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Scaling net primary production to a MODIS footprint in support of Earth observing system product validation

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Abstract. Release of an annual global terrestrial net primary production (NPP) data layer has begun in association with the Moderate Imaging Spectroradiometer (MODIS) sensor, a component of the NASA Earth Observing System. The task of validating this product will be complicated by the mismatch in scale between ground-based NPP measurements and the coarse resolution (1 km) of the NPP product. In this paper we describe three relevant approaches to scaling NPP from the plot level to the approximately 25-km^2 footprint of the sensor, and discuss issues associated with operational comparisons to the MODIS NPP product. All approaches revealed considerable spatial heterogeneity in NPP at scales less than the resolution of the MODIS NPP product. The effort to characterize uncertainty in the validation data layers indicated the importance of treating the combination of classification error, sampling error, and measurement error. Generally, the optimal procedure for scaling NPP to a MODIS footprint will depend on local vegetation type, the scale of spatial heterogeneity, and available resources. In all approaches, high resolution remote sensing can play a critical role in characterizing land cover and relevant biophysical variables.

1. Introduction

Global net primary production is a significant component of the global carbon budget (Schimel 1995) and is of interest as an indicator of the human influence on biogeochemical cycling at the global scale (Vitousek *et al*. 1997, Running *et al*. 1999, Rojstaczer *et al*. 2001). Satellite sensors such as the Advanced Very High Resolution Radiometer (AVHRR, Prince and Goward 1995) and the Moderate Resolution Imaging Spectroradiometer (MODIS, Justice *et al*. 1998) now achieve approximately daily global coverage at a spatial resolution of about 1 km^2 and this data is being used to estimate global NPP based primarily on light use efficiency approaches (Potter *et al*. 1993, Ruimy *et al*. 1996, Goetz *et al*. 1999, Running *et al*.

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2000, Behrenfeld *et al*. 2001). The resulting estimates of global NPP vary from 40 to $70\,\mathrm{Pg\,yr^{-1}}$ and are poorly constrained by alternative approaches to assessing global NPP, including estimates based on biome areas (Saugier *et al*. 2001), process modelling (Cramer *et al*. 1999), and inverse modelling (Denning *et al*. 1996). One strategy that will contribute to validating the satellite-based global NPP estimates is a network of sites where ground measurements are scaled to areas on the order of several satellite pixels (the sensor footprint). This paper describes three alternative approaches to accomplishing that scaling objective and discusses issues associated with operational comparisons to products from coarse resolution sensors.

A critical issue in linking ground measurements to satellite-based NPP estimates that cuts across all approaches is a mismatch in spatial scale between the coarse resolution satellite pixels and the ground measurements. The 1-km^2 resolution of the MODIS product is a compromise between the desire for daily global coverage needed for the NPP algorithm and the requirements for data processing and storage (Townshend and Justice 1988). However, NPP is typically measured in plots on the order of $1\,\mathrm{m}^2$ for low vegetation such as grassland, and up to $2500\,\mathrm{m}^2$ in taller stature forest vegetation. Thus, the satellite-based estimates are being generated at a scale that is several orders of magnitude larger than the measurement plots.

A number of viable approaches to scaling NPP over domains of multiple km^2 has been investigated. The purely 'additive' scaling approach is relatively simple, relying chiefly on a land cover map and a sample of NPP measurements within each land cover type (Schimel and Potter 1995). The NPP estimate for a given km^2 is then the weighted average NPP of the component cover types. A systematic sampling of each land cover polygon, allowing for redundancy across a cover type, is a more intensive form of the additive approach. Geostatistical approaches offer a refinement of the additive approach (e.g. Dungan 1998) but plot-level NPP measurements are labour intensive and are rarely made in sufficient number to permit those approaches. More commonly, process-based models that are initialized with high-resolution remote sensing of land cover and biophysical parameters, driven by local meteorological data and validated by dispersed NPP measurements, provide a means of locally scaling NPP (Martin and Aber 1997, Reich *et al*. 1999a).

Ultimately, a globally distributed sample of NPP validation sites is needed (CEOS 2003). The effort to validate the MODIS NPP product is currently organized under the auspices of the MODIS Land Validation Group (MODLand 2003), however, only a limited number (<10) of sites have been funded to produce new NPP validation data (Reich *et al*. 1999a, Justice *et al*. 2000). In an effort to encourage the participation of additional field sites in the validation of global NPP estimates, the Global Terrestrial Observing System (GTOS 2003) is supporting a demonstration project that is assembling contemporary field-based NPP estimates and facilitating the transfer of mid- to coarse-resolution satellite data to participating sites to aid in their local scaling efforts.

One result of expanded participation in global NPP validation is that an increasing number of data collection methods and spatial scaling approaches will be drawn upon, raising the need for comparison of the various approaches used. Although this would ideally be achieved by applying all scaling methods to each of a diverse series of research sites, the resources for such a comprehensive effort are not presently available. Nevertheless, comparing a representative series of approaches, even at a small number of non-overlapping sites, can still be informative as long as the sites chosen have been adequately characterized with field measurements, and the data limitations at each location are clearly presented.

2. Methods

An area on the order of 5 km by 5 km is needed to effectively make a comparison between the MODIS 1-km resolution NPP product and scaled NPP estimates on the ground. For smaller areas, the issue of geolocation becomes more problematic, and for larger areas the issue of sampling intensity becomes an increasing limitation. Here we report the results of three case studies in which NPP was scaled to a 25 km^2 domain.

2.1. *Case study 1, the additive approach*

In this case study, NPP was mapped with the additive approach in an area of intensively managed agricultural land in the Midwest United States. The methods are described here briefly and can be found in detail in Turner *et al.* (2002). To produce the required land cover map, a Landsat ETM+ image dating from 29 July 1999 was acquired from the MODIS Land Team website (MODLand 2003). The positional accuracy of the image was assessed by direct comparison with USGS digital orthophoto quadrangles (DOQs) of the study area. Land cover mapping was performed using an unsupervised clustering of the six ETM+ reflectance bands. Clusters were assigned to five classes: water, urban & built, barren & sparsely vegetated, corn, and soybean. This assignment was performed with reference to the DOQs, air photographs, interpreter knowledge, and spectral characteristics examined in bivariate frequency distributions. Validation of the classification was based on the 80 points sampled for NPP (see below) plus 20 additional points distributed randomly over the 25 km^2 area. Locations for all land cover validation points were registered to within several metres using an Ashtech GG-24 Surveyor Global Positioning System unit.

Two cover classes—corn and soybean—dominated the area, and to determine the mean NPP for these crop types, 80 measurements of aboveground NPP were made. A complete description of the sampling scheme and the field measurement protocols is given in Campbell *et al.* (1999). A plot was considered to be $25\,m \times 25\,m$. Plot-level aboveground NPP estimates were based on determination of plant density over the 625 m^2, and measurements of biomass per plant at the time of harvest from each quadrat of the plot. For the total NPP estimates, ANPP was converted to total NPP using an aboveground to total production ratio of 0.9 (Gower *et al.* 1999).

To obtain complete land surface coverage of NPP, corn and soybean cells were assigned their respective mean NPP from the measurements and non-crop cells were assigned an NPP of zero.

2.2. *Case study 2, the forest inventory approach*

Forest inventories in many regions of the world provide spatially distributed data potentially useful for estimating NPP. Notably, the forest inventory system in Russia collects consistent and detailed stand-level information on millions of ha annually (Krankina *et al.* 1998). In this case study, the Russian inventory data were used to develop an NPP data layer for an area of boreal forest in the north-western part of the country.

Under Russian protocols, homogeneous forest polygons ($\sim$0.5–50 ha) within a forest management unit are initially mapped based on management history and air photos. A standard set of data gathered in the field for each polygon includes tree species composition, mean height, diameter and age, canopy structure, wood volume, and characteristics of different types of land without tree cover (e.g. clearcuts, bogs, meadows). Over 200 different variables measured or visually estimated in the field are used to describe the polygons, depending on the land-cover category and the management requirements for a given forest management unit (Kukuev *et al.* 1997).

For this case study, a sample was extracted from a set of forest inventory data that was compiled by the Northwestern Forest Inventory Enterprise (St. Petersburg, Russia) for purposes of a joint research project with the Oregon State University (Krankina *et al.* 1998). The data were spatially referenced to a Landsat TM image and a $5\,\mathrm{km} \times 5\,\mathrm{km}$ study area was selected. The selection was made among the 25-km^2 cells with available ground data based on two considerations: (i) the greatest number of stand polygons for which the area and vegetation cover type could be verified with Landsat imagery; (ii) a maximum area coverage with closed-canopy forests within the cell. In the selected cell, 2205 ha out of the 2500 ha of land area were covered by ground data. Based on the Thematic Mapper classification, the area that was not covered included 114 ha of developed land and 181 ha of forest. The nonforest areas were aggregated into two land-cover types: unvegetated (buildings, pond, stream) and grasslands (clearings, tertiary roads, young plantations, transmission lines, ditches, clearcuts).

Fields that indicate the dominant species, the volume of live stem and bark, the site productivity class, and the average age of trees for the dominant species were retrieved from the forest inventory records. For each record the stem volume per hectare was converted to biomass using allometric conversion factors, then an estimate of understory biomass was added. This method and the associated allometric equations were developed by Alexeyev and Birdsey (1998) based on a compilation of biomass measurements in research plots from north-west Russia. Total aboveground biomass was estimated for each forest stand, and age was used to compute the mean annual increment (MAI) in terms of biomass increment per year averaged over the life of the stand. The current annual increment may be underestimated in young stands and overestimated in older stands using this approach because of changes in growth rates over the course of succession. After conversion of biomass to carbon (a factor of 2), generalized empirical relationships developed by Gower *et al.* (2001) were used to estimate annual production of branches and foliage to yield aboveground NPP (ANPP). For evergreen species:

$$\mathrm{ANPP}\left(\mathrm{gC\,m}^{-2}\right) = 42 + 2.34 \times \mathrm{MAI}. \tag{1}$$

And for deciduous species:

$$\mathrm{ANPP}\left(\mathrm{gC\,m}^{-2}\right) = 80 + 2.62 \times \mathrm{MAI}. \tag{2}$$

Subsequently another generalized equation (Gower *et al.* 2001) was used to account for belowground production. For all species:

$$\mathrm{NPP} = 114 + 1.21 \times \mathrm{ANPP}. \tag{3}$$

These calculations were performed for 506 polygons, and final NPP values were converted back to biomass. The average values of NPP and their standard deviations were determined for different categories of forest stands (table 1).

Forest land not covered by ground data was assumed to have the average NPP associated with the remaining forest area. NPP was assumed to be 0 for

Table 1. NPP estimates in forests of different species and age class (case study 2).

Species	Age	Number of observations	NPP, $g\,m^{-2}\,yr^{-1}$ (mean $\pm$ STD)
Pine	<41	1	962
	41–80	15	786 ± 142
	>80	52	722 ± 100
	All ages	68	740 ± 116
Spruce	<41	22	710 ± 256
	41–80	115	938 ± 224
	>80	174	850 ± 136
	All ages	311	874 ± 192
Birch	<41	8	1150 ± 276
	41–80	50	1290 ± 228
	>80	2	1056
	All ages	60	1264 ± 238
Aspen	<41	2	824
	41–80	65	1292 ± 194
	All ages	67	1280 ± 208
All species	All ages	506	956 ± 268

unvegetated lands, and the average productivity of grasslands in the region ($1250\,g\,m^{-2}\,yr^{-1}$, Basilevich 1993) was assigned to the grassland area.

2.3. *Case study 3, the spatially explicit modelling approach*

This case study involved the use of remotely-sensed canopy nitrogen in combination with a process-based productivity model. The value of detecting canopy nitrogen stems from well-known relationships between foliar N concentrations and maximum net photosynthesis or Amax (Reich *et al.* 1995, 1999b). Because photosynthesis is the basis of carbon acquisition in plants, spatial coverages of canopy N should provide useful information about spatial patterns of ecosystem productivity. In theory, this could be realized either through direct empirical relationships between canopy N and measured NPP, or through the use of canopy N in process models. The former approach is appealing for its simplicity, but the challenge of making the necessary measurements over large numbers of plots and the potentially confounding effects of other environmental factors (e.g. moisture limitations) pose considerable hurdles to its widespread application. Process models offer another approach to estimating NPP from remotely-derived canopy N coverages because models typically have the capacity to use additional site and climatic information to scale Amax to realized photosynthetic rates.

To explore this potential, the approach undertaken here relied on incorporation of remotely-sensed estimates of canopy nitrogen concentration into a forest process model known as PnET-II. PnET-II (Aber *et al.* 1995, Ollinger *et al.* 1998), developed in the north-eastern US and validated in a number of temperate forest systems, is a monthly time-step model of water and carbon balances (gross and net) in which the productive potential of forest canopies is dependent on the relationship between photosynthetic capacity and canopy nitrogen and on the scaling of leaf structure and function through the canopy. In this case study, spatial estimates of NPP were produced for a $5\,km \times 5\,km$ area of the Bartlett Experimental Forest (BEF), New Hampshire, USA by integrating the model with a coverage of canopy-level foliar nitrogen concentrations derived from airborne imaging spectrometer data.

To produce the canopy-level nitrogen coverage, hyperspectral remote sensing data from NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS, Green *et al.* 1998) were obtained for the BEF and surrounding White Mountain National Forest. AVIRIS data for BEF were acquired on 12 August 1997 under nearly cloud-free conditions with a nominal spatial resolution of 20 m. AVIRIS at-sensor radiance data were transformed to apparent surface reflectance using the ATmosphere REMoval program (ATREM) of Gao *et al.* (1993). AVIRIS images were then georeferenced through image registration to a geo-coded SPOT panchromatic coverage of the study area.

Along with the AVIRIS image acquisition and as part of a related study, 48 0.1 ha plots at BEF were sampled for foliar N concentrations and aboveground productivity (Smith *et al.* 2002). Plot elevations ranged from approximately 200 to 800 metres. Major tree species include sugar maple (*Acer saccarum* L.), American beech (*Fagus grandifolia* Ehrn.), paper birch (*Betula papyrifera* Marsh.), yellow birch (*Betula alleghaniensis* Britt.), red maple (*Acer rubrum* L.), eastern hemlock (*Tsuga canadensis* L. Carr.), red spruce (*Picea rubens* Sarg.) and balsam fir (*Abies balsamea* (L.) Mill.). Most plots contained mixtures of two or more species.

Foliar sampling allowed atmospherically-corrected AVIRIS spectral data to be calibrated directly to field-measured canopy N concentrations for creation of a canopy N coverage. Plot-level whole canopy nitrogen concentrations (g N per 100 g foliar biomass) were calculated as the mean of leaf-level values for individual species in each stand, weighted by fraction of canopy foliar mass per species (Smith and Martin 2001). Field-based estimates of aboveground wood production were derived from sequential stem diameter surveys (1992, 1998) converted to biomass via allometric equations. Complete descriptions of the sampling scheme and of the field and lab measurement protocols are summarized in Smith *et al.* (2002) and Ollinger *et al.* (2002a).

AVIRIS reflectance spectra for 2×2 pixel areas covering each plot coupled with field measured foliar chemistry from these same plots were used to develop predictive equations for the estimation of canopy nitrogen. Relationships among plot-level spectral response and canopy-level nitrogen concentration were examined using a full spectrum analytical method—Partial Least Squares (PLS) regression (Kramer 1998). The PLS calibration approach, developed using first difference derivative absorbance spectra, produced robust canopy-level nitrogen calibrations both within (BEF; $R^2 = 0.84$) and among ($R^2 = 0.82$) AVIRIS scenes (Smith *et al.* 2002). Coverages are used as direct scalars of ecosystem process (e.g. Ollinger *et al.* 2002a) and, as in this exercise, as driving variable input data for spatially explicit ecosystem process models.

PnET-II requires a number of input parameters summarizing vegetation and site characteristics, along with monthly climatic data. Foliar N is perhaps the most important of the vegetation variables because it relates directly to canopy photosynthetic capacity. Other vegetation parameters include leaf mass per area (LMA), leaf retention time and growing-degree day variables describing the phenology of leaf production and senescence. A complete description of PnET's vegetation parameters is given by Aber *et al.* (1995). Required climatic and environmental inputs include temperature, precipitation, solar radiation, and soil water holding capacity (WHC).

For pixel-by-pixel application at BEF, PnET-II was run in conjunction with the AVIRIS-derived foliar N coverage and a 20 m resolution DEM. For each pixel, geographic coordinates and elevation were used to calculate maximum and minimum temperature, vapour pressure, precipitation and solar radiation (30 yr mean, Ollinger *et al*. 1998). Data for soil water holding capacity (WHC) were not available for BEF, so a value of 120 mm was assumed based on data from the nearby Hubbard Brook Experimental Forest (Federer and Lash 1978) and regional estimates for glacial till soils with 1 m rooting depth.

NPP was modelled and mapped at a 20 m resolution. For each grid cell, the relative proportions of deciduous and evergreen forests were determined from the imagery, and the foliar N concentration of each cover type was estimated from the observed linear relationships between AVIRIS-estimated whole-canopy N and measured values for the deciduous and evergreen components of the field plots. Vegetation-specific input parameters such as LMA and leaf retention time were determined for each forest type using data from field measurements.

3. Results

3.1. *Case study 1*

The land cover map indicated that close to 90% of the study area was classified as corn or soybean, with nearly equal proportions of the two crop types. Classification accuracy was 94%. The mean measured NPP for the soybean plots was 1180 ($\pm$218) $g\,m^{-2}\,yr^{-1}$ and that for corn was 2159 ($\pm$558) $g\,m^{-2}\,yr^{-1}$. The field sizes were much smaller than the 1-km grid that will be associated with the 1-km MODIS NPP product (figure 1). Thus the average NPP for any 1-km grid cell was intermediate between the mean NPPs of the two crop types. For the 25 1-km cells, the standard deviation (260 $g\,m^{-2}\,yr^{-1}$) was small relative to the mean (1482 $g\,m^{-2}\,yr^{-1}$).

3.2. *Case study 2*

The average value of NPP varied widely among the forest stands as a function of species and age class (table 1, figure 2). NPP was generally higher in forests dominated by hardwoods than in those dominated by conifers, and forests between

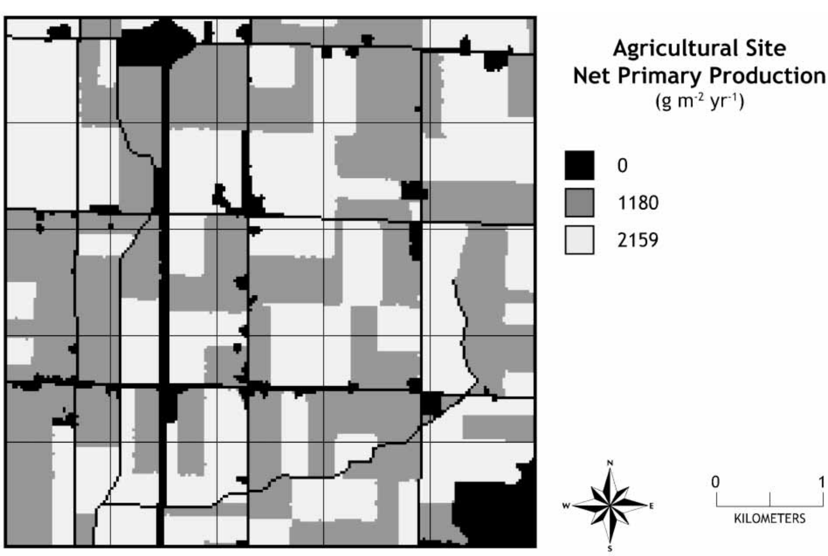

Figure 1. NPP data layer for the agricultural site generated using the 'additive' approach.

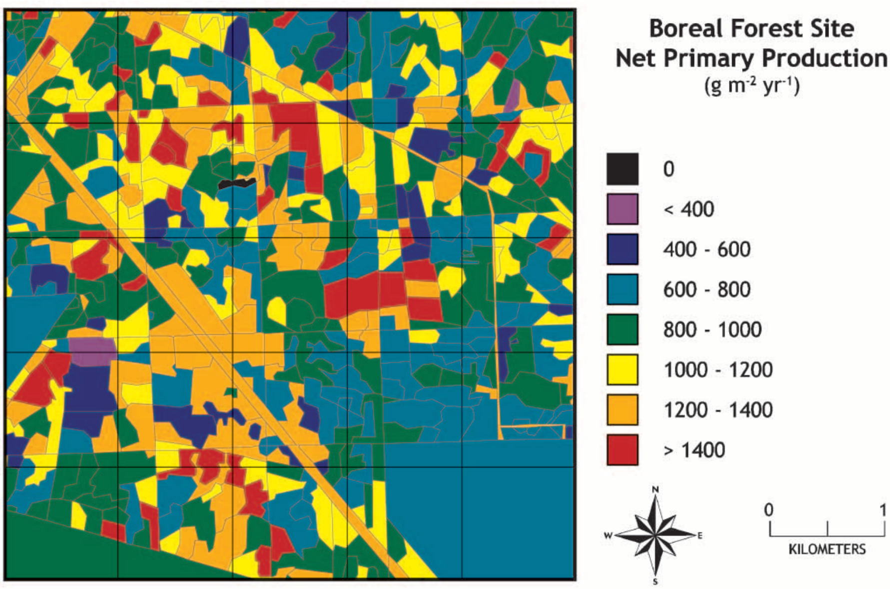

Figure 2. NPP data layer for a boreal forest area generated using the forest inventory approach.

ages 40 and 80 had higher NPP than forests outside this age group. Any 1-km cell had multiple polygons, with often large variation in NPP among them (figure 2). As with case 1, the standard deviation among the 25 cells ($124\,\mathrm{g\,m^{-2}\,yr^{-1}}$) was small relative to the mean ($953\,\mathrm{g\,m^{-2}\,yr^{-1}}$).

3.3. *Case study 3*

Simulated NPP across BEF at a 20 m pixel resolution ranged from less than 600 to greater than $1200\,\mathrm{g\,m^{-2}\,yr^{-1}}$ with a mean of 951 (± 110) $\mathrm{g\,m^{-2}\,yr^{-1}}$ (figure 3). At a 1-km pixel resolution, the mean and standard deviation of the resulting 25 cells was of a narrower range, 914 (± 67) $\mathrm{g\,m^{-2}\,yr^{-1}}$. In general, areas of lower productivity represent higher elevation or shallow soil sites dominated by needle-leaved evergreens, red spruce and hemlock. Mid-range values represent areas of mixed deciduous and evergreen forest (hemlock, red maple, American beech) on either coarse-textured or poorly drained soils. The highest values represent deciduous forest dominated by sugar maple, white ash, yellow birch growing on deep, fine textured soils or early-successional deciduous species stands dominated by pin cherry and paper birch.

Model performance was evaluated by comparing predictions for wood production with the field-measured estimates obtained by Smith *et al.* (2002). Wood production estimates were averaged over 2×2 cell windows oriented around the plot centres. Wood production is presented because (i) many more independent validation data were available for wood growth than for other components of productivity, (ii) allometric estimators of aboveground biomass developed for the forest types of this region are quite robust (Arthur *et al.* 2001), and (iii) because wood growth is typically the largest single component of NPP in temperate forests. Allocation to wood production also has the lowest priority in PnET-II and is least constrained by the model's structure (Aber *et al.* 1995). This makes wood

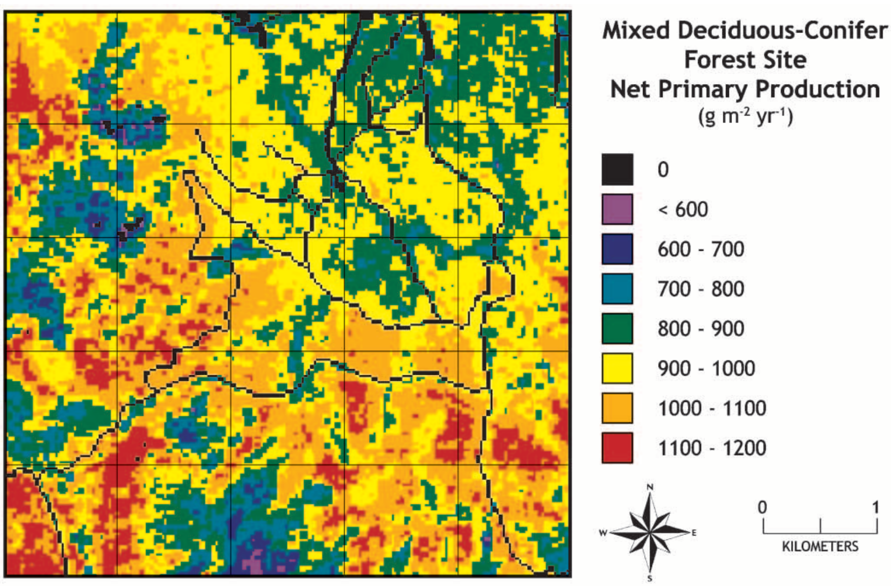

Figure 3. NPP data layer for a mixed conifer-deciduous forest generated using the process model scaling approach.

production a rigorous test of the model's carbon allocation routines and provides a reasonable, although incomplete, test of predicted NPP. Other components of NPP (most notably roots) could not be validated because they were not included in the field measurements.

Overall, model predictions corresponded well with measured values (figure 4).

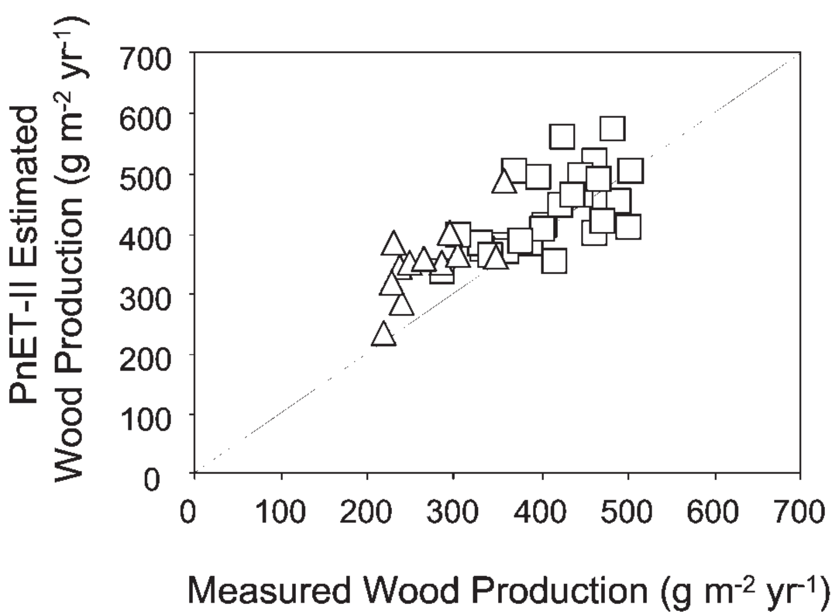

Figure 4. Comparison of model-simulated and measured wood production in a mixed conifer/deciduous forest.

The r^2 of predicted versus observed values was 0.55 with a standard error of $49.7\,g\,m^{-2}\,yr^{-1}$ or 13.6% of measured mean woody biomass production. Model predictions overestimated measured values by approximately 13%. This bias could arise from errors in the model or differences between the specific plant tissues included in the modelled versus measured values. In PnET, wood production includes woody roots as well as aboveground stem plus branch production. Measured wood production was derived from allometric equations that include standing woody tissues (stem, branch, bark, etc), but not woody roots or woody litter. Whittaker *et al.* (1974) estimated that woody root biomass at the Hubbard Brook Experimental Forest was approximately 10% of total wood biomass, hence this difference in calculation between allometrically-derived and modelled estimates alone could account for a large fraction of the discrepancy.

4. Discussion

4.1. *The scale of spatial heterogeneity in NPP*

In each of the case studies, there was considerable heterogeneity in NPP within most 1-km grid cells. At the agricultural site, the original ownership units were 640-acre ($1.6\,km \times 1.6\,km$) sections and these are typically managed as quarter sections ($800\,m \times 800\,m$) or less. Within a management unit there was also significant heterogeneity in NPP that appeared to be associated with microtopographic gradients (i.e. on the order of 1 m elevation difference between hilltop and swale). A surprisingly large amount of heterogeneity in soil resources and NPP is commonly found even in fields that have been plowed and cropped for decades (Robertson *et al.* 1997).

At the boreal forest site, sub 1-km grid scale heterogeneity is associated primarily with differences in site drainage, which are driven by microtopography and soil texture. This heterogeneity was shaped by the repeated glaciations during the Quaternary period (Lyufanov 1983). Better-drained sites in boreal forests are generally more productive than adjacent more poorly drained sites (O'Connell *et al.* in press). The area in this study has also been logged repeatedly, which created an additional source of heterogeneity.

At BEF, fine scale heterogeneity is introduced by a variety of factors, including topography, soil parent material, vegetation type and site history, although these do not always vary independently. The topography of BEF is complex, with elevations ranging from 200 to over 900 m across valleys and several mountain summits. Most soils were derived from coarse-textured glacial tills, but there are also areas of fine till or outwash, as well as shallow bedrock at upper elevations (see Leak 1982 for description of soils at BEF). Vegetation type and condition are affected by both topography and soils (via their influence on climate and moisture availability), but another important factor is historical disturbance. Most of Bartlett has been harvested at least once since the early 1800s, with about half of the $5\,km \times 5\,km$ area remaining in active forest management (Leak and Smith 1996). Portions of the area were also affected by a post-logging slash fire in the late 1800s, although the complete extent and severity of fire occurrence is not known with certainty. In aggregate, these disturbances are known to have significant long-term consequences on species composition, soil N availability and canopy N concentrations (Ollinger *et al.* 2002a), all of which should translate to variation in present-day NPP.

The presence of sub-kilometre scale heterogeneity suggests that the validation data layers should generally be developed at relatively fine spatial resolution and then aggregated by area weighted averaging to obtain NPP estimates for comparison to the 1-km MODIS cells. In principle, it shouldn't matter if there is sub-kilometre grid scale heterogeneity, as long as the MODIS algorithm is successful in producing the correct average value. However, in practice, fine-scale heterogeneity may be important because it can affect the accuracy of the derived validation layers (e.g. Reich *et al.* 1999a, Jenkins *et al.* 1999), as well as the methods chosen to create them. Considering the issues associated with precisely co-locating MODIS grid cells and validation grid cells (see below), it may be desirable to choose validation sites where the standard deviation among the 25 1-km cells is relatively low. Analysis of local variance in spectral vegetation indices at different spatial resolutions has been suggested as a possible tool for screening the land surface with regard to spatial heterogeneity (Turner *et al.* 2000, Rahman *et al.* 2003).

Another aspect of characterizing the scale of the heterogeneity is a constraint on the scale of NPP measurements. Because the measured productivity of a forest stand represents the contribution of multiple trees of varying size and species designation, there is a minimum plot size (and minimum number of plots) below which the measurements may not be representative of stand variability (Schreuder *et al.* 1993, Clark *et al.* 2001). That minimum plot size (e.g. $\sim$0.1 ha for forest systems; see Williams 2001, Schifley and Schlesinger 1994, Gonzales *et al.* 1993) is approximately the same as the pixel size for ETM+ and AVIRIS, which makes these sensors particularly appropriate for NPP scaling analyses. However, the agreement in plot size and pixel size also means that close attention must be paid to co-registration of the imagery and the plot data. Averaging reflectances or model outputs over multiple pixel windows oriented around the plot centre is usually used to help minimize problems with co-registration.

4.2. *Characterizing uncertainty*

To be useful for the purpose of validating the MODIS NPP product, uncertainties in a scaled NPP data layer for a specific MODIS footprint would have to be small relative to the reported differences between the MODIS NPP and the validation NPP. Factors potentially contributing to error in the validation data layers will include classification error, measurements error, sampling error, and model error.

4.2.1. *Classification error*

The scaling algorithms for the three case studies all rely upon classification of the land surface with remote sensing imagery. The additive approach is particularly sensitive to classification error because cover class becomes the sole determinant of NPP. The general availability of digital reflectance data at relatively high spatial and spectral resolutions has resulted in considerable progress in the specificity with which the land cover can be classified. Accurate classifications have been made based on vegetation cover type (Steyaert *et al.* 1997), successional stage (Cohen *et al.* 1995, Moran *et al.* 1994), and species composition (Martin *et al.* 1998). Classification error can be assessed by field checks of points not used in the mapping analysis, as was done in the additive case study here. Classification error will decrease as the number of classes decreases, but highly aggregated classes may subsume heterogeneity relevant to scaling NPP so may not be appropriate.

4.2.2. *Measurement error*

Two of the case studies (1 and 2) rely on biomass or NPP measurements in their scaling algorithm, and the other (case 3) used field-based productivity measurements in the evaluation phase. Measurement error is the uncertainty associated with the measurement technique. While the theoretical definition of NPP is quite simple (gross primary production – autotrophic respiration), many components of NPP are difficult or impossible to quantify because of their inaccessibility (e.g. fine roots) or because they are transformed or leave the system between measurement intervals (e.g. via herbivory, root exudates, volatile organic carbon emissions). The components of NPP that typically *are* estimated (e.g. leaf and aboveground wood growth) are still subject to measurement error, especially among perennial vegetation of large stature such as forests (Clark *et al.* 2001). Clark *et al.* noted that most of the problems associated with NPP measurement methods result in underestimation, rather than overestimation, and collectively, can cause substantial systematic bias ($>200\%$ in one cited case study). In a strict sense, NPP cannot be directly measured, but must be approximated by a combination of direct and indirect methods. In practice, an NPP measurement usually amounts to quantifying the accumulation of the largest biomass pools (typically aboveground) over a period of one or more years. A recent survey of extant NPP measurements for tropical and boreal forests found just a few dozen well documented and virtually complete measurements of NPP for these forest ecosystems (Clark *et al.* 2001, Gower *et al.* 2001).

The corn and soybean in case study 1 represent perhaps the simplest possible case of NPP measurement. Both plants are annuals, and total NPP is based on aboveground biomass at the time of harvest and a ratio for belowground NPP to aboveground NPP derived from numerous previous studies. In other herbaceous or grassy cover types, issues such as herbivory, periods of growth separated by drought-induced dieback (Knapp *et al.* 2001), and a large, poorly quantified, allocation below ground become significant (Gower *et al.* 1999). In the boreal and temperate forest case studies, only wood volume and stand age were established by field measurements and then used to estimate production. Because of its economic significance, foresters have paid close attention to estimation of wood volume, thus the measurement error there was probably low. However, foliage and fine root production are approximately half of total production and allocation varies widely among biomes (Mahli *et al.* 1999). In the boreal forest study, MAI proved to be a better predictor of NPP than other often used variables such as leaf area index and biomass (Gower *et al.* 2001), however, the potential error with respect to estimation of total NPP in the forest polygons remained significant considering the r^2 value (0.6).

4.2.3. *Sampling error*

Sampling error refers to the degree to which the mean and distribution of measured productivity within a land cover class represents the true mean and distribution. It is particularly important in the additive approach. As noted earlier, logistical constraints generally restrict the number of growth measurements that can be made, so the issue of optimizing sampling design is an important one. There is often significant autocorrelation around any given point, and the optimal sampling scheme would avoid placement of samples too close together. Remote sensing can potentially help in this regard because vegetation indices such as the Normalized

Difference Vegetation Index (NDVI) are used in estimating vegetation production (e.g. Prince and Goward 1995) and the distribution of NDVI could be used to indicate the scale of the autocorrelation and hence contribute to designing the optimal sampling scheme.

4.2.4. *Model error*

The distributed process model scaling approach (case 3) introduces a variety of additional uncertainties that stem from errors in both data inputs and model algorithms. Process-based NPP models are typically driven by meteorological data that are either extrapolated from a base meteorological station within the study area (e.g. Running *et al.* 1987), or interpolated among an array of regional meteorological stations (Thornton *et al.* 1997). In PnET, meteorological data has a significant impact on the simulated NPP in the northeastern US, with deciduous stands being more sensitive to precipitation inputs and evergreen stands being more sensitive to temperature and growing season length (Ollinger *et al.* 1998). Both original meteorological data (e.g. McKennney *et al.* 1996) and algorithms used for distributing that data (e.g. Dodson and Marks 1997) have limitations, and their accuracy should be considered when interpreting model predictions. While these meteorological data sets are beneficial for coarse environmental gradients, they often ignore finer-scale factors such as cold air drainage, which may also influence growth.

Other spatially explicit input data layers that influence model-based NPP estimates include cover type, leaf area index (LAI), foliar nitrogen content, and soil water holding capacity (WHC). Of these, the PnET model is typically most sensitive to foliar N because of its effect on net photosynthesis. In the absence of foliar N data, the model is run using fixed values assigned to each cover type. However, in case study 3, spatial estimates of canopy N were obtained for BEF from the AVIRIS remote sensing instrument, providing a level of detail that is usually absent at most study sites.

Vegetation cover type is an important constraint in model-based approaches because it determines the specification of physiological properties such as maximum stomatal conductance and leaf retention time. The sensitivity of the model outputs to classification error will depend in part on the degree of difference in the physiological properties of the different cover types. LAI and the fraction of photosynthetically active radiation absorbed by the canopy (f_{APAR}) can also be estimated from remote sensing (e.g. White *et al.* 1997) but limitations include the problems of saturation in the relationships of spectral vegetation indices to foliage amounts at high LAI (Turner *et al.* 1999), recurrent cloudiness (often addressed with maximum valued temporal compositing, Holben 1986), and atmospheric effects on the reflectance data that must be corrected with radiation transfer modelling (Ouaidrari and Vermote 1999).

Mapping of soil water holding capacity based on State Soil Geographic databases is possible but has large uncertainties, particularly at fine spatial scales (Kern 1995, Zheng *et al.* 1996). In case study 3, WHC was held constant because spatial data were not available at the appropriate scale and because foliar nitrogen was a more readily mapped indicator of NPP potential. In the western US, LAI and NPP are strongly correlated with site water balance (Grier and Running 1977, Gholz *et al.* 1982) and soil WHC is more important. Indeed, remotely sensed LAI has been used to infer soil depth in coniferous forests of the Pacific Northwest because LAI is so strongly regulated by site water balance (Turner *et al.* 2003a).

Beyond the uncertainties in the input data layers is the issue of the effectiveness of the model itself. Verification (*sensu* Rykiel 1996) is concerned with ensuring that the intended logic in the algorithms is implemented by the computer code. A general approach to verification includes model runs covering the range of conditions over which the model is intended to operate. Results should be interpretable based on the model formulation and the spatially varying inputs.

The term 'validation' may not be useful with respect to computer process models because there is often a multitude of ways to get the 'right answer' for the wrong reason. Comparisons of model simulations with field-based productivity estimates can reveal if the model is performing adequately for the intended purpose. A plot of predicted versus observed values can show possible bias, and a root mean square error or standard error of the estimate will indicate departure from field observations (e.g. figure 4). As noted earlier, the availability of NPP measurements for one-to-one comparisons may be limited because of logistical constraints on NPP measurements.

Simple comparisons of observed and modelled annual NPP can be augmented in some cases with comparisons of shorter time step model outputs such as daily gross primary production (Aber *et al.* 1996, Reich *et al.* 1999a). At sites with eddy covariance flux towers, the tower measures net ecosystem exchange (NEE), but gross primary production is commonly derived as NEE minus ecosystem respiration (Re) during daylight periods (Goulden *et al.* 1996a, Turner *et al.* 2003b). Re is based on the daytime temperature and the relationship of night-time temperature to NEE. Flux tower estimates of evapotranspiration (ET) also offer possibilities for evaluating modelled ET.

4.3. *Operational comparison of MODIS products and validation data layers*

Achieving direct comparisons between validation site NPP data layers and those based on MODIS imagery will require close agreement in space and time. ETM+ digital data can be registered to the nearest several metres within conventional coordinates systems such as Universal Trans Mercator (UTM) or Albers Equal Area. Global Positioning System instruments likewise make it possible to establish the location of field measurement plots to the nearest several metres. In contrast, the georegistration of the MODIS products is nominally to the nearest 0.1 km (Justice *et al.* 1998). An additional georegistration uncertainty will be introduced if the MODIS data is reprojected from its native Integerized Sinusoidal Projection (Masuoka *et al.* 1998) to a more conventional coordinate system. The 1-km cell size of the MODIS NPP products will mean potentially large reprojection errors relative to the certainty about the georegistration of ETM+ based validation data layers. The most rigorous comparisons may therefore require that the ETM+ validation data layers be reprojected to the MODIS coordinate system (W. Cohen, USDA Forest Service, Corvallis, OR, personal communication). Average values of NPP across the ETM+ cells within a MODIS cell could then be compared directly with the MODIS value for that cell.

The MODIS NPP product will be responsive to interannual variation in absorbed photosynthetically active radiation and surface meteorological conditions (Running *et al.* 2000), thus an ideal comparison to validation data would be for a specified year. An indication of the importance of interannual NPP variation is the observation that at the agricultural site in case study 1, mean NPP for corn and soybean were 20% less in 2000 than 1999. Multiple year observations at eddy covariance flux towers also indicate large interannual variation in carbon flux (Goulden *et al*. 1996b, Barford *et al*. 2001).

The temporal coupling of validation measurements to MODIS products will be straightforward in some cases but not others. For northern temperate zone vegetation, the validation measurements are simply made in the calendar year associated with the MODIS NPP product. Southern hemisphere MODIS NPP will still be based on the calendar year and thus be split between two growing seasons. Woody vegetation will present additional issues because wood production is measured in a variety of ways but is most often reported as a multi-year mean (Gower *et al*. 1999). Hence the degree of coupling between the MODIS products for a given year and the validation products will be moderated. In that regard, the process model scaling approach is desirable because it can use current year meteorological data to drive the model. For example, in an analysis of temporal patterns at the Hubbard Brook LTER site, PnET model estimates indicated interannual variation in wood growth due to climate variation that was approximately 7% of the mean over a 100-year period (Ollinger *et al*. 2002b).

Conclusions

Operational monitoring of global NPP has begun with the EOS MODIS sensor, and validation of the annual NPP products will require a network of sites where NPP can be accurately scaled to the MODIS footprint ($\sim 5\,\text{km} \times 5\,\text{km}$). Because of the great diversity in ecosystem structure and function, and the desirability of including as many validation sites as is possible, there will be a variety of NPP scaling approaches implemented. An additive approach may be appropriate in situations where classification is not problematical and an adequate sampling is made of NPP throughout each cover type. Forest inventory can provide the basis for scaling NPP but the dependence on allometry to estimate total NPP from wood or biomass production increases uncertainty. Scaling NPP with process-based models serves to integrate a great deal of information on climate, soils, land cover, and surface biophysical properties, but brings the added challenge of deriving high quality input data sets and developing models that accurately simulate observed patterns of growth. Some of the input data can be provided by high-resolution satellite or airborne sensors. For all approaches, it will be important to characterize uncertainty in plot-level NPP measurements used in the scaling procedure.

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