contribute to differences between the MODLand and BigFoot NPP products. First, both approaches use PAR, T_{min} (minimum temperature), T_{max} (maximum temperature), and daily average VPD. S. Running will therefore compare the BigFoot meteorological time series data for each site (derived from the flux towers) with that delivered to the MODLand algorithm by the [NASA Data Assimilation Office climate model](#). A second factor is the spatial and temporal variability in light use efficiency. We can determine ϵ_n (NPP/APAR) for each cover type from our NPP measurements and APAR accounting. We then run a simple ϵ_n

type LUE algorithm (Ruimy et al. 1994) with variations in the spatial resolution (25 m to 1 km) and land cover generality. These comparisons are informative about the sensitivity of LUE algorithms to spatial resolution and land cover generalization (Turner et al., in preparation).

Objective 5: Facilitating the continued development of GTOS.

GTOS has the aim of improving the quality and coverage of terrestrial ecosystem data, and integrating them into a worldwide knowledge base that will help us manage our planet wisely for future generations. A priority activity within GTOS is the Global Terrestrial Observing Network (GT-Net), which is envisaged as a "system of networks," formed by linking existing monitoring sites and networks as well as planned satellite remote sensing systems, with the aim of better understanding global and regional change. The main objective of GT-Net is to encourage existing networks, with similar objectives and geographical coverage to become more efficient in making observations, share and exchange environmental data, define data and information access policy, develop metadata standards as well as local, regional, and global *in situ* datasets, and undertake demonstration projects. The first demonstration project concentrates on improving current estimates of global terrestrial NPP. The project adopts a hierarchical approach and uses models that combine both satellite data and *in situ* observations. A set of output products, which have NPP as their common foundation, will be produced. The NPP Demonstration Project has two primary goals: distribute global standard NPP products (e.g., MODLand) to regional networks for evaluation/validation, and translate this standard product to regionally specific crop, range, and forest yield maps for land-management applications.

BigFoot is in a position to facilitate advancement of GTOS goals. Although we have not explicitly requested funds to conduct any specific GTOS activities, we think it is important to integrate our work within the context or framework of GTOS. To this end, we are collaborating with Jim Gosz, the Chair of the GTOS Steering Committee, on this proposal. Through his leadership role in LTER, Gosz supported BigFoot by funding the 1996 workshop and is now funding a second workshop in 2001 for BigFoot to bring together scientists from the International LTER community to take the first solid step towards fulfilling the goals of the GTOS NPP project. BigFoot (Turner) organized a carbon flux scaling workshop at the 2000 LTER All Scientists Meeting (ASM). The 2001 workshop is a follow-on to the ASM workshop. At this workshop participants integrate their NPP field and related data with remote sensing and models to develop NPP surfaces using BigFoot protocols. These surfaces are then tested against MODLand NPP surfaces in the same way that BigFoot is comparing surfaces. Additionally, we are updating our field manual (Campbell et al. 1999, see Appendix) for further distribution throughout the GTOS network. The BigFoot conceptual design is also shared with other interested scientists via Gower's involvement in GCTE. Gower is a member of the GCTE Science Steering Committee and the development of a global terrestrial observing systems is recognized as an important goal by this organization (Canadell et al. 1999).

Project Overview

Intro	Objectives	Background	Site Selection	Sampling Design	Methodology	References
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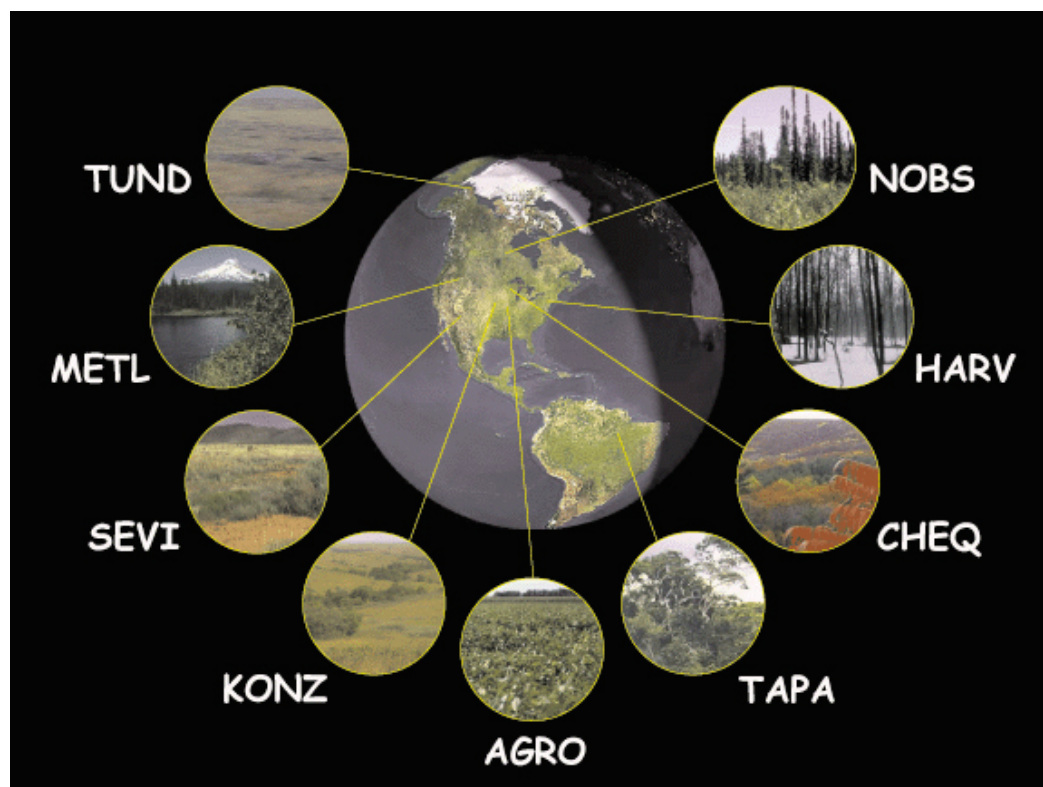
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Study Sites



Site Name	Latitude	Longitude	Path	Row	UTM X Coord	UTM Y Coord	UTM Zone
NOBS Center	55.885260	-98.477268	33	21	532698	6193433	14N
NOBS Tower	55.879547	-98.480843	33	21	532479	6192795	14N
KONZ Center	39.089073	-96.571398	28	33	710046	4329469	14N

KONZ Tower	39.082286	-96.560251	28	33	711030	4328742	14N
AGRO Center	40.0066580	-88.291535	22	32	389764	4429295	16N
AGRO Tower	40.006627	-88.291030	22	32	389807	4429291	16N
HARV Center	42.528513	-72.172907	13	30	732194	4712333	18N
HARV Tower	42.538259	-72.171378	13	30	732283	4713419	18N
TUND Center	71.271908	-156.613307	79	10	585509	7909410	4N
TUND Tower	71.280866	-156.612205	79	10	585509	7910410	4N
SEVI Center	34.350858	-106.689897	33	36	344578	3802353	13N
SEVI Tower	34.360290	-106.700285	33	36	343640	3803415	13N
TAPA Center	-2.869745	-54.949355	227	62	727950	9682600	21S
TAPA Tower	-2.856664	-54.958919	227	62	726889	9684049	21S
METL Center	44.450722	-121.572812	45	29	613554	4922926	10N
METL Tower, Old Pine	44.499166	-121.622369	45	29	609520	4928239	10N
METL Tower, Young Pine	44.437189	-121.566756	45	29	614062	4921431	10N
CHEQ Center	45.945404	-90.272475	25	28	246360	5093190	16N
CHEQ Tower	45.945278	-90.274444	25	28	245207	5093182	16N

Publications and Presentations

Peer-Reviewed

Reports and Misc.

Presentations

Peer-Reviewed Publications

(reverse chronological order)

- **Turner, D.P., S.V. Ollinger, and J.S. Kimball.** Submitted. Integrating Remote Sensing and Ecosystem Process Models for Landscape to Regional Scale Analysis of the Carbon Cycle. *BioScience*.
- **Morisette, J.T., J. Nickeson, P. Davis, Y. Wang, Y. Tian, C. Woodcock, N. Shabanov, M. Hansen, D.L. Schaub, A.R. Huete, W.B. Cohen, D.R. Oetter, and R.E. Kennedy.** Submitted. The use of NASA's Commercial Data Purchase Program in support of MODIS land validation. *Remote Sensing of Environment*.
- **Berterretche, M., W.B. Cohen, A.T. Hudak, T.K. Maersperger, K.S. Fassnacht, and S.T. Gower.** Submitted. Comparison of regression and geostatistical methods for LAI mapping with Landsat ETM+ data over a Canadian boreal forest. *Remote Sensing of Environment*.
- **Kennedy, R.E., W.B. Cohen, A.A. Kirschbaum, and S.T. Gower.** Submitted. Constrained stochastic sampling for large-area studies in ecology. *BioScience*.
- **Lee, K-S., W.B. Cohen, R.E. Kennedy, T.K. Maersperger, and S.T. Gower.** Submitted. Comparison of hyperspectral and multispectral data for estimating leaf area index in four biomes. *Remote Sensing of Environment*.
- **Burrows, S.N., S.T. Gower, A.A. Kirschbaum, D.C. Feldkirchner, J.L. Campbell, W.B. Cohen, D.P. Turner, and S.W. Running.** Submitted. Geostatistical estimation of leaf area index to validate remote sensing products in four North American biomes. *Ecological Applications*.
- **Turner, D.P., M. Guzy, M. Lefsky, W.D. Ritts, S. VanTuyl, and B.E. Law.** In Press. Monitoring Forest Carbon Sequestration with Remote Sensing and Carbon Cycle Modeling. *Environmental Management*.
- **Turner, D.P., W.D. Ritts, W.B. Cohen, S.T. Gower, M. Zhao, S.W. Running S.C. Wofsy, S. Urbanski, A. Dunn, and J.W. Munger.** 2003. Scaling gross primary production (GPP) over boreal and deciduous forest landscapes in support of MODIS GPP product validation. *Remote Sensing of Environment* 88:256-270.
- **Cohen, W.B., T.K. Maersperger, Z. Yang, S.T. Gower, D.P. Turner, W.D. Ritts, M. Berterretche, and S. W. Running.** 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*. 88:221-362.
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- **Turner, D.P., S. Ollinger, M.L. Smith, O. Krankina, and M. Gregory.** In Press. Scaling Net Primary Production to a MODIS Footprint in Support of Earth Observing System Product Validation. *International Journal of Remote Sensing*.
- **Gower, S.T.** In Press. Patterns and mechanisms of the forest carbon cycle. *Annual Reviews Energy and Environment*.

- **Cohen, W.B., T.K. Maier-sperger, S.T. Gower, and D.P. Turner.** 2003. An improved strategy for regression of biophysical variables and Landsat ETM+ data. *Remote Sensing of Environment* 84:561-571.
 - **Turner, D.P., S. Urbanski, D. Bremer, S.C. Wofsy, T. Meyers, S.T. Gower and M. Gregory.** 2003. A Cross-biome Comparison of Light Use Efficiency for Gross Primary Production. *Global Change Biology* 9:383-395.
 - **Turner, D.P., M. Guzy, M.A. Lefsky, S. VanTuyl, O. Sun, C. Daly, and B.E. Law.** 2003. Effects of Land Use and Fine Scale Environmental Heterogeneity on Net Ecosystem Production over a Temperate Coniferous Forest Landscape. *Tellus* 55B:657-668.
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