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Remote Sensing for Terrestrial Biogeochemical Modeling

Gregory P. Asner
Department of Global Ecology
Carnegie Institution
Stanford, CA 94305
Tel: 650.492.1047
Email: gpa@stanford.edu

Scott V. Ollinger
Department of Natural Resources
Complex Systems Research Center
University of New Hampshire
Durham, NH, 03824
Email: scott.ollinger@unh.edu

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INTRODUCTION

Remote sensing and biogeochemical modeling share a highly complementary nature, which has led to a growing number of applications that involve some degree of coupling between the two. Whereas remote sensing represents the only means by which landscape and vegetation properties can be sampled over large and contiguous portions of the Earth's surface, models focus on the underlying biogeochemical processes that regulate the flow and storage of water, carbon and nutrients, often over much longer time scales than can be considered through remote sensing alone. The aims and goals of biogeochemical modeling are wide ranging and include studies of carbon (C) and water cycling, analyses of nitrogen (N) enrichment and leaching to aquatic ecosystems, and trace gas transfers from soils to the atmosphere. Biogeochemical models are also used as part of larger, integrated modeling environments of regional and global biosphere-atmosphere interactions, biogeography, and climate change (e.g., Sellers et al. 1997, Cramer et al. 2001). More recently, biogeochemical modeling has taken a role in decision support for conservation, management and policy development (Potter et al. 2006).

Remote sensing can provide biogeochemical models with information on vegetation type, leaf area index (LAI), canopy height, the fraction of absorbed photosynthetically active radiation (*f*PAR), light-use efficiency (LUE), leaf N concentration, pigments and other biochemical compounds to simulate plant growth and mortality. Other remote sensing-related inputs have included temperature, precipitation, solar radiation levels, and soil moisture. In this chapter, we review a number of approaches through which remote sensing data can be applied to the detection of vegetation properties, and discuss the tradeoffs of various methods with respect to biogeochemical modeling. Given the breadth of the topic, our goal in preparing this chapter was not to provide a working manual of all remote sensing-model integration methods available. Instead, we sought to summarize important overall strategies for vegetation detection into a framework that involves the types of instruments used, the ecological properties they can be designed to detect, and the manner in which those properties can be utilized by models.

MODELS UTILIZING REMOTE SENSING

This section provides a brief overview of major categories of ecosystem biogeochemistry models that can be driven or guided by remote sensing. In the interest of simplicity, we describe each type of model as being distinct from one another, but readers should be aware that the boundaries between them are often blurry, and hybrid approaches are also available.

Simple Empirical Models

The simplest type of remote sensing/model linkage consists of a small number of empirically derived algorithms that combine field-based relationships with remotely sensed vegetation properties that correlate strongly with some aspect of ecosystem behavior. For example, Ollinger et al. (2002a) used imagine spectroscopy to detect leaf lignin to nitrogen ratios in temperate forests, which provided a direct connection to decomposition, C:N ratios and N cycling rates in soils. When such relationships are available, this approach offers a straightforward means of producing estimates that are constrained to known patterns. The resulting accuracy is dependent only on the strength of the observed trends and on the accuracy of the vegetation property estimates. The principal disadvantage is that these approaches include no mechanisms that would allow extrapolation in time or under varying environmental conditions.

Light Use Efficiency Models

Of intermediate complexity are the light-use efficiency (LUE) models, also called production efficiency models (PEM), which use remotely sensed *f*PAR to estimate maximum carbon C assimilation rates and then adjust for suboptimal climate conditions, using a series of simple climate response algorithms. These models have evolved from the original arguments of Monteith (1972) that the amount of carbon fixed per unit of incident radiation can be used as an organizing principle for estimating overall vegetation productivity. There are now a large number of efficiency models which differ in their details and complexity, but all derive from the idea that knowledge of incident radiation and the light-absorbing properties of the plant canopy can determine the maximum potential photosynthesis for that canopy (Potter et al. 1993, Field et al. 1995, Running et al. 2000). Nearly all applications of efficiency-type methods are based on the idea that the rate of C accumulation by plants (*P*) depends on environmental and biochemical factors in the following way:

$$P\ (NPP\ or\ GPP) = fPAR \times PAR \times \varepsilon^* \times W \times T \qquad (1)$$

where PAR is the downwelling photosynthetically active radiation at the top of canopy, ε^* represents the maximum photochemical conversion efficiency of vegetation foliage under optimal conditions (g MJ^{-1}), and W and T are dimensionless scalars (0-1) that down-regulate ε^* based on modeled water and temperature stress, respectively. Production efficiency models are particularly appealing for large-scale analyses because of the availability of absorbed PAR estimates from multi-spectral sensors, and because ε^* is both conceptually straightforward and physiologically meaningful. However, a persistent challenge has been the lack of understanding concerning factors controlling variation in ε^* both within and among vegetation types (e.g. Gower et al. 1999).

Ecosystem Process Models

Of greatest complexity are ecosystem process models, which use remote sensing primarily to initialize important vegetation input variables and then simulate ecological processes—such as photosynthesis, C allocation, respiration, litterfall, decomposition, and water balances—that affect ecosystem behavior. The added complexity in these models allows them to predict a range of additional variables, and to examine responses to environmental factors such as rising CO_2, atmospheric pollution, and physical disturbance. Because they are often designed to be run over longer time scales, they are more suitable for considering changes in ecosystem components such as soil C and nutrient pools that have very long turnover times.

Independent of the application, ecosystem process models often require a large number of parameters, measured in the field or via remote sensing, or from a cumulative knowledge based on the literature (Figure 1). Some models, such as Century (Parton et al. 1988a, 1998b) and PnET-CN (Aber et al. 1997, Ollinger et al. 2002b) require more than 30 input parameters needed to simulate the growth and mortality of plants, and the subsequent accumulation and turnover of soil organic matter (SOM) and nutrients (Table 1). Although many of these models were not originally designed to ingest remotely sensed data, they can greatly benefit from the use of remote observations to constrain simulated processes. Other models, such as the Carnegie-Ames-Stanford Approach (CASA; Potter et al. 1993, Field et al. 1995) were designed to be run with fewer parameters, emphasizing those which can be routinely retrieved via remote sensing. Some of these models represent hybrid approaches between efficiency and process-based models, whereby estimates of *f*PAR and ε^* are linked with algorithms describing more complex biogeochemical processes. To date, these models use remotely sensed data to constrain simulated rates of photosynthesis, plant growth, evapotranspiration, and other plant-related processes. Other more specialized models, such as TerraFlux (Asner et al. 2001), use remotely sensed data to simulate nutrient flows between plants and soils.

ECOSYSTEM PROPERTIES FROM REMOTE SENSING

Vegetation Type

Vegetation type is one of the most basic yet important remote sensing products required by many biogeochemical models (Table 2). This is particularly true when the models are run in a spatially-explicit mode at regional to global scales. At a minimum, the models require vegetation classifications such as broadleaf deciduous trees, needleleaf evergreen canopies, and shrub (e.g., Running et al. 1993, 1994, Bonan 1995). This information is critical to setting up model parameterizations related to physiological, biochemical, and structural properties that ultimately affect growth, mortality, and decomposition of plants. For example, the lifespan of temperate deciduous and coniferous trees often differ, and thus the timing and rate of foliage, wood, and root mortality affects C losses to the atmosphere. Similarly, the decomposability of plant tissues varies by vegetation type, and thus a vegetation map is needed to ultimately parameterize decomposition rates spatially in a biogeochemical model. Vegetation type is thus a key entry point for remote sensing into the models.

Plant Physiology and Growth

Vegetation type is also important for setting up basic model parameters associated with photosynthetic rates, stomatal conductance, light-use efficiency and carbon allocation, all of which directly impact gross and net rates of primary production (GPP, NPP; Table 2). For example, variables such as leaf retention time or maximum photosynthesis per unit light intensity might be defined as a function of vegetation type where more explicit information is not available (Ollinger et al. 1998, Bondeau et al. 1999). This and other vegetation and ecosystem parameters are often derived from a look-up table organized by vegetation type (Sellers et al. 1995).

With the advent of high temporal resolution, global remote sensing instruments such as the Advanced Very High Resolution Radiometer (AVHRR) and the Terra Moderate Resolution Imaging Spectrometer (MODIS), monitoring of vegetation properties directly related to physiology, phenology, and growth became commonplace. The basis for using these sensors rests in the field-based knowledge that *f*PAR, LAI and several vegetation indices, such as the NDVI, are positively inter-correlated (Myneni et al. 1997). The ability to detect *f*PAR in this manner was quickly incorporated in light-use efficiency models to predict GPP and NPP, although the resulting need for estimates of ε represents a difficult and ongoing challenge. Some models select a constant value for ε, or set it by vegetation type (Potter et al. 1993, Running et al. 2000). Field et al. (1995) argue that a moderately dynamic ε caused by climatological stress factors should be more realistic. Other field-based and remote sensing studies have subsequently highlighted the variability of light-use efficiency at local to regional scales (Lobell et al. 2002, Turner et al. 2003). Nonetheless, modeling of GPP and NPP dynamics has remained most closely tied to the temporal variation in *f*PAR and LAI.

Thus far, the derivation of remotely sensed LAI and *f*PAR has mostly relied upon optical vegetation indices such as the NDVI, but other methods based on canopy gaps, structure, and the probability of light penetration are gaining momentum. This latter group of methods benefits especially from multi-view angle (MVA) or light detecting and ranging (LiDAR) observations that can determine inter- and intra-crown gaps related to LAI and leaf biomass (Means et al. 1999, Zhang et al. 2000). These approaches are still novel since neither the data nor processing methods are as accessible to non-experts as are optical vegetation indices, but the potential use of these structurally-sensitive remote sensing approaches could change the way biogeochemical and land-surface models are designed and implemented (Asner et al. 1998).

Although the NDVI- *f*PAR -NPP connection has been utilized to explore the spatial and temporal dynamics of plant growth and carbon uptake globally (e.g., Field et al. 1998), other local-to-regional scale studies have demonstrated considerable variation in LUE, prompting a number of more detailed studies.

In one example, a meta-analysis by Green et al. (2003) compiled published values of ε* and a variety of leaf and canopy-level traits from a wide array of C3 plant communities, including deciduous and evergreen tree species, and herbaceous species consisting of grasses, forbs, and legumes. Their results showed that most of the variation in ε* could be related to mass-based concentrations of N in foliage, suggesting a link with leaf-level photosynthetic capacity and models that include canopy N as determinants of C assimilation. Aber et al. (1997) and Ollinger et al. (2002b) developed and explored linkages between leaf N and photosynthetic capacity in their model PnET. They found leaf N to be one of the most important predictors of growth rates, and eventually incorporated remotely sensed estimates of canopy N to provide a spatially explicit understanding of NPP in temperate forests (Figure 2). Their approach focuses on airborne and space-based imaging spectroscopy, along with partial least squares (PLS) regression analysis, to estimate canopy N at fine to moderate spatial resolution. Retrieval of canopy N from sensors such as the NASA Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) has become routine in forested ecosystems, where canopy cover is high, and when shadowing is minimal, although the small scene size and limited data volume have prevented more widespread application of this approach.

Leaf N provides one important window into the physiological functioning of canopies, but leaf pigments are another common approach to remote estimation of plant function. Chlorophyll concentration has been a core remote sensing target in many studies (e.g., Yoder and Waring 1994, Zarco-Tejada et al. 2001) and has been used to estimate annual rates of biomass production and carbon exchange in agricultural systems (Gitelson et al. 2005, 2006), but few biogeochemical models have been designed to explicitly incorporate chlorophyll measurements. Gamon et al. (1990) took a major step toward remote detection of xanthophyll-cycle pigments that may directly express the LUE of plants. They developed the Photochemical Reflectance Index (PRI) to estimate leaf and top-of-canopy LUE, and many have since used the PRI to understand spatial and inter-specific variations in LUE among plants (reviewed by Ustin et al. 2004). Only recently, however, has the PRI been used in a biogeochemical model. Asner et al. (2004) used Earth Observing-1 Hyperion hyperspectral data to compute the NDVI and PRI of tropical rainforest canopies in the Brazilian Amazon. They found that the NDVI lacked responsiveness to canopy drought conditions that were leading to NPP declines, and this was caused by saturation of the NDVI in the high LAI canopies found in the central Amazon basin. However, the PRI, which expresses top-of-canopy leaf pigment concentrations, did account for about 20-25% of the field-observed decreases in plant production. Moreover, they found that remote sensing metrics of canopy water content, which penetrate deep into the tropical forest canopies, were highly sensitive to NPP declines. Using the PRI and hyperspectral indices of canopy water, they modeled these NPP decreases with a new version of the CASA model, demonstrating that drought periods could be detected in the tropical forest canopy, and the effect incorporated into a biogeochemical model (Figure 3).

Beyond the current hyperspectral metrics for the major pigment groups such as chlorophylls and carotenoids, there is a growing effort to understand how less abundant but functionally important leaf compounds, such as phenolics, might be remotely sensed. Secondary compounds provide information pertinent to plant physiology, leaf herbivory, and a variety of other processes pertinent to biogeochemical models. To date, we know of no models that incorporate remotely sensed (or field-measured) estimates of secondary plant compounds, so this is an area ripe for exploration.

Phenology and litterfall are two additional variables having a major impact on the C, water and nutrient fluxes of ecosystems. The timing and amount of litterfall is a central determinant of CO_2 emissions via microbial decomposition processes. AVHRR and MODIS timeseries of the NDVI have been used to observe seasonal and inter-annual changes in phenology, and to estimate rates of litterfall production (White et al. 1997). These estimates have subsequently been used to simulate C flows from live to detrital pools in the models (Keyser et al. 2000). Such efforts have shown that phenology exerts major control over the seasonal cycle of CO_2 concentrations in our atmosphere (Sitch et al. 2003).

Carbon and Nutrient Storage

Growth, phenology and litterfall are all directly related to the flow of C, nutrients and water within ecosystems. These processes are also related to C and nutrient storage, although indirectly. Storage is a function of inputs and outputs, and thus the flows of materials dictate the standing stock at any given time. Historically, remote sensing has addressed C and nutrient flows in plants more so than the standing stocks. Recently, however, new remote sensing technologies and techniques are gaining access to a more direct mapping of aboveground C and nutrient storage. First, in many environments the fractional cover of live and senescent or dead vegetation is a principal determinant of aboveground C stocks. At the global scale, DeFries et al. (1999, 2000) used fractional canopy cover from the MODIS Vegetation Continuous Fields (VCF) product to simulate changing C stocks and biochemical fluxes. They showed that fractional cover changes exert a major influence on the C dynamics of terrestrial ecosystems worldwide. At regional scales, detailed mapping of fractional canopy cover can be closely related to aboveground C stocks in shrublands, savannas and open woodlands (Asner et al. 2005a).

In forested ecosystems without major disturbances or canopy openings, fractional cover does not always provide sufficient information for modeled C and nutrient stocks. Other techniques, such as from LiDAR, fine-scale optical (e.g. IKONOS), synthetic aperture radar (SAR), and multi-view angle passive optical remote sensing (MVA) provide canopy structural information that can be used to estimate C storage (reviewed by Wulder and Franklin 2003). For example, both LiDAR and interferometric SAR provide detailed information on tree canopy height and profile that can be combined with field-based allometric equations to map aboveground biomass and C storage (Lefsky et al. 2002, Treuhaft et al. 2003). To date, only a few models can ingest this information directly (Hurtt et al. 2004), but the straightforward nature of height-based allometrics should make this a more common approach as remotely sensed canopy height estimates become more widely available. Future model developments will make increased use of remotely sensed vegetation structure that is related to C storage.

In parallel with carbon, the nutrient stocks of canopies can be estimated and/or modeled when information pertaining to stand structure, aboveground biomass and tissue nutrient concentrations are available. In situations where nutrient concentrations are relatively invariant within functional groups (as in needleleaf evergreen species or desert shrubs), this can be achieved using a look-up table approach that combines remotely sensed canopy structure (biomass) and vegetation type with known nutrient levels in foliage and wood. However, there are many cases where greater variation in plant tissue stoichiometry require a more direct means of detecting foliar nutrient concentrations, such as through use of imaging spectroscopy. For example, in temperate deciduous forests, variation in soil type, disturbance history and atmospheric deposition can lead to a wide range of leaf N concentrations both within and among species (Ollinger et al. 2002a, McNeil et al. 2005). Where nitrogen-fixing trees are present, detection of their location and abundance is important because they typically have far higher N:C ratios than do non-fixing species. Finally, the nutrient-to-carbon ratios of foliage among humid tropical tree species are typically more variable than is found in other biomes (Townsend et al. 2007). This translates to much greater uncertainty in biogeochemical modeling studies of tropical forests, unless direct detection of nutrient concentrations in canopy foliage can be achieved.

High spatial resolution data and/or sub-pixel fractional cover algorithms are starting to provide information on tree-fall gaps and dynamics (Asner et al. 2005b) that are important to a class of biogeochemical models that incorporate gap-phase processes in forests (Moorcroft et al. 2001). These models require spatially explicit (or statistically sound) information on the rate of gap formation, closure, and regrowth to simulate the light environment as well as C fluxes and storage. Progress in sub-pixel unmixing (spectral mixture analysis) with both hyperspectral and multispectral optical imagery is opening doors for mapping forest canopy gap fraction. As the remote sensing technologies and analytical techniques mature over time, the biogeochemical models will follow with more detailed integration of the observations, thereby supplanting the need for statistical parameterizations based purely on field data that is offset geographically or temporally from that of the modeling study.

Evapotranspiration

Plants and soils mediate the hydrology of ecosystems. Plant canopies intercept precipitation, and a fraction of this water is subsequently lost to the atmosphere via evaporation. Soils intercept remaining precipitation, and either lose moisture to evaporation or ground water flow. However, a major fraction of soil water is taken up by the vegetation to support stomatal conductance for photosynthetic function. Water is thus lost via transpiration, and this flux is a major determinant of ecosystem hydrology (Dickenson 1991).

Evapotranspiration (ET) is a function of canopy cover, LAI, roughness, wind speed, energy exchange, and other factors (Table 2). ET is also related to the residual energy exchanged between the canopy and atmosphere after taking into account net radiation, sensible heat exchange, and ground heat flux. Both of these perspectives defining ET lead to methods by which this important process is estimated in biogeochemical models. Some models simulate ET based on canopy and micrometeorological parameters (e.g., Sellers et al. 1997). Methods such as the two-source resistance model (Lhomme et al. 1994a,b), utilize LAI, vegetation height and aerodynamic resistance to simulate sensible and latent heat exchange, and thus evapotranspiration. Other models rely on micrometeorological measurements alone, and do not directly incorporate vegetation structural properties (e.g., Kustas et al. 1990).

For those ET modeling approaches that rely on vegetation properties, canopy cover and LAI can be estimated from optical and other remotely sensed imagery. However, canopy roughness and derived canopy resistance remain difficult to quantify (Shoshany 1993). Roberts et al. (2004) recently estimated canopy rugosity – a metric of roughness – using airborne hyperspectral imagery. Others have used more explicit structural remote sensing technologies such as radar and LiDAR to understand canopy roughness (Lefsky et al. 2002).

Another approach to estimating ET utilizes the visible, near-infrared, and thermal imaging data provided by aircraft and satellite sensors to estimate energy exchanges between the land surface and atmosphere (e.g., Engman 1991, Kustas et al. 1996). This approach affords a means to bypass, at least to some degree, any need to explicitly estimate vegetation structural properties. For example, Bastiaanssen et al. (1998, 2002) developed the Surface Energy Balance Algorithm for Land (SEBAL) to estimate a complete radiation and energy balance, including resistances for water vapor, heat and momentum. The primary input to this model is broadband radiance observations from Landsat, MODIS and similar sensors. Independent of the precise approach, it has long been argued that remote sensing is the only technology that can deliver the suite of radiative and vegetative parameters needed to estimate ET in a consistent manner at regional to global scales (Choudhury 1988).

CHALLENGES IN USING REMOTE SENSING FOR BIOGEOCHEMICAL MODELING

We have highlighted the major remote sensing measurements used in terrestrial biogeochemical models, and we described how these measurements constrain simulations of C, water, and nutrient cycling. The models are often complex, with many parameters that cannot be directly constrained with remote sensing (Figure 1). On the other hand, a set of key variables, such as LAI, *f*PAR and nitrogen concentrations, can be remotely estimated, and these vegetation properties have far-reaching control over a range of ecosystem processes (Sellers 1985, 1987).

The challenge remains to improve the remote sensing estimates, but also to find how a broader suite of model parameters co-vary in nature as a way to extend the power of remote sensing controls (or reality checks) in simulations of biogeochemical cycles. Leaf N is a good example of this issue. Leaf N is one of the most important descriptors of canopy function, and it is highly correlated with a range of plant properties such as leaf mass per area, leaf lifespan and photosynthetic capacity (Reich et al. 1997, Wright et al. 2004). These parameters, in turn, are tightly linked to canopy light capture (e.g., *f*PAR), plant growth rates, turnover, and decomposition (Aber and Melillo 1991). Leaf N is thus a major target measurement in remote sensing for biogeochemical research (e.g., Wessman et al. 1988, Martin and Aber 1997). However, despite nearly two decades of research, remote sensing of leaf N remains challenging because the physical basis for N retrievals is not clear and because remote sensing data needed to retrieve N are not available over broad spatial scales. N is expressed in chlorophyll in the visible (400-700 nm) region, and in proteins in the shortwave-infrared (1500-2300 nm) range (Curran 1989). A hyperspectral remote sensing signature of a forest canopy is, however, equally or more sensitive to canopy architecture than it is to leaf chlorophyll and proteins (Asner 1998). Nonetheless, leaf N can be estimated remotely using empirical techniques, such as partial least squares (PLS) regression, which does not resolve the contribution of leaf chemistry and canopy structure to the spectral measurement (e.g., Smith et al. 2002, 2003). This fact suggests strong biophysical covariance of leaf and canopy properties in a reflectance spectrum, and this covariance is precisely what is needed to improve strength of remote sensing constraints over modeled processes. In this way, remote sensing and biogeochemical modeling require the same, ecological approach to increase both the accuracy and breadth of the measurements and simulations. Sellers (1985, 1987) was one of the first to express this well in his work on the covariance of physiological processes in plants with respect to remotely sensed signatures. Future work should continue to expand these connections, and to seek broader inter-relationships between remotely sensed and modeled properties of ecosystems.

A second need in remote sensing-modeling research is to address the inherent temporal and spatial mismatch of the observations and the simulated processes. Remotely sensed parameters are often temporally sparse, but spatially rich. In contrast, biogeochemical models require continuous time-series calculations of pertinent fluxes, but the complexity of the models often precludes a pixel-by-pixel simulation approach when high spatial resolution is required. One major research area focuses on the use of remotely sensed data in model-data assimilation (e.g., Bach and Mauser 2003, Rayner et al. 2005). Data assimilation involves a suite of approaches including: (1) model initialization from remote sensing data (e.g. land cover type), (2) update of model state variables through remote sensing (e.g. LAI), (3) remote sensing parameter adjustment through model recalibration (e.g. leaf N concentrations), and (4) estimation of model state variables through model inversion (e.g. fPAR) (Bach and Mauser 2003, Zhang et al. 2006).

Data assimilation also facilitates the integration of multi-temporal remotely sensed parameters from differing spatial sampling schemes (e.g. Landsat land-cover and MODIS phenology) into a biogeochemical and/or land-surface modeling environment. These approaches allow for temporally sparse and spatially detailed observations to be ingested into continuous modeling streams, thereby adjusting model trajectories through time. One problem in doing this, however, is that high frequency changes in vegetation properties (e.g. canopy pigments and physiology) may be missed, since neither the models nor the remote sensing data would capture these changes. On the other hand, model-data assimilation approaches tend to constrain the "solution space" of current models to a relatively tight degree, thereby decreasing uncertainty of simulated processes over time. Nonetheless, this research area continues to challenge both the remote sensing and modeling communities, and will require further attention as the sensors systems and models evolve in the future.

Finally, it seems that there has been slow recent growth in the area of remote sensing/model integration. Early on, there were rapid advances in the use of remotely sensed data from AVHRR and MODIS-like sensors in land-surface and biogeochemical models (e.g., Running et al. 1993, Potter et al. 1993, Sellers et al. 1997). As discussed, vegetation type, cover, LAI and fPAR were readily incorporated into a class of production-efficiency models born during the 1980s-1990s. Since then, however, only a few models have expanded the list of remotely sensed parameters, mainly in the area of 3-D structure (e.g., Hurtt et al. 2004, Huang et al. 2005). However, today we have a range of airborne and space-based observations of canopy properties that have yet to be fully incorporated into the terrestrial models. The use of canopy height information, in particular, represents an underutilized opportunity for modelers, in that making use of these data can require no more than the addition of simple allometric equations relating height to biomass. Such equations are commonly available from field observations and could be added to some models with minimal restructuring. In a sense, the modeling community is not keeping pace with remote sensing developments, or at least has not begun utilizing them fully, and thus a challenge for the modeling community is to develop appropriate constraints in simulations using the newest portfolio of observations now available from remote sensing. Future studies and programs should place emphasis on the co-evolution of these complimentary research areas.

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Table 1. Common biogeochemical models and the types of remote sensing observations currently used to constrain them.

Model	Remote Sensing Constraints	References
CENTURY	Vegetation Type	Parton et al. 1988a, 1998b
Biome-BGC	Vegetation Type, LAI, fPAR	Running and Hunt 1993, Running et al. 1994
PnET-II, PnET-CN	Vegetation Type, Leaf N	Aber and Driscoll 1997, Ollinger and Smith 2005
CASA-1	Vegetation Type, fPAR	Potter et al. 1993, Field et al. 1995
CASA-3D	Vegetation Type, fPAR, LAI, Tree Height, Crown Dimensions, LUE	Huang et al. 2005
SiB	Vegetation Type, fPAR, LAI, ET, Albedo	Sellers et al. 1986, 1997

Table 2. Remote sensing observations used to constrain terrestrial biogeochemical models.

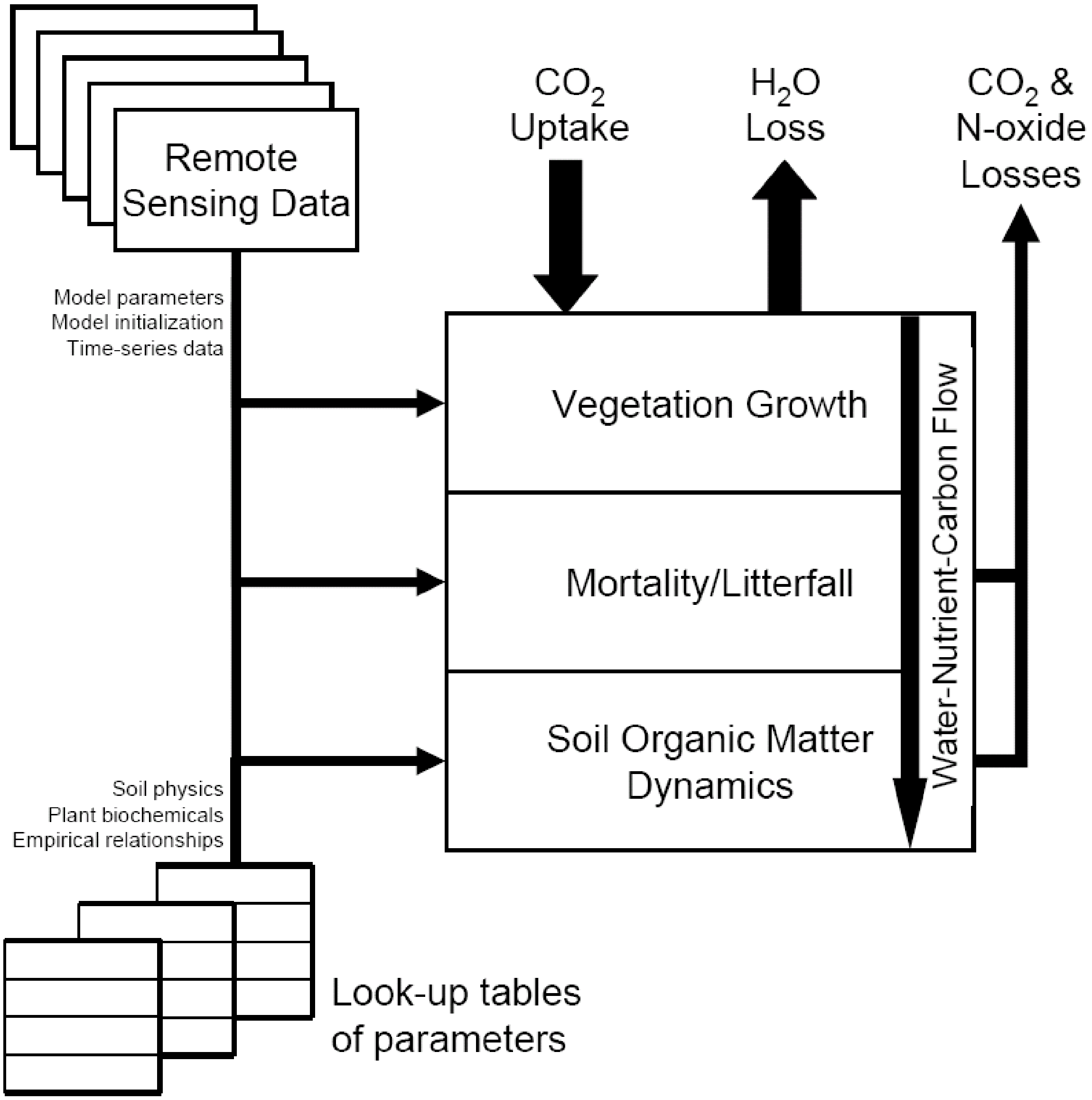
Measurement	Model Control	Typical values	Units
Vegetation Type	Many processes related to growth, phenology, litterfall, and decomposition	Broadleaf evergreen forest, shrubs, C3 grasses	categorical
Fractional PAR Absorption	Light interception, GPP, NPP	0 to 100	percentages
Leaf area index	Light interception, foliar C and nutrient stocks, GPP, NPP, ET, stress	0 to 8+	m^2 foliage/m^2 ground
Leaf Pigments	Light-use efficiency, GPP, NPP, stress	Chlorophyll a+b, carotenoid concentrations	$\mu g/cm^2$
Leaf Nitrogen	Leaf N concentration, photosynthetic capacity, site fertility, decomposition	0.4 to 5+	percentages or per leaf area
Vegetation Height, Crown Dimensions	Aboveground biomass (via field-based allometrics), C stocks, tree mortality, forest succession	0.5 to 40+	meters

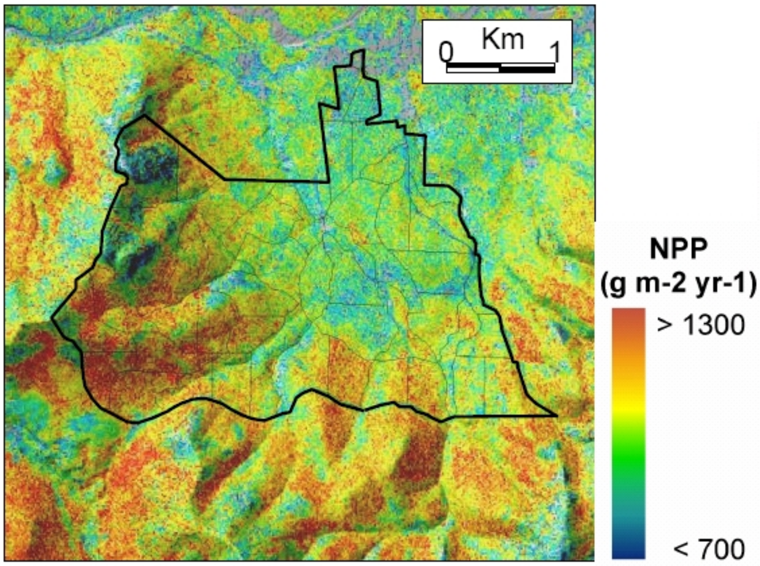
FIGURE LEGENDS

Figure 1. Despite the wide range of biogeochemical models available today, nearly all those that provide a spatially explicit rendering of ecosystem processes ultimately require geographic data from remote sensing. Some models use only a few remotely sensed parameters, such as vegetation cover and type, whereas others employ information on physiological, biochemical and structural properties of vegetation derived from airborne and satellite remote sensing. All models must balance the relative contributions of detailed spatial information from remote sensing with process-oriented data and parameterizations stored in look-up tables.

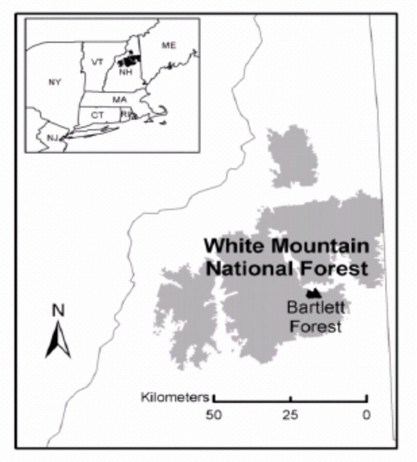
Figure 2. Remote sensing of canopy nitrogen provides a spatially-explicit and mechanistic means to constrain biogeochemical model simulations of photosynthesis, net primary production (NPP), and other ecosystem processes. Here, the NASA Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) was used to estimate leaf nitrogen concentrations throughout the Bartlett Forest in New Hampshire, USA. The nitrogen maps were then used to constrain PnET model simulations of photosynthesis and NPP. The resulting NPP maps were far more accurate than those derived simply by parameterizing leaf nitrogen from a look-up table based on vegetation type (Ollinger and Smith 2005).

Figure 3. Remote sensing of leaf pigments and canopy water content provide new ways to simulate NPP in terrestrial ecosystems. Here, the NASA Earth Observing-1 Hyperion satellite sensor was used to measure differences in leaf pigments, light-use efficiency, and canopy water content between two 1-ha rainforest stands in the central Amazon (upper left), where seasonal drought occurs (upper right). One “dry-down” forest stand (d) was treated to remove ~80% of incoming rainfall (red dot, upper left), while a control stand was left unchanged (green dot, upper left; Nepstad et al. 2002). Both stands underwent decreases in plant available water during the dry season, with the dry-down site experiencing a ~50% lower water availability than the control stand (upper right). Hyperion observations of pigments, light-use efficiency, and water captured seasonal and inter-site differences in the ratio of NPP between dry-down and control sites (d:c), whereas the traditional NDVI-based modeling approach failed to do so.

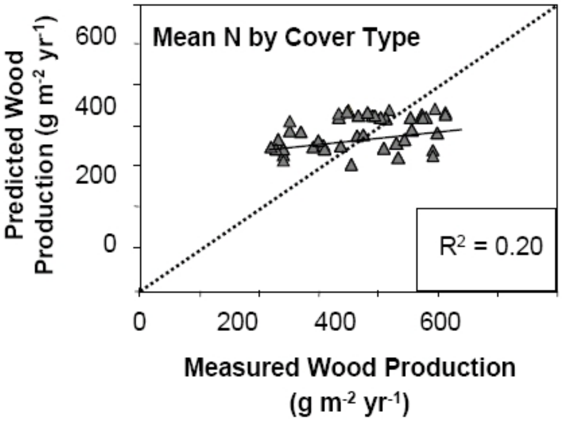

Remote Sensing Data
Model parameters
Model initialization
Time-series data
CO_2 Uptake
H_2O Loss
CO_2 & N-oxide Losses
Vegetation Growth
Mortality/Litterfall
Soil Organic Matter Dynamics
Water-Nutrient-Carbon Flow
Soil physics
Plant biochemicals
Empirical relationships
Look-up tables of parameters



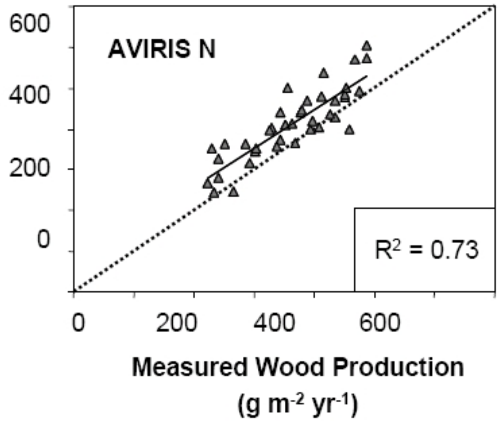
0 Km 1
NPP
(g m-2 yr-1)
> 1300
< 700



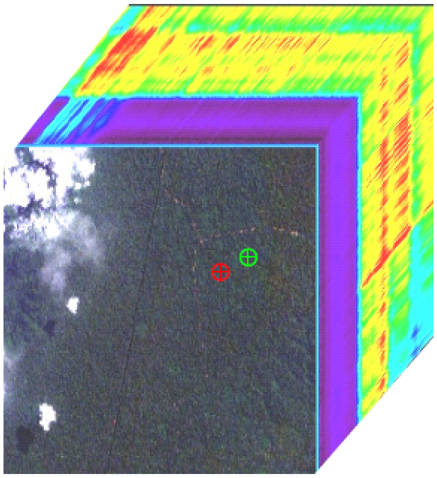
NY
VT
NH
ME
MA
CT
RI
NJ
White Mountain National Forest
Bartlett Forest
N
Kilometers
50
25
0

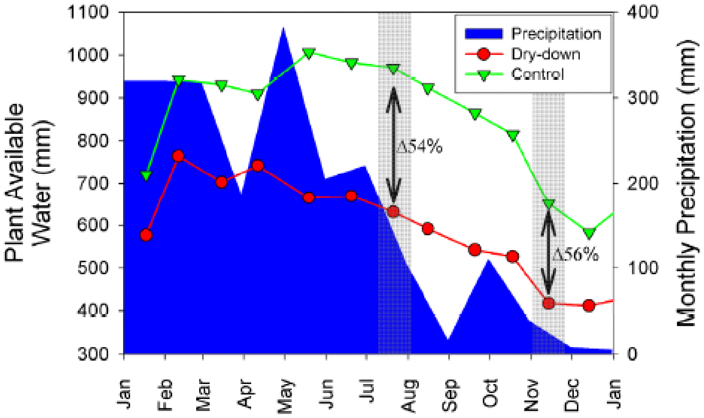


Mean N by Cover Type
R^2 = 0.20
Predicted Wood Production (g m^{-2} yr^{-1})
600
400
200
0
0
200
400
600
Measured Wood Production (g m^{-2} yr^{-1})



AVIRIS N
R^2 = 0.73
600
400
200
0
0
200
400
600
Measured Wood Production (g m^{-2} yr^{-1})





Model and Field Results	**NPP$_{d:c}$(July)**	**NPP$_{d:c}$(Nov)**	**NPP$_{d:c}$(2001)**
NDVI-NPP Model	0.99	0.98	0.98
Hyperion-NPP Model	0.81	0.42	0.67
Field NPP Data	0.84	0.55	0.73