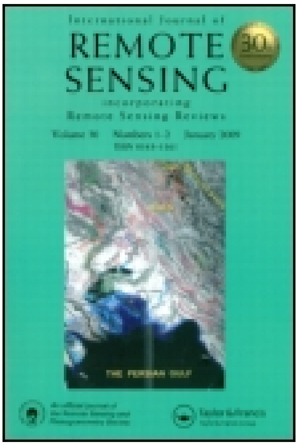

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Use of pixel- and plot-scale screening variables to validate MODIS GPP predictions with Forest Inventory and Analysis NPP measures across the eastern USA

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Moderate Resolution Imaging Spectroradiometer (MODIS) estimates of gross primary production (GPP) were validated using field-based estimates of net primary production from the Forest Inventory and Analysis (FIA) Program across the eastern USA. A total of 54 969 MODIS pixels and co-located FIA plots were analysed to validate MODIS GPP estimates. We used a data resolution of individual MODIS pixels and co-located FIA plots, and used detailed pixel- and plot-specific attributes by applying screening variables (SVs) to assess conditions under which MODIS GPP was most strongly validated. Eight SVs were used to test six hypotheses about the conditions under which MODIS GPP would be most strongly validated. The six hypotheses addressed were (1) MODIS pixel quality checks, (2) FIA plot quality checks, (3) land-cover classification comparability of co-located MODIS pixels and FIA plots, (4) FIA plot homogeneity, (5) FIA plot tree density and (6) MODIS seasonal variation. SVs were assessed in terms of trade-off between improved relations and reduced number of samples. MODIS seasonal variation and FIA plot tree density were the two most efficient SVs, followed by basic quality checks for each data set. Sequential application of SVs indicated that combined usage of five of the eight SVs provided an efficient data set of 17 090 co-located MODIS pixels and FIA plots, which raised the Pearson correlation coefficient from 0.01 for the Complete data set of 54 969 plots to 0.48 for this screened subset of 17 090 plots. The screened subset of plots exhibited good representation of the Complete data set in terms of species abundance, plot distribution and mean productivity. We conclude that the application of SVs provides a useful approach to ensure compatibility of two data sets for broad-scale forest carbon budget analysis and monitoring.

1. Introduction

Monitoring of the forest carbon cycle over large areas provides valuable information for a variety of applications including managing wood supply for the forest industry (Bettinger *et al*. 2009), balancing the carbon budget (Turner *et al*. 1995, Birdsey 1996) and identifying the imprint of climate change (Nemani *et al*. 2003, Nakawatase

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and Peterson 2006). The carbon cycle in vegetation has three major components: gross primary production (GPP), autotrophic respiration (AR) and net primary production (NPP), which is equal to GPP minus AR (DeLucia *et al*. 2007). The two basic approaches to monitoring the carbon cycle are field-based (Clark *et al*. 2001) and remotely sensed (Prince and Goward 1995) approaches. Field-based approaches have the advantage of accurate measures of NPP for the measured plots and the disadvantage of the spatial coverage being limited to just the plots, whereas remotely sensed approaches have the advantage of spatially extensive predictions of GPP and the disadvantage of an unknown prediction accuracy for different environments.

In terms of field-based monitoring, many countries have a national forest inventory that uses field methods, such as the Forest Inventory and Analysis (FIA) Program in the USA (McRoberts *et al*. 2005a), the Finnish National Forest Inventory (Tomppo *et al*. 2008), the Canadian Forest Inventory (Gillis *et al*. 2005) and the more loosely organized Russian Forest Inventory (Houghton *et al*. 2007). The US FIA Program adopted a standardized nationwide inventory methodology in 1998 that enables spatially unbiased and timely monitoring of the amount and health of the nation's forestland (Bechtold and Patterson 2005). This FIA annual inventory has replaced and greatly improved upon the less frequent periodic inventory, which used a variety of survey standards that may have created geographic variations in the estimates of tree growth rates. The annual inventory collects tree-specific information, such as tree diameter, on over three million trees in a network of over 100 000 permanent ground plots using a 5 year cycle. This tree-specific information can be used to calculate plot-level changes in wood volume. Additional plot-level data such as forest type and stand density are collected. Examples of the many uses of FIA plot-level data to monitor forest conditions across the eastern USA include mapping of county-level production and mortality of woody biomass (Brown and Schroeder 1999), and evaluation of species range changes (Murphy *et al*. 2010).

The type of remotely sensed imagery chosen for monitoring forest growth requires a compromise between spatial extent and spatial resolution (Lu 2006) – for example, compromise between the broad extent but coarse resolution of the Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) and compromise between the small extent but finer resolution of Landsat, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Système Pour l'Observation de la Terre (SPOT). MODIS has a great advantage in monitoring forest conditions, especially for sub-continental and larger areas, due to its spatial extent and frequent acquisition (Lu 2006, Muukkonen and Heiskanen 2007). MODIS imagery provides a standard suite of 8 day interval, 1 km spatial resolution global products including leaf area index (LAI; Yang *et al*. 2006), fraction of photosynthetic active radiation (*f*PAR; Steinberg and Goetz 2009), land-cover classification (Lotsch *et al*. 2003) and GPP (Zhao *et al*. 2005, Potter *et al*. 2007). A MODIS NPP product is created at the University of Montana as the difference between the annual sum of daily MODIS GPP and the modelled annual plant respiration. But because the modelling of respiration has not been well validated, these MODIS NPP estimates are not publicly available (Turner *et al*. 2005).

Efforts have been made to calibrate and validate the MODIS predictions of GPP in the USA through comparisons with flux tower sites, with process-based ecosystem models and with field-based forest inventory sites. The ground-based flux tower site approach (Law *et al*. 2000, Turner *et al*. 2003, 2005, Heinsch *et al*. 2006, Xiao *et al*. 2008) has provided information that is necessary for calibration of the MODIS algorithms, but can be undertaken in only a few of the many plant community types present in the USA that have measurement towers. Process-based models such as Physiological Principles Predicting Growth (3-PG) make predictions of GPP for many other forest types in the USA, and although these have been used to validate predictions made by MODIS from areas ranging in size from county to US states (Law *et al*. 2000, Landsberg *et al*. 2001, Nightingale *et al*. 2007), since the MODIS and 3-PG models use the same radiation input data, the two data sets are not completely independent and, thus, these validations are not robust. Studies that have compared MODIS estimates with FIA measurements at the scale of US states (Zhang and Kondragunta 2006) have been limited in the variety of environments considered as they averaged together the unique environments present in individual FIA plots and MODIS pixels. Examination of plot-level FIA forest variables allows the characterization of stand-level forest dynamics necessary for management decisions (McRoberts 2008). The use of field-based growth data is valuable for two reasons: first, the MODIS and inventory data are independent of each other and, second, field data allow the validation of MODIS predictions across many different plant community types and biophysical conditions (Zhang and Kondragunta 2006, Muukkonen and Heiskanen 2007).

Validation of MODIS GPP predictions using FIA NPP data has been challenging, however, mainly because of the inherent scaling mismatch between the two data sets (Morisette *et al*. 2002, Cohen *et al*. 2003, Lu 2006). The mismatch is that while MODIS provides its data in a spatially contiguous square grid with a 1 km^2 resolution, FIA data typically consist of one plot for every 6000 acres (24.3 km^2), with that plot itself consisting of four 24 ft radius subplots, which together have a total area of 1/6 acre (0.0041 km^2; Bechtold and Patterson 2005). Minnesota, Wisconsin, Michigan and Maine have a sampling intensity that is approximately two to three times higher than that of the other states, but the scaling mismatch remains. Three approaches that might be taken to deal with this scaling mismatch, which limits the ability to validate MODIS predictions using FIA measurements, are outlined below.

One popular approach to overcome the mismatch, useful for study areas that cover several hundred square kilometres, is to use intermediate ancillary data that bridge the coarse-resolution MODIS pixels and the fine-resolution FIA plots. For example, Blackard *et al*. (2008) developed a spatially explicit forest biomass map that covered 65 ecologically segmented mapping zones across the USA. In their tree-based mapping model, FIA plot-level biomass measurements were modelled with several predictor variables including MODIS-derived vegetation index, land cover from intermediate resolution of Landsat data and topographic and climatic data. Muukkonen and Heiskanen (2007) and Zheng *et al*. (2007, 2008) also estimated aboveground biomass by using high-resolution satellite imagery to integrate coarse-resolution MODIS data with field-based national inventory data. The second approach to dealing with the mismatch is to aggregate both data sets to a larger area. For example, Zhang and Kondragunta (2006) compared the estimates of aboveground biomass using a combination of MODIS data and allometric models with FIA data averaged for each of the contiguous 48 US states. Although they obtained good agreement between the data sets, the spatial resolution of the whole US states does not tell us whether this validation is equally strong for smaller areas that contain different forest types and environments.

The third approach to dealing with the spatial mismatch is to maintain the plot- and pixel-scale observations and to use plot and pixel attributes to screen out co-located pixels and plots that are not comparable in characteristics or quality. Since the FIA sampling procedures were designed to meet the mandated error standards at the level of the US state, it is believed that the reliability of the estimates decreases for smaller areas (Bechtold and Patterson 2005). Phillips *et al*. (2000) suggested that although the total error could be decreased by tallying a large number of trees, it could also be done by examining possible error sources at the scale of individual trees and plots. MODIS also has sensor error due to sensitivity to atmospheric conditions and a suggested problem of band saturation (Myneni *et al*. 2002). The utilization of plot-level FIA attributes has rarely been addressed in the use of FIA data to estimate forest NPP, although Jenkins *et al*. (2001) used data quality criteria and Powell *et al*. (2010) used 'single condition' plots as a proxy for homogeneous forest areas to minimize potential modelling errors. Although these screening criteria were used, it was not shown how much their use influenced the results.

The aforementioned studies that compared MODIS GPP and FIA NPP implicitly assumed that autotrophic respiration (AR) is relatively stable and independent of ecosystem type. This perspective has been supported by some research that suggests that AR is a constant proportion of GPP (Potter *et al*. 1993, Waring *et al*. 1998, Reich *et al*. 2006). However, if AR is a varying fraction of GPP as suggested by other researchers (Chapin *et al*. 2002, Xiao *et al*. 2003, DeLucia *et al*. 2007), then their findings may contain small errors. Although the correlation approach that we use in this study does assume that AR is a constant proportion of GPP, we will map the residuals of those relations to assess whether the proportion varies geographically.

The overall objective of this research is to validate MODIS pixel-level predictions of GPP by assessing their statistical relations with co-located FIA plot-level estimates of NPP across the eastern USA. The screening variables (SVs) will be applied to explore the specific conditions under which the MODIS predictions are more and less strongly validated. The SVs will focus especially on the influences of FIA and MODIS data quality and spatial mismatch between the two data sets. Furthermore, we assess whether AR is a constant or varying fraction of GPP by mapping the residual in the optimal relation between MODIS GPP and FIA NPP. With this knowledge, it can become known under what conditions MODIS GPP predictions are correct and, conversely, for what conditions MODIS needs to be improved so that its GPP predictions can be corrected.

2. Data preparation

2.1 *Study area*

The data from 31 easternmost US states were used in this sub-continental-scale analysis. The study area contains 140 million hectares of forest, which is approximately 50% of the total forested area in the USA (USDA Forest Service 2003). The study area is diverse, containing 5 of the 11 ecosystem divisions that Bailey (1995) identified in the conterminous USA: continental hot, continental warm, prairie, savannah and subtropical.

2.2 *FIA plot data*

The FIA Program of the Forest Service, US Department of Agriculture, has conducted a nationwide forest inventory since the 1920s to determine various forests, attributes (Bechtold and Patterson 2005). Until 1998, the FIA Program used a periodic system that inventoried all of the plots in a US state once every 10–15 years; different states used different plot configurations and either fixed or variable radius sampling methods. Since 1998, the FIA program has used an annual inventory system in which approximately 20% of the plots in eastern US states and 10% in western US states are inventoried every year, using a nationally common, fixed-area plot configuration. Phase 1 of the annual FIA sampling procedure stratifies land into forest and non-forest using remotely sensed imagery or aerial photographs. This is done to reduce variance of estimation at population level. One plot is identified for approximately every 6000 acres (24.3 km^2) of forest. Phase 2 of the inventory involves field measurements at FIA's network of ground plots; field crews visit forest land-use plots and measure various vegetative attributes (Bechtold and Patterson 2005).

All privately owned FIA plots have, for privacy reasons, had their recorded location 'perturbed' by up to 1.6 km (but usually within 0.8 km), and up to 20% of private plots have also had their geographic coordinates 'swapped' with a nearby similar plot. It is likely that this will only have a small effect on relations with MODIS data as the pixel resolution is similar to the radius of perturbation. It has been suggested that the effect of perturbation on spatial patterns of FIA forest volume is negligible when non-perturbed volumes are compared with perturbed volumes smoothed over an area within a 5 km radius of the FIA plot (McRoberts *et al*. 2005b).

The FIA database for the 31 easternmost US states has records for a total of 2 237 529 trees from 61 317 phase 2 ground plots. Newly established plots could not be used for the computation of growth rates as that requires two sequential measurements; their exclusion resulted in the data set being reduced to 2 029 490 tally trees from 54 969 ground plots. We refer to the 61 317 plots as the Original data set and the 54 969 plots as the Complete data set as it is more complete in the sense of it having the sequential measures required to calculate NPP.

2.2.1 Net annual growth rate from FIA. Tree growth was calculated by measuring the changes in volume between two sequential measurements for each inventory plot. Given the 20% per year sampling intensity in the FIA annual inventory system, growth was calculated based on the 5 years of growth between the consecutive measurements. In US states where the second cycle of annual inventory has not yet been completed (table 1), the plots established during the last periodic inventory that were co-located with the annual inventory were used as the first measure, with the second measure provided by the first cycle of the annual inventory.

Table 1. Progress of the annual inventory in the 31 eastern US states used in this study.

States	Progress (%)
Alabama, Arkansas, Georgia, Illinois, Indiana, Iowa, Kentucky, Louisiana, Maine, Michigan, Minnesota, Mississippi, Missouri, Ohio, Pennsylvania, South Carolina, Tennessee, Wisconsin	100
New York, New Hampshire, Rhode Island	80
Connecticut, Delaware, Florida, Maryland, Massachusetts, North Carolina, Vermont	60
New Jersey, West Virginia	40

To calculate a plot-level estimate of NPP, field-measured net annual growth rates were calculated on a per acre basis using the Structured Query Language (SQL) in a relational database. The net annual volume increment (G_i) was, following Bechtold and Patterson (2005), calculated as

$$G_i = \sum_j^4 \sum_t y_{ijt} \Big/ \sum_j^4 a_{0ij}\,, \tag{1}$$

where y_{ijt} is the annual net change in volume in cubic feet (1 cubic foot = 0.0283 m^3) for tree t on macro-plot, subplot or micro-plot j of plot i. y_{ijt} is computed as $[(V_2 - V_1)/(T_2 - T_1)]$, where V is the volume, T is the year of measurement and subscripts 1 and 2 denote the past and current measurements, respectively; a_{0ij} is the total area in acres (1 acre = 4047 m^2) used to observe the volume increment on plot i. Subscript j has the same meaning here as above.

2.2.2 Woody carbon budgets from volume increment. An FIA plot's net annual volume increment measured in cubic feet per acre per year was converted to a measure in grams of carbon per square metre per year (g C m^{-2} year^{-1}), the unit of measure used for MODIS GPP, by applying species- and region-specific conversion factors (table 2). Forest types varied from those with a low density such as the spruce and fir in the north-central region to those with a high density such as oak and hickory in the southern region (Birdsey 1996). Forest types not listed in table 2 were converted using the average of the conversion factors for the appropriate region.

2.3 *MODIS GPP*

MODIS GPP data were obtained as 8 day composites for the period from 1 January 2001 to 31 December 2004 from the Land Processes Distributed Active Archive Center (LP DAAC; http://lpdaac.usgs.gov). A total of 11 MODIS tiles were mosaicked to cover the 31 eastern states, resulting in a total of 1980 tiles for the 4 year collection period (45 composites per year × 11 tiles per composite × 4 years). This total does not include the three missing 8 day composites that were lost due to a reset of the

Table 2. Factors to convert volume (ft^3 acre^{-1}) to carbon content (g C m^{-2}) for major forest types.

US region	Forest type	Conversion factors
South	Loblolly pine	27.93
	Longleaf pine	32.09
	Oaks and hickories	32.7
Northeast and mid-Atlantic	Pines	23.91
	Spruces and firs	21.58
	Oaks and hickories	34.01
	Maples, beeches, birches	34.01
North Central	Pines	23.91
	Spruces and firs	21.58
	Oaks and hickories	34.01
	Maples and beeches	32.33
	Aspens and birches	25.63

MODIS instrument (day of year (DOY) 209 to DOY 224 in 2001) and due to LP DAAC download errors (DOY 96 to DOY 104 in 2002). To minimize distortion, the mosaics were processed into an Albers equal-area conic projection using the MODIS Reprojection Tool.

2.3.1 MODIS land cover. The estimation of MODIS GPP values uses a land-cover system with 14 classes, developed at the University of Maryland (UMD), because land covers differ in their radiation-use efficiency (Running *et al*. 2000). A total of 34.7% of the eastern US study area had pixels with one of the five forest-related land-cover classes: evergreen needleleaf (1.6%), evergreen broadleaf (2.7%), deciduous needleleaf (0.1%), deciduous broadleaf (15.6%) and mixed forest (14.7%). In this research, the MODIS forest classes were used to assess the consistency of the forest classification between MODIS pixels and co-located FIA plots.

2.3.2 Pixel-level quality assurance data. The MODIS collection 5.0 land product, produced at the University of Montana, provides pixel-level quality assurance (QA) data to allow maximum control over the data set. Each pixel contains quality-scoring 'flags' whose values are 8-digit-long binary equivalent numbers. Binary numbers are divided by four separate bit fields corresponding to specific QA schemes: SCF-QC, cloud state, dead detector and MODLAND-QC.

2.3.3 Annual GPP. The values of annual GPP were smoothed to minimize spatial and temporal discrepancies between the MODIS and FIA data. Individual values of GPP and corresponding QA layer were, for two reasons, spatially smoothed using a 5×5 pixel moving average window. First, this would minimize the effect of geolocational mismatches from the perturbed and swapped FIA plots (cf. McRoberts *et al*. 2005b). Second, the 25 km^2 area of the smoothing window would be similar to the 6000 acre (24.3 km^2) area that each FIA plot represents.

Complete sets of 8 day composites of the spatially smoothed pixels were then summed to each month for the period from 2001 to 2004. The three missing 8 day composites and the MODIS pixels excluded after the quality check presented in §3.3.1 were replaced by linear interpolation between the values of the previous good 8 day period and the next good 8 day period. The 4 year sums of GPP values were then averaged to get a mean annual GPP, resulting in some temporal smoothing.

3. Methods

3.1 *Overview*

Field-based NPP was calculated for each FIA plot using the net annual growth rate measurements for each tree as modified by species- and region-specific conversion factors; these data were stored in a relational database. Monthly and yearly (2001–2004) summed MODIS GPP pixel values, QA pixel values and land-cover classification codes were also overlaid to corresponding FIA plot locations. Those three MODIS layers were then appended to the FIA plot-level table stored in a relational database. To determine the conditions under which MODIS GPP predictions were most strongly validated against co-located FIA NPP plots, the relational database was then used

Table 3. The eight SVs used to test six hypotheses about relations between the FIA NPP and MODIS GPP data.

Hypothesis	Data	SV	Criteria
1. MODIS pixel-level quality checks	MODIS	1. Quality assurance data	≤48 (QA scoring values, best quality pixels); >48 (not best)
2. FIA plot-level quality checks	FIA	2. Net growth values	Quality check plots (plots without artificial plot condition and outliers of extremely high values of volume increments)
3. Assessment of land-cover classification	MODIS	3a. UMD land-cover classification	Only forest land cover; non-forest land cover
	MODIS and FIA	3b. Land-cover assessment	Correctly classified; misclassified
4. FIA plot homogeneity	FIA	4a. Condition proportion (condprop)	If =1: homogeneous plots; if<1: heterogeneous plots
		4b. Species group code (spgrpcd)	≥75% of single species group code; <75% of single species group code
5. FIA sample size	FIA	5. Number of trees	<36; ≥37
6. Seasonal variation in MODIS GPP	MODIS	6. Bimonthly averaged GPP	Six groups of non-overlapping 2 month periods

Note: FIA, Forest Inventory and Analysis; GPP, gross primary production; MODIS, Moderate Resolution Imaging Spectroradiometer; NPP, net primary production; SV, screening variable.

to test the following six hypotheses using eight SVs (table 3). We infer a stronger validation where the statistical correlation between the two data sets is higher.

First, as the quality of MODIS observations varies because of interference by factors such as clouds and shadow, it is hypothesized that the use of only MODIS pixels that have passed quality checks will improve relations. Second, as FIA data sets that indicated evidence of plot-level stand treatment such as cutting or clearing might be too localized to influence the MODIS pixel, it is hypothesized that the removal of such extreme values or logging artefacts will improve relations. Third, as the different size of MODIS pixels and FIA plots could lead to scaling mismatches in their land-cover classifications, it is hypothesized that the use of only co-located MODIS pixels and FIA plots that have the same predicted forest type will reduce scaling mismatches and thus improve relations. Fourth, as heterogeneous forest types and conditions within FIA plots would increase the chance of scaling mismatches with MODIS pixels, it is hypothesized that the use of only homogeneous FIA plots will improve relations. Fifth, as MODIS reflectance data are of higher quality in closed-canopy forests (Yang *et al.* 2007), the use of FIA plots with higher numbers of trees will improve relations. Sixth, as there is evidence that the MODIS GPP signal becomes saturated during the mid-summer (Myneni *et al*. 2002), it is hypothesized that relations between MODIS GPP from different seasons and annual FIA NPP will be lowest for the summer season.

3.2 *Analytical methods*

Relations between MODIS GPP and FIA NPP were reported using Pearson correlation coefficients. All data sets for each hypothesis were tested for normality using the Anderson–Darling test (Anderson and Darling 1952).

The correlation coefficients and slopes of the two different criteria used for each SV were compared to assess whether the criterion with the highest correlation had a significantly different correlation coefficient and regression slope than the other criterion for that SV. The procedures developed by Fisher (1921) were used to compare correlation between two subgroups after the application of an SV and the Pearson correlation coefficient (r) value was transformed to the normally distributed r' using Fisher's transformation:

$$r' = 0.5 \ln \left| \frac{1+r}{1-r} \right|. \tag{2}$$

The z-statistic was calculated to compare correlation coefficients:

$$z = \frac{r'_1 - r'_2}{\sqrt{\frac{1}{n_1-3} - \frac{1}{n_2-3}}}, \tag{3}$$

where correlation coefficients (r) were transformed to r' (equation (2)), n is the number of plots and subscripts 1 and 2 represent the criterion for that SV with the highest and lowest correlation coefficients, respectively.

The regression slopes for the pair of criteria for each SV were compared as follows. For each two linear regression models $y_i = x_i\beta_i + \varepsilon_i$, where β_i is the regression coefficient, ε_i is the error term and $i \in 1, 2$ we tested the null hypothesis, H_0: $\beta_1 = \beta_2$. Separate regression analyses were conducted to calculate the unrestricted sum of squares (URSS). Let $\hat{\beta}_1$ and $\hat{\beta}_2$ be the slope estimates with residuals $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$ from the separate regressions, respectively; then the unrestricted sum of squares for the whole data set is URSS $= \hat{\varepsilon}'_1\hat{\varepsilon}_1 + \hat{\varepsilon}'_2\hat{\varepsilon}_2$. The data were then pooled to calculate the restricted sum of squares (RRSS). Let $\hat{\beta}$ be the common slope with the residuals $\hat{\varepsilon}$ from the pooled data sets; then the restricted sum of squares is RRSS $= \hat{\varepsilon}'\hat{\varepsilon}$. Under the null hypothesis, there should be no significant difference between URSS and RRSS; the test statistic was calculated using an F-test as

$$F = \frac{(\text{RRSS}) - (\text{URSS})/k}{(\text{URSS})/(n-2k)}, \tag{4}$$

where URSS is the unrestricted residual sum of squares from the separate regressions with $n - 2k$ degrees of freedom, RRSS is the restricted residual sum of squares from pooled data with $n - k$ degrees of freedom, n is the total number of observations in the two subgroups and k is the number of parameters. If the correlation coefficient and slope of the relationship between the two criteria for an SV were not significantly different from each other, then the data for the criterion with the lower correlation value would not be removed from the optimal validation data set.

3.3 *Validation of MODIS GPP with FIA NPP*

3.3.1 Hypothesis 1: MODIS pixel quality check. The first SV (SV 1) to be used was a pixel-level application of MODIS QA scoring data and non-terrestrial fill-values to filter out low-quality MODIS pixels. A QA scoring indicates the quality of preceding input products such as *f*PAR and LAI that exert direct influence on the quality of GPP. The QA numbers for a pixel were converted to eight-digit binary equivalents and screened by the last three-digit binary numbers for the factors MODLAND and the condition of the detector. If the QA number was 48 or less, with lower numbers indicating higher quality, it was assumed that the pixel was of high enough quality to use. Non-terrestrial or non-modelled pixels indicated by especially high numeric integer codes (32 761–32 767) were used to mask pixels whose values are above the biophysically relevant limit range of 30 000. We hypothesize that the use of higher quality pixels will be more strongly validated, because the removal of atmospheric interference should make their GPP estimates more accurate.

3.3.2 Hypothesis 2: FIA plot condition quality check. This hypothesis involved SV 2 as an FIA plot condition quality check that removed plots where a significant stand treatment occurred within the last 5 year cycle or where extremely high growth values existed. The FIA stand treatment code of TRTCD was used to select the plots affected by artificial site preparation such as artificial regeneration, cutting and clearing. Extremely high growth values were screened as outliers by examining the histogram graphically. The cut-off value of maximum NPP was set to 1500 g C m^{-2} $year^{-1}$ resulting in approximately 0.4% of the plots with the highest growth values being excluded. We hypothesize that FIA plot conditions without evidence of artificial treatments and outliers will be more strongly validated because these conditions would be highly localized and thus undetectable in the relatively larger MODIS pixels.

3.3.3 Hypothesis 3: Consistency of forest classifications for MODIS pixels and FIA plots. Two SVs (i.e. SVs 3a and 3b) were used to assess the influence of consistency of forest classifications between MODIS pixels and FIA plots. SV 3a entailed comparison of the NPP from forested FIA plots first with co-located MODIS pixels that the MODIS land-cover data classified as forest and secondly with the MODIS pixels that were not classified as forest.

SV 3b involved organizing the MODIS forest pixels into softwoods (a combination of the two evergreen classes), hardwoods (a combination of the two deciduous classes) and mixed forest. The FIA plots were organized into three similar groups by using the 28 FIA species group codes; an FIA plot was classified as hardwood (or softwood) if more than 75% of both the basal area and number of stems were hardwood (or softwood), while plots containing less than 75% of one type were classified as mixed forest. Relations between MODIS GPP and FIA NPP were then assessed first using just the MODIS pixels and co-located FIA plots that had the same forest class and then using MODIS pixels and co-located FIA plots that had different forest classes. We hypothesize that the use of conditions with similar classifications between MODIS pixels and FIA plots will be more strongly validated because MODIS GPP estimation relies heavily on land-cover types (Heinsch *et al*. 2006).

3.3.4 Hypothesis 4: FIA plot homogeneity. Two SVs (i.e. SVs 4a and 4b) were employed to assess the influence of using only homogeneous FIA plots. SV 4a inferred homogeneity using the ‘condition proportion’ information for each FIA plot.

Relations between MODIS GPP and FIA NPP were first considered for homogeneous FIA plots in which all of their subplots had the same land-use or vegetation type (as indicated by a condition proportion of 1) and were then considered for heterogeneous FIA plots in which their subplots had more than one land-use or vegetation type (as indicated by a condition proportion of less than 1).

SV 4b inferred homogeneity using forest composition information represented by the species group codes within each FIA plot. A plot was considered homogeneous if any particular species group comprised more than 75% of its total basal area and stems of trees, and was otherwise considered heterogeneous. Relations between predicted GPP for MODIS pixels and co-located measured NPP for FIA plots were first considered for the FIA plots considered to have a homogeneous forest composition and then for those considered to have a heterogeneous forest composition. In addition to the use of the 75% cut-off value, the effect of progressively increasing the cut-off values was explored, beginning at a value of zero and using equal steps of homogeneity. Equally sized groups were not used as was done for SV 5, because this resulted in some cut-off values being too close to each other to be meaningful. We hypothesize that homogeneous FIA plots will be more strongly validated because homogeneous plots should minimize the chances of spatial mismatches between two data sets.

3.3.5 Hypothesis 5: FIA plot tree density. FIA plot-level tree density was calculated by counting the number of tally trees (SV 5) with a diameter at breast height (dbh) larger than 5.0 inches (about 12 cm) within each plot. It was assumed that as all trees were enumerated within each fixed-radius plot, greater numbers of tally trees may indicate a progressively denser and more closed-canopy forest. FIA plots were put into two criteria, using the median number of 36 tally trees per plot as the dividing point. In addition to the use of the median cut-off value, the effect of progressively increasing the cut-off value was explored using five equally sized, independent groups of FIA plots. We hypothesize that closed-canopy forest will be more strongly validated because MODIS estimations are reported to have higher quality in closed-canopy forest (Yang *et al*. 2007).

3.3.6 Hypothesis 6: MODIS seasonal signal. SV 6 involved comparing FIA's annual NPP signal with seasonalized signals of MODIS GPP. The 8 day composites of MODIS GPP pixels were seasonalized by aggregating them into six non-overlapping groups of 2 months. Relations between MODIS GPP and FIA NPP were then considered separately for each 2 month period of MODIS GPP. We hypothesize that MODIS GPP estimates will be more strongly validated at the start and end of the growing season because the MODIS GPP signal becomes saturated during the mid-summer (Myneni *et al*. 2002).

3.4 *Selection of optimal validation data sets*

An optimal data set for the validation of MODIS pixels using FIA plots should have a high correlation coefficient and also contain many samples. To this end, in the case of SVs 4b and 5, which showed an increasing correlation as the criterion cut-off was progressively changed, an exception was made so that the criterion cut-off was modified to include a greater number of plots, though at the expense of a reduced correlation.

The trade-off between improved correlation coefficient and reduced number of samples was evaluated using Fisher's z-statistic (equation (3)). The z-statistic was used in three different ways to determine the following three different relative performances of SVs. First, a within-SV z-value was calculated by comparing two different criteria of a particular SV. It evaluated the trade-off between improved relations obtained by using the best criterion of a particular SV and reduced samples obtained by using the other criterion of that particular SV. The higher within-SV z-value indicated the better performance of FIA criteria for characterizing plot attributes. Second, a between-SV z-value was calculated by comparing the best criterion of SV 1 and SV 2 relative to the Complete data set, and the remaining SVs relative to the best criterion of SV 2. Third, a sequential-SV z-value was calculated to assess the relative performance of the data set with the sequential addition of the best criterion of different SVs.

To select optimal validation data sets, SV 1 and SV 2 were applied first as basic data quality controls and the remaining SVs were applied sequentially in the order of most to least efficient based on their between-SV z-value. If the addition of a particular SV did not result in a significantly increased Pearson correlation between the MODIS and FIA data sets ($p > 0.05$), then that SV was not included in the final optimal validation data set.

3.5 *Representativeness of SV's data sets*

It is possible that the sequential application of SVs to create the optimal validation data set would result in a subset of data that were not representative of the range of conditions and locations found in either the Original or Complete data sets. The Complete data set of 54 969 plots used in the optimal validation data set has sequential inventories that allowed for the measurement of NPP; the Original data set of 61 317 plots is the sum of 54 969 Complete data sets and an additional 6348 newly established plots that lack a second inventory that allowed NPP to be measured. Representativeness of the reduced optimal validation data sets was assessed in terms of relative species composition and relative state representation. In terms of species composition in each data set, the percentage relative abundance of each tree species was calculated as the total basal area of the species divided by the total basal area of all species. In terms of state representation in each data set, the percentage of forested plots in each state was calculated as the number of plots in that state divided by the total number of plots for the whole study area. Representativeness of the species composition and state representation of the reduced data sets created through the sequential applications of SVs was assessed by calculating the Pearson correlation coefficients between these values of species composition and state representation and those in the Original data set. In addition to relative examinations of representation, mean MODIS GPP and FIA NPP values of each reduced data set were also calculated to support representativeness of reduced data sets. The mean GPP and NPP values after the application of sequential SVs should be stable if the reduced data sets maintain the representativeness of the Original data sets.

3.6 *Residual map*

A map of the residuals of the optimal relation between MODIS GPP and FIA NPP was created to assess whether autotrophic respiration (AR) is a constant (Potter *et al*. 1993, Dewar *et al*. 1998, Waring *et al*. 1998) or varying (Chapin *et al*. 2002, Xiao *et al*. 2003, DeLucia *et al*. 2007) proportion of GPP. The residuals were calculated as

$$\hat{\varepsilon} = y - \hat{y}, \tag{5}$$

where $\hat{\varepsilon}$ is the residual of the relation between MODIS GPP and FIA NPP, is the observed value of MODIS GPP and $\hat{y}$ is the predicted value of GPP as a linear function of FIA NPP.

The geographic pattern of the residual map was assessed using a trend surface analysis of the residuals where the spatial coordinates are the predictors.

4. Results

4.1 *MODIS GPP and FIA NPP across the eastern USA*

Similar spatial patterns are apparent in the maps of MODIS GPP following the application of SV 1 and FIA NPP following the application of SV 2 (figure 1). MODIS GPP (figure 1(*a*)) exhibited particularly low values in Lake States (Michigan, Wisconsin and Minnesota) and progressively higher values from north to south. FIA NPP (figure 1(*b*)) exhibited a similar pattern, although high values were also scattered within the Lake States.

4.2 *Validation of MODIS GPP with FIA NPP*

Correlation of the MODIS GPP data set with the Complete FIA data set, prior to the application of any SVs, had a Pearson correlation coefficient of 0.01 (table 4). The 54 969 FIA plots and co-located MODIS pixels were used to test the following six hypotheses, and their corresponding eight SVs, regarding ways to improve the correlation between MODIS GPP and FIA NPP. The results from test statistics (equations (3) and (4)) showed that the correlation coefficient and regression slope coefficient for the different criteria for each SV were all significantly different from each other ($p < 0.05$). As the Anderson–Darling tests suggested that the data sets were not normally distributed, we report a Pearson correlation coefficient using Fisher's transformation procedures at a 95% confidence level. Spearman correlations were also calculated and were slightly higher than the Pearson values (median increase was 0.03), and the

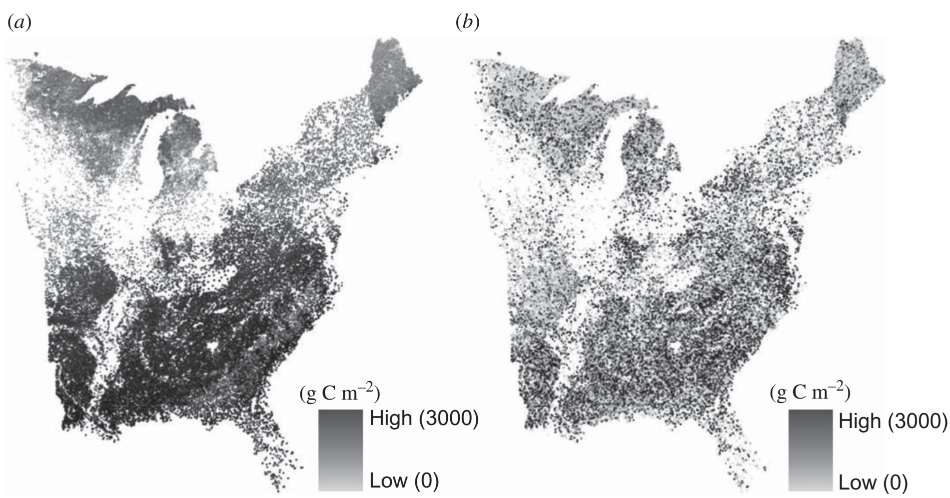

Figure 1. Values of (*a*) MODIS GPP and (*b*) FIA NPP for locations that remain following the application of screening variables 1 and 2.

Table 4. The influence of eight SVs from the six hypotheses on relations between MODIS GPP and FIA NPP.

Hypothesis	SV	Criteria	Individual data set: Pearson r-value	No. of plots used	Within-SV z-value	Between-SV z-value
Complete	Non-screened	None	0.01	54 969	N/A	N/A
1. MODIS pixel-level quality checks	1. MODIS QA data	***≤48 (QA scores for best quality pixels) and excluding non-terrestrial fill-values***	0.11	54 969		16.65
2. FIA plot-level quality checks	2. Growth rate	***Non-artificial stand treatment and outliers***	0.20	46 640		14.65
3. Assessment of land-cover classification	3a. UMD land cover	***Forest cover***	0.25	26 289		
		Non-forest cover	0.18	20 351	7.86	5.47
	3b. Land-cover assessment	***Similarly classified***	0.34	10 768	16.59	13.17
		Non-similarly classified	0.17	35 872		
4. FIA plot homogeneity	4a. Condition proportion (condprop)	***=1: homogeneous plots***	0.26	25 647	5.68	6.80
		≠1: plots are heterogeneous	0.20	20 993		
	4b. Species group code (spgrpcd)	***≥75% of single spgrpcd***	0.35	9910	15.29	13.75
		<75% of single spgrpcd	0.19	36 730		
5. FIA sample size	5. Number of trees	***≥37***	0.35	21 404	23.06	18.43
		<36	0.15	25 236		
6. Seasonal variation in MODIS GPP	6. Bimonthly averaged GPP	January–February	0.14	46 640	N/A	19.80
		March–April	0.32	46 640		
		May–June	0.27	46 640		
		July–August	0.10	46 640		
		September–October	0.34	46 640		
		November–December	0.19	46 640		

Notes: FIA, Forest Inventory and Analysis; GPP, gross primary production; MODIS, Moderate Resolution Imaging Spectroradiometer; NPP, net primary production; SV, screening variable.

For each SV, the criterion with the highest Pearson correlation coefficient is in bold and italics; in all cases, it had a correlation coefficient and slope parameter that was significantly different from the other criterion at a p-value of <0.000001. The within-SV z-value for each SV indicates the performance of the criterion with the highest Pearson r-value relative to the other criterion. The between-SV z-value indicates the performance of the addition of that SV relative to the Complete data set for SV 1 and SV 2, and of that SV relative to the data set following the application of SV 2 for the remaining SVs.

relative size of both of them and the resulting z-values were the same for Pearson and Spearman correlations. However, we report Pearson correlations to ease comparison of results with other studies.

4.2.1 Validation following MODIS pixel-level quality checks. Low-quality pixel values comprised 18% of the MODIS forest pixels, with 16% due to low QA values and 2% due to non-terrestrial fill-values. Replacement of these data with, respectively, temporally and spatially smoothed fills resulted in an increase in r from 0.01 to 0.11.

4.2.2 Validation following FIA plot-level quality checks. The implementation of SV 2 resulted in the exclusion of a total of 8329 FIA plots: 5527 plots with an artificial plot condition and 2802 plots with extremely high values of volume increments. This application of SV 2 increased the r-value from 0.11 to 0.20.

4.2.3 Validation following consistency of forest classifications. The application of SV 3a indicated that more than half of FIA plots were located in MODIS pixels with non-forest covers. Correlations between MODIS GPP and FIA NPP dropped from $r = 0.20$ to $r = 0.18$ if only non-forested pixels were used and rose to 0.25 if only forested pixels were used.

The application of SV 3b indicated that less than one-quarter of the FIA plots had the same type of forest class as indicated by the MODIS data. Correlations between MODIS GPP and FIA NPP dropped from $r = 0.20$ (following the application of SVs 1 and 2) to $r = 0.17$ if only non-similarly classified pixels were used and rose to 0.34 if only similarly classified pixels were used. The classification error matrix (table 5) shows that mixed forest made up 51% of MODIS pixels and 33% of FIA plots. Deciduous forest made up 41% of MODIS pixels and the corresponding hardwoods made up 50% of FIA plots, whereas evergreen forests made up 8% of MODIS pixels and the corresponding softwoods made up 17% of FIA plots. A producer's accuracy, computed as the proportion of correctly classified FIA plots, shows that mixed forest had the highest classification accuracy (64.9%), deciduous forest had an intermediate accuracy (60.1%) and evergreen forest had the lowest accuracy (22.6%). A map-based user's accuracy, computed as the proportion of correctly classified MODIS pixels, shows that hardwoods had the highest classification accuracy (72.4%), softwood had an intermediate accuracy (50.0%) and mixed forest had the lowest accuracy (42.0%).

Table 5. The classification error matrix for MODIS land cover and FIA plots, for the 25 989 MODIS pixels and co-located FIA plots that passed the criteria for SVs 1, 2 and 3a.

		FIA					
		Softwood	Hardwood	Mixed forest	Number of MODIS pixels	Producer's accuracy (%)	User's accuracy (%)
MODIS	Evergreen	1005	411	595	2011	22.6	50.0
	Deciduous	570	7805	2406	10 781	60.1	72.4
	Mixed	2876	4771	5550	13 197	64.9	42.0
	No. of FIA plots	4451	12 987	8551	25 989		

Note: FIA, Forest Inventory and Analysis; MODIS, Moderate Resolution Imaging Spectroradiometer; SV, screening variable.

4.2.4 Validation following FIA plot homogeneity. The application of SV 4a showed that slightly more than half of the FIA plots had a homogeneous condition. The use of plots with a non-homogeneous condition resulted in no change in the correlation coefficient, which remained at 0.20. The use of plots that were homogeneous increased the *r*-value to 0.26.

The application of SV 4b suggested that in approximately one-fifth of the FIA plots, more than 75% of the trees had the same species group code. The use of FIA plots in which less than 75% of the trees had the same species group code resulted in the value of *r* dropping to 0.19, whereas the use of plots in which more than 75% of the trees had the same species group code resulted in *r* increasing to 0.35.

4.2.5 Validation following FIA sample size. The application of SV 5 indicated that the mean and median numbers of tally trees per plot were 37 and 35, respectively. The use of plots that contained fewer than the mean number of trees resulted in the correlation coefficient dropping from 0.20 to 0.15, whereas the use of plots that contained the mean number of trees or greater resulted in *r* increasing to 0.35.

4.2.6 Validation following MODIS seasonal signal. Eight day composites of MODIS GPP for the study region showed that GPP was low but above 0 for January and February, steadily rose to a peak in late July and then steadily decreased to near zero in December (figure 2(*a*)). In contrast, the Pearson correlation between the MODIS pixels of each of those 8 day composites and of the co-located FIA plots of annual NPP showed a bimodal pattern (figure 2(*b*)). Correlations were 0.1 in early January, steadily rose to a peak near 0.3 in late April, decreased and varied around 0 from early July to late August, steadily rose again to a peak near 0.4 in late October and then dropped progressively after that.

The spatial pattern and frequency distribution of GPP values varied by month (figure 3). In April, there was a bimodal distribution, with a cluster of low values in the north. In August, there was still a bimodal distribution, with the two peaks shifted

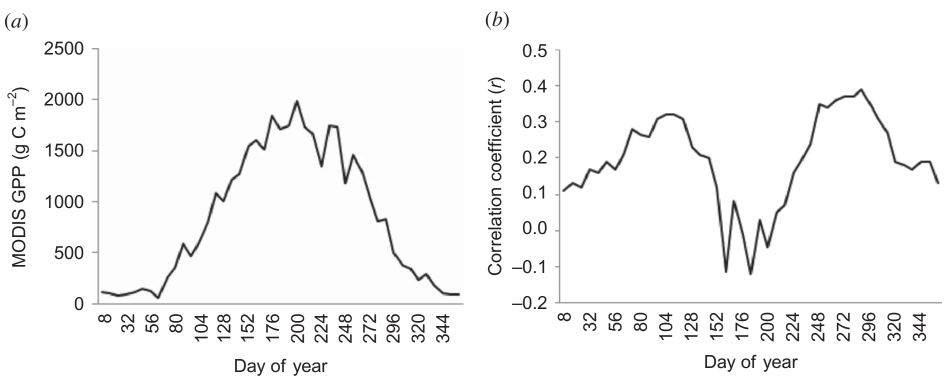

Figure 2. (*a*) Eight day composite of MODIS GPP averaged for 2001–2004. (*b*) Correlations between each 8 day composite of MODIS GPP with annual FIA NPP. These results are based on analyses of the data set following the application of screening variables 1 and 2.

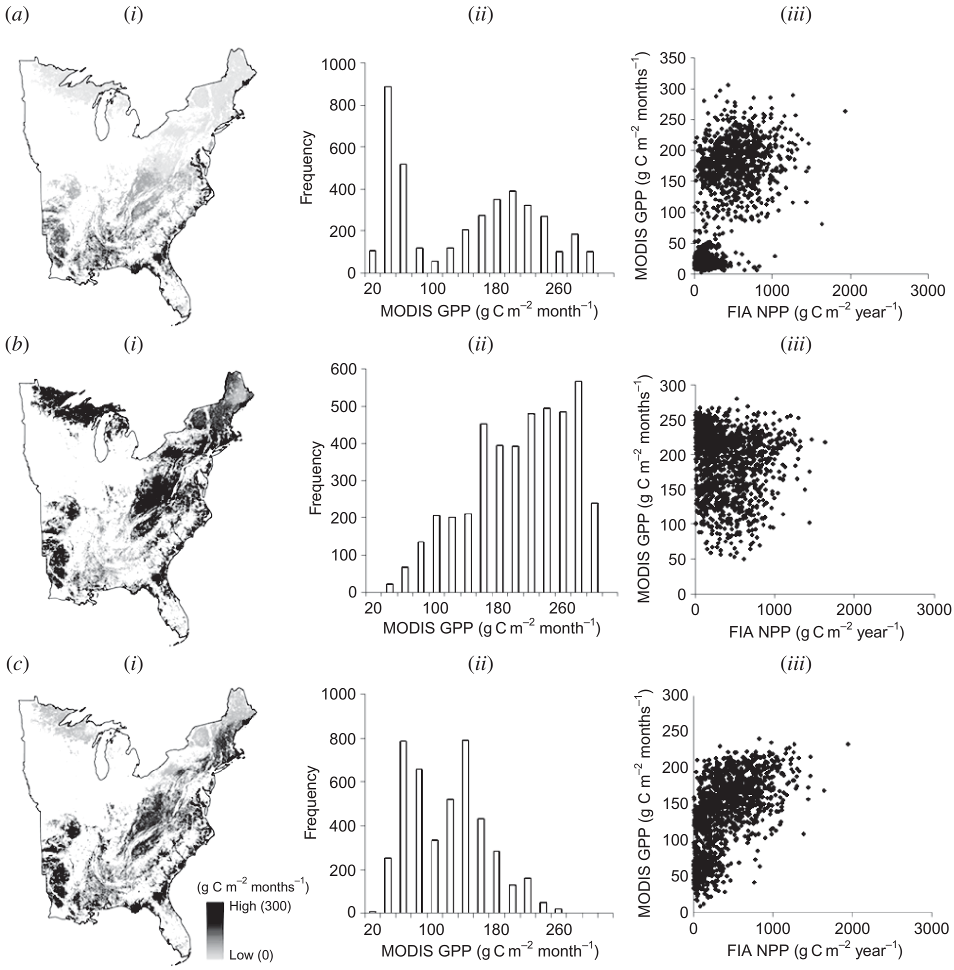

Figure 3. Maps of monthly averaged MODIS GPP for (*a*(*i*)) April, (*b*(*i*)) August and (*c*(*i*)) September. Histograms of MODIS GPP for (*a*(*ii*)) April, (*b*(*ii*)) August and (*c*(*ii*)) September. Scatter plots of MODIS GPP and FIA NPP for (*a*(*iii*)) April, (*b*(*iii*)) August and (*c*(*iii*)) September. The data are for co-located MODIS pixels and FIA plots following the application of screening variables 1–3.

to higher values of GPP. In September, there was a unimodal distribution, with the peak frequency shifted yet again to a higher GPP.

The application of SV 6 involved assessing how correlations between MODIS GPP and FIA NPP varied when the MODIS data were aggregated into different pairs of months. For the 2 month pairs, correlations were highest for September–October and slightly lower for March–April, lowest for July–August and second-lowest for January–February.

4.3 *Selection of optimal validation data sets*

The optimal validation data sets used in this study were selected to have high correlations between the MODIS and FIA data sets and to have many samples. The use

Table 6. Correlations between MODIS GPP and FIA NPP when different criterion cut-offs were used for SVs 4b and 5.

	Degree of homogeneity	Pearson *r*-value	Number of samples		Number of trees in a plot	Pearson *r*-value	Number of samples
SV 4b	=0	0.20	46 097	SV 5	<21	0.08	8993
	>25	0.25	40 979		21–31	0.17	9512
	>50	0.29	23 828		32–41	0.20	10 007
	>75	0.34	9910		42–54	0.27	9267
	=100	0.38	2407		≥55	0.44	8318

Notes: FIA, Forest Inventory and Analysis; GPP, gross primary production; MODIS, Moderate Resolution Imaging Spectroradiometer; NPP, net primary production; SV, screening variable. Criteria for SV 4b were regrouped into different degrees of homogeneity. Criteria for SV 5 were regrouped to contain equal sample sizes of approximately one-fifth of the FIA plots.

of FIA plots with higher degrees of homogeneity (SV 4b) and tree density (SV 5) resulted in higher correlations with MODIS GPP, though at the expense of number of plots (table 6). To enable a higher number of samples in the optimal validation data set, though at the expense of a lower correlation, the optimal validation data set was created using the criteria of >50% homogeneity for SV 4b and >20 tally trees for SV 5.

In the creation of the optimal validation data set, the SVs were applied in the sequence from highest to lowest efficiency as indicated by the *z*-values. The individual evaluation of SVs exhibited approximately the same sequence of relative efficiency for the within- and between-SV *z*-values (table 4). SVs 1 and 2 were applied first as they are considered necessary quality checks, then the remaining SVs were applied in descending order of their between-SV *z*-value from table 4.

The results of the sequential *z*-value approach indicate that while the application of each SV resulted in an increase in the Pearson *r*-value and a decrease in number of plots (N), only SVs 1, 2, 6, 5 and 4b significantly increased the efficiency of the optimal validation data set (table 7). SVs 3b and 3a did not increase the Pearson *r*-value, and SV 4a increased it by only a non-significant amount of 0.03. The optimal validation data set following the application of the five significant SVs consisted of 17 090 MODIS pixels and co-located FIA plots and had a Pearson correlation coefficient of 0.48. The correlation decreased to 0.45 if the same five SVs were used, except that annual GPP was used for SV 6 instead of the best seasonal criterion of September–October GPP.

4.4 *Representativeness of SV's data sets*

Application of SVs 1 and 2 maintained representativeness of the Original data set in terms of FIA species and FIA plots, as indicated by Pearson correlations of not lower than 0.97, but had large differences in mean MODIS GPP and FIA NPP (table 8). The application of SVs 6 and 5 again maintained representativeness of the Original data set in terms of FIA species and FIA plots, as indicated by Pearson correlations of not lower than 0.97, and also had similar values of MODIS GPP and FIA NPP. The application of SV 4b of the statistically significant optimal validation data set maintained representativeness of species with a Pearson correlation of 0.95, while that for plots dropped to 0.85, though MODIS GPP and FIA NPP remained similar. Application of the remaining three SVs, which were not part of the statistically

Table 7. Changes in the number of plots, the correlations between GPP and NPP, and the sequential z-value, as SVs are applied. The SVs were applied in the order of first the basic quality control SVs 1 and 2, and then the remaining SVs in descending order of their between-SV z-value as given in table 5.

Sequence of SVs for optimal data sets	Pearson *r*-value	Number of plots used	Sequential *z*-value	*p*-Value
Complete, non-screened	0.01	54 969	N/A	
SV 1	0.11	54 969	16.65	< 0.001
SV 2	0.20	46 097	14.61	< 0.001
SV 6	0.34	46 097	22.97	< 0.001
SV 5	0.38	36 782	6.57	< 0.001
SV 4b	0.48	17 090	13.27	< 0.001
SV 3b	0.52	3767	1.46	0.14
SV 3a	0.52	3767	0.00	1.00
SV 4a	0.55	2436	1.03	0.30

Notes: SV, screening variable.
The sequential *z*-value indicates the performance of the optimal validation data set used upon the addition of that SV, relative to the optimal validation data set created by the addition of the previous SV.

significant optimal validation data set, exhibited poor representativeness in terms of plots with the Pearson correlation dropping to lower but still statistically significant values between 0.50 and 0.53, though representativeness in terms of species and productivity still remained good.

Although species representation remained high following the application of the SVs, of the 240 species in the Original data set, 22 were lost by the time SV 4b was applied and 68 were lost by the time SV 4a was applied. FIA plot representation remained high for the optimal validation data set of five SVs, but when all eight SVs are applied, several states (Illinois, Iowa, Kentucky, Maryland and Indiana) had weak spatial representation with less than one FIA plot for every 100 000 acres. MODIS GPP dropped dramatically following the application of SV 6, and then both MODIS GPP and FIA NPP showed slight increases following the application of each subsequent SV except the last one (SV 4a).

4.5 *Residual map*

The residuals in the relation between annual MODIS GPP and annual FIA NPP were calculated using the optimal data set with $N = 17\,090$ (table 7), except that instead of using the bimonthly value of GPP from September and October suggested for SV 6 (table 4), the annual value of GPP was used. The linear relation between MODIS GPP and FIA NPP was $y = 0.62x + 1036.8$ (coefficient of determination (R^2) = 0.23). The spatial pattern of the residuals was fitted with a quadratic model in the trend surface analysis as it had the lowest root mean square (RMS) of the available polynomial functions (RMS = 198.4, $p < 0.05$). The residual map exhibited negative values in the northern half of the study area and positive values in the southern half (figure 4).

5. Discussion

5.1 *Screening variables*

The eight different SVs that were used to test six different hypotheses each had a criterion that provided significant increases ($p < 0.05$) in the correlations between the MODIS GPP and FIA NPP data sets. The *z*-value computed for both within-SV

Table 8. Representativeness of reduced data sets in terms of three conditions: the relative abundance of tree species across the whole study area (species), percentage of the plots in each US state (plots) and mean productivity of each data set.

		Correlations between data set and the Original		Mean productivity (g C m^{-2} $year^{-1}$)	
SV applied	No. of plots	Condition compared	Pearson *r*-value	MODIS GPP	FIA NPP
Complete, non-screened	61 317	Species	1.00	2101	N/A
		Plots	1.00		
SV 1	54 969	Species	0.98	1378	214
		Plots	0.98		
SV 2	46 097	Species	0.98	1330	208
		Plots	0.97		
SV 6	46 097	Species	0.98	211	208
		Plots	0.97		
SV 5	36 782	Species	0.98	235	239
		Plots	0.97		
SV 4b	17 090	Species	0.95	253	245
		Plots	0.85		
SV 3b	3767	Species	0.89	267	252
		Plots	0.50		
SV 3a	3767	Species	0.89	271	252
		Plots	0.50		
SV 4a	2436	Species	0.84	264	249
		Plots	0.53		

Notes: FIA, Forest Inventory and Analysis; GPP, gross primary production; NPP, net primary production; SV, screening variable.
Data are presented in the order in which SVs were selected during the creation of the optimal validation data set. Pearson correlations are reported for species and plots (all significant at a *p*-value of <0.0000001). Mean productivity (g C m^{-2} $year^{-1}$) was calculated using the data set following the sequential application of SVs. The Original data set contains 61 317 FIA plots, but only 54 969 of them, which comprise the Complete data set, had the two surveys required to calculate NPP. Note that mean productivity values after the sequential application of SV 6 are bimonthly (September–October) averaged values of GPP.

and between-SVs, however, indicated that the performance of individual SVs varied (table 4). For each SV, the best criterion evaluated by within-SV *z*-value had a Pearson *r*-value that was higher than the other criterion by at least 0.06 (SV 4a) and by at most 0.20 (SV 5). The between-SV *z*-values showed similar results, with the best criterion for each SV having a Pearson *r* higher than that for SV 2 ($r = 0.20$) by at least 0.05 (SV 5) and by at most 0.15 (SV 5). Individual SVs are discussed in order from the most to least efficient, with higher between-SV *z*-values indicating greater efficiency.

The MODIS seasonal signal (SV 6) exhibited the highest efficiency, with a between-SV *z*-value of 19.80. The high correlation coefficients during March to April and September to October occurred when the spatial pattern of MODIS GPP exhibited a continuous latitudinal gradient (figures 3(*a*)(*i*) and (*c*)(*i*)), whereas low correlation coefficients during the summer were found when MODIS GPP reached its maximum value across most of the eastern USA (figure 3(*b*)(*i*)). These results are similar to the close agreement between MODIS seasonal GPP and process-based model estimates of GPP at the beginning and end of the growing season (Turner *et al*. 2003, Nightingale

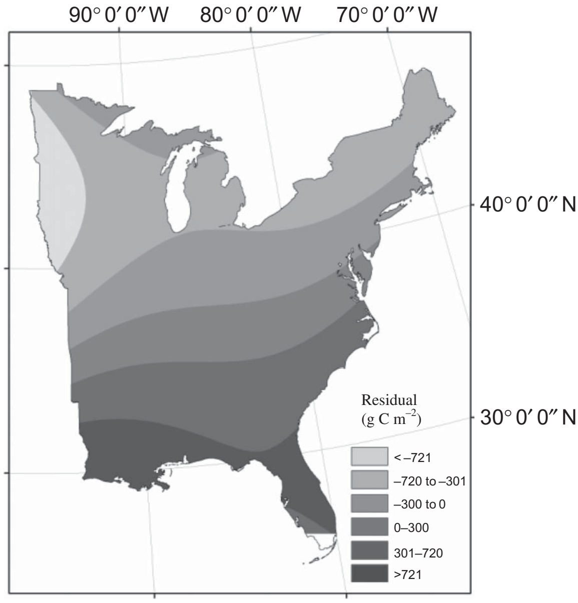

Figure 4. The geographic pattern of residuals of relation between MODIS GPP and FIA NPP following trend surface analysis.

et al. 2007). These patterns may be attributed to a saturation problem of a particular remote-sensing bandwidth when crown densities are high (Myneni *et al*. 2002).

The second most efficient SV was FIA sample size (SV 5). If a greater number of trees indicate a more highly closed forest canopy, then the higher correlation coefficient with the larger FIA sample size may result from more stable MODIS pixel reflectance coming from such closed-canopy plots (Drolet *et al*. 2005). In addition, a large FIA sample size should reduce the variance in the FIA estimate of NPP, and thus relations with MODIS GPP, as small numbers of samples within a fixed-radius plot tend to consist of a few large trees.

The MODIS pixel-level QA check (SV 1) and the FIA quality check (SV 2) were the third and fourth most efficient SVs, respectively. The MODIS pixel-level QA check (SV 1) filtered out low-quality pixels, without a reduction in total N. The low-QA pixels were more common in summer, with 68% of them occurring in June, July and August. This likely does not compromise the summer measures of GPP, however, because 72% of the summer pixels had acceptable QA values. The FIA quality check filtered out plots affected by artificial stand treatment and extremely high growth values (SV 2). We traced plot-level extremely high growth values to tree-level measurement errors of unlikely large tree diameters used for volume calculation. The belief that artificial stand treatment plots should be excluded because they would be from highly localized growth or mortality events is supported by there being higher standard deviation (214 g C m^{-2} year^{-1}) in artificial plots than non-artificial plots (143 g C m^{-2} year^{-1}).

SVs 4b and 4a, which assessed whether increased FIA plot homogeneity would improve relations with MODIS GPP by reducing spatial mismatches with MODIS data, had the fifth and eighth highest efficiencies. The use of highly homogeneous plots in SV 4b did create a large increase in the Pearson r-value for both the within-SV criteria and the optimal validation data set; however, as it resulted in the loss of 80% of the samples, it had a relatively low efficiency. Although the cut-off value of 75% for strict homogeneity seemed reasonable, different cut-off values can be used to control species composition homogeneity. Table 6 for SV 4b shows that the Pearson *r*-value increased from 0.25 to 0.38 as the extent of homogeneity increased by a cut-off value of 35% to 100%, while the number of samples reduced from 34 487 to 1717. These increases in the Pearson *r*-value suggest that MODIS, as a passive optical sensor measurement, is more suitable for relatively simple stand structures than it is for complex ones (Lu 2006).

The two SVs that assessed land-cover classification to reduce spatial mismatches, SVs 3b and 3a, had the sixth and seventh highest efficiencies, respectively. It is not surprising that SV 3b was more efficient than SV 3a, as its requirement that MODIS pixels and FIA plots had the same forest type actually includes the SV 3a requirement that the pixels and plots are both forested. The high Pearson *r* for SV 3b confirms the importance of spatial land-cover matches that the MODIS algorithm relies on to calculate biome-specific carbon storage and turnover rates based on land-cover types (Running *et al*. 2000).

5.2 *Optimal validation data sets*

The Pearson *r*-value for the optimal validation data sets corresponds to a coefficient of determination of 0.23 for the five-SV optimal validation data set with an *N* of 17 090 and of 0.30 for the eight-SV optimal validation data set with an *N* of 2436. These values are lower than the results obtained by Nightingale *et al*. (2007) and Zhang and Kondragunta (2006), who reported R^2 of 0.85 and 0.58, respectively. These results are lower than the R^2 of 0.58 that Zhang and Kondragunta (2006) found between MODIS predictions and FIA measures of biomass at the scale of US states. Their better results may be due to lower errors for biomass than for either GPP or NPP, or simply that errors decrease when measurements are aggregated to larger areas. The results were much lower than the R^2 of 0.85 that Nightingale *et al.* (2007) found between MODIS GPP and those generated using a simple process-based model at the scale of a level-one ecoregion containing five forest classes. However, the much better results of Nightingale *et al*. (2007) lacked true independence as the two data sets that they compared shared some of the same input data.

The 17 090 FIA plots and co-located MODIS pixels in the statistically significant validation data set appear to be a representative sub-sample of the Original 61 317 plots and pixels in terms of both species composition and spatial distribution of plots. As the Original data set itself was designed to provide reliable estimates for large sampling areas, the same could now be said of the optimal validation data set for representation of the whole of the eastern USA.

The residuals of the relation between MODIS GPP and FIA NPP indicate that AR is not a constant proportion of GPP as suggested by some (Waring *et al*. 1998) but is a varying proportion as suggested by others (DeLucia *et al*. 2007). The negative residuals shown in the northern area indicate that the observed MODIS GPP is lower than the predicted GPP as a linear function of FIA NPP, while the positive residuals mean a higher observed MODIS GPP than that predicted by FIA NPP. Therefore, the residual map indicates that AR is highest in the southern states where the climate is hot and wet and decreases to the north and west as the temperature and precipitation decrease. These patterns conform to the ecological explanation that plants growing under cooler and drier conditions need to expend less energy on sustaining living biomass (Ryan *et al*. 1994, Teskey *et al*. 1995). Since these results indicate non-linear relations between GPP and NPP, the sequential z-value approach was also done using non-parametric Spearman correlations; the results indicated the same order of importance of SVs.

5.3 *Spatial mismatch*

A key motivation for this research was to address the inherent scaling mismatches between the MODIS and FIA data sets (Cohen *et al*. 2003), without scaling the data up to larger spatial units (Zhang and Kondragunta 2006) or using bridging remote-sensing products (Muukkonen and Heiskanen 2007). Instead, the mismatch between MODIS pixels and FIA plots was addressed by applying SVs to maximize compatibility between the two spatial units, while maintaining the plot- and pixel-scale resolution. In this regard, it is interesting that the four SVs that focused on spatial mismatches (SVs 3a, 3b, 4a and 4b) had the least influence on the Pearson r-value, suggesting that the issue of spatial mismatch may not be as important as is ensuring data quality (SVs 1 and 2) and data compatibility (SVs 5 and 6). However, it is also possible that some SVs regarding spatial mismatch could have been improved through more judicious application as noted in table 6. Restricting analyses to just homogeneous plots, however, would greatly limit the types of forests that would be studied.

5.4 *Prospective SVs*

There are a number of possible SVs that could be developed to potentially improve the validation of MODIS GPP with FIA NPP. First, MODIS GPP upstream products such as LAI and fPAR could be related to FIA stand-level attributes such as ‘crown class’ or ‘stand size class’; however, at present, they are unsuitable because they are not estimated rigorously and contain many missing values. Second, soil properties could also provide a valuable SV because tree growth is highly affected by soil conditions. FIA NPP has been related to physical and chemical properties of soil (Jackson *et al*. 2000, Schwarzel *et al*. 2009), and MODIS GPP was overestimated in areas of infertile soils with limited water storage capacity (Nightingale *et al*. 2007). It will become possible to explore relations between soil characteristics of FIA plots and MODIS pixels when sufficient FIA plots have been inventoried as part of the forest health monitoring inventory (FIA phase 3). Third, MODIS GPP estimates could be improved, especially in topographically diverse areas, if meteorological inputs such as temperature and vapour deficit were obtained from finer spatial resolution sources than the $1°$ latitude $\times$ $1.25°$ longitude DAO inputs that are currently used. The application of these additional SVs should result in further improvements to the optimal validation data set.

6. Conclusions

The results of this study highlight five key considerations in the method that uses FIA plot-level and MODIS pixel-level primary productions. First, the application of simple quality checks for both MODIS (SV 1) and FIA (SV 2) should be employed by all studies using these types of data for analyses of tree growth. Second, poor correlations between the two data sets during the mid-summer add further evidence to the belief that the MODIS signal becomes saturated at high levels of productivity, which would result in underestimation of summer productivity. As this could result in it providing erroneous information to carbon budgets, this issue requires serious attention. Third, the better validation of MODIS GPP predictions for dense and homogeneous forests indicates the applicability of FIA plot-level attributes to minimize scaling mismatches between MODIS and FIA data. Fourth, the systematically selected network of FIA ground plots shows good representation of the larger MODIS pixels. Fifth, latitudinal variation in the residuals of the relationship between MODIS GPP and FIA NPP indicates that respiration is a varying portion of GPP. In sum, the optimal validation data set suggests that MODIS GPP is more strongly validated for certain conditions than for others, and that changes in its algorithms should be made to improve its predictions.

References

Anderson, T.W. and Darling, D.A., 1952, Asymptotic theory of certain 'goodness-of-fit' criteria based on stochastic processes. *Annals of Mathematical Statistics*, **23**, pp. 193–212.

Bailey, R.G., 1995, *Descriptions of the Ecoregions of the United States*, 2nd ed. Miscellaneous Publication No. 1391, 108 p. (Washington, DC: US Department of Agriculture, Forest Service).

Bechtold, W.A. and Patterson, P.L. (Eds.), 2005, *The Enhanced Forest Inventory and Analysis Program – National Sampling Design and Estimation Procedures* (Asheville, NC: Forest Service, Department of Agriculture, Southern Research Station).

Bettinger, P., Clutter, M., Siry, J., Kane, M. and Pait, J., 2009, Broad implications of southern United States pine clonal forestry on planning and management of forests. *International Forestry Review*, **11**, pp. 331–345.

Birdsey, R.A., 1996, Carbon storage for major forest types and regions in the conterminous United States. *American Forests*, **2**, pp. 261–371.

Blackard, J.A., Finco, M.V., Helmer, E.H., Holden, G.R., Hoppus, M.L., Jacobs, D.M., Lister, A.J., Moisen, G.G., Nelson, M.D., Riemann, R., Ruefenacht, B., Salajanu, D., Weyermann, D.L., Winterberger, K.C., Brandeis, T.J., Czaplewski, R.L., McRoberts, R.E., Patterson, P.L. and Tymcio, R.P., 2008, Mapping US forest biomass using nationwide forest inventory data and moderate resolution information. *Remote Sensing of Environment*, **112**, pp. 1658–1677.

Brown, S.L. and Schroeder, P.E., 1999, Spatial patterns of aboveground production and mortality of woody biomass for eastern US forests. *Ecological Applications*, **9**, pp. 968–980.

Chapin, F.S., Matson, P.A., Mooney, H.A. and Chapin, M.C., 2002, *Principles of Terrestrial Ecosystem Ecology* (New York: Springer-Verlag).

Clark, D.A., Brown, S., Kicklighter, D.W., Chambers, J.Q., Thomlinson, J.R. and Ni, J., 2001, Measuring net primary production in forests: concepts and field methods. *Ecological Applications*, **11**, pp. 356–370.

Cohen, W.B., Maiersperger, T.K., Yang, Z.Q., Gower, S.T., Turner, D.P., Ritts, W.D., Berterretche, M. and Running, S.W., 2003, Comparisons of land cover and LAI estimates derived from ETM plus and MODIS for four sites in North America: a quality assessment of 2000/2001 provisional MODIS products. *Remote Sensing of Environment*, **88**, pp. 233–255.

DeLucia, E.H., Drake, J.E., Thomas, R.B. and Gonzalez-Meler, M., 2007, Forest carbon use efficiency: is respiration a constant fraction of gross primary production? *Global Change Biology*, **13**, pp. 1157–1167.

Dewar, R.C., Medlyn, B.E. and McMurtrie, R.E., 1998, A mechanistic analysis of light and carbon use efficiencies. *Plant Cell and Environment*, **21**, pp. 573–588.

Drolet, G.G., Huemmrich, K.F., Hall, F.G., Middleton, E.M., Black, T.A., Barr, A.G. and Margolis, H.A., 2005, A MODIS-derived photochemical reflectance index to detect inter-annual variations in the photosynthetic light-use efficiency of a boreal deciduous forest. *Remote Sensing of Environment*, **98**, pp. 212–224.

Fisher, R.A., 1921, On the 'Probable error' of a coefficient of correlation deduced from a small sample. *Metron*, **1**, pp. 3–32.

Gillis, M.D., Omule, A.Y. and Brierley, T., 2005, Monitoring Canada's forests: the national forest inventory. *Forestry Chronicle*, **81**, pp. 214–221.

Heinsch, F.A., Zhao, M.S., Running, S.W., Kimball, J.S., Nemani, R.R., Davis, K.J., Bolstad, P.V., Cook, B.D., Desai, A.R., Ricciuto, D.M., Law, B.E., Oechel, W.C., Kwon, H., Luo, H.Y., Wofsy, S.C., Dunn, A.L., Munger, J.W., Baldocchi, D.D., Xu, L.K., Hollinger, D.Y., Richardson, A.D., Stoy, P.C., Siqueira, M.B.S., Monson, R.K., Burns, S.P. and Flanagan, L.B., 2006, Evaluation of remote sensing based terrestrial productivity from MODIS using regional tower eddy flux network observations. *IEEE Transactions on Geoscience and Remote Sensing*, **44**, pp. 1908–1925.

Houghton, R.A., Butman, D., Bunn, A.G., Krankina, O.N., Schlesinger, P. and Stone, T.A., 2007, Mapping Russian forest biomass with data from satellites and forest inventories. *Environmental Research Letters*, **2**, 045032, doi:10.1088/1748-9326/2/4/045032.

Jackson, R.B., Sperry, J.S. and Dawson, T.E., 2000, Root water uptake and transport: using physiological processes in global predictions. *Trends in Plant Science*, **5**, pp. 482–488.

Jenkins, J.C., Birdsey, R.A. and Pan, Y., 2001, Biomass and NPP estimation for the mid-Atlantic region (USA) using plot-level forest inventory data. *Ecological Applications*, **11**, pp. 1174–1193.

Landsberg, J.J., Johnsen, K.H., Albaugh, T.J., Allen, H.L. and McKeand, S.E., 2001, Applying 3-PG, a simple process-based model designed to produce practical results, to data from loblolly pine experiments. *Forest Science*, **47**, pp. 43–51.

Law, B.E., Waring, R.H., Anthoni, P.M. and Aber, J.D., 2000, Measurements of gross and net ecosystem productivity and water vapour exchange of a *Pinus ponderosa* ecosystem, and an evaluation of two generalized models. *Global Change Biology*, **6**, pp. 155–168.

Lotsch, A., Tian, Y., Friedl, M.A. and Myneni, R.B., 2003, Land cover mapping in support of LAI and FPAR retrievals from EOS-MODIS and MISR: classification methods and sensitivities to errors. *International Journal of Remote Sensing*, **24**, pp. 1997–2016.

Lu, D.S., 2006, The potential and challenge of remote sensing-based biomass estimation. *International Journal of Remote Sensing*, **27**, pp. 1297–1328.

McRoberts, R.E., 2008, Using satellite imagery and the *k*-nearest neighbors technique as a bridge between strategic and management forest inventories. *Remote Sensing of Environment*, **112**, pp. 2212–2221.

McRoberts, R.E., Bechtold, W.A., Patterson, P.L., Scott, C.T. and Reams, G.A., 2005a, The enhanced forest inventory and analysis program of the USDA Forest Service: historical perspective and announcement of statistical documentation. *Journal of Forestry*, **103**, pp. 304–308.

McRoberts, R.E., Holder, G.R., Nelson, M.D., Liknes, G.C., Moser, W.K., Lister, A.J., King, S.L., LaPoiint, E.B., Coulston, J.W., Smith, W.B. and Reams, G.A., 2005b, Estimating and circumventing the effects of perturbing and swapping forest inventory plot locations. *Journal of Forestry*, **103**, pp. 275–279.

Morisette, J.T., Privette, J.L. and Justice, C.O., 2002, A framework for the validation of MODIS land products. *Remote Sensing of Environment*, **83**, pp. 77–96.

Murphy, H.T., VanDerWal, J. and Lovett-Doust, J., 2010, Signatures of range expansion and erosion in eastern North American trees. *Ecology Letters*, **13**, pp. 1233–1244.

Muukkonen, P. and Heiskanen, J., 2007, Biomass estimation over a large area based on standwise forest inventory data and ASTER and MODIS satellite data: a possibility to verify carbon inventories. *Remote Sensing of Environment*, **107**, pp. 617–624.

MYNENI, R.B., KNYAZIKHIN, Y., PRIVETTE, J.L. and GLASSY, J., 2002, Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sensing of Environment*, **83**, pp. 214–231.

NAKAWATASE, J.M. and PETERSON, D.L., 2006, Spatial variability in forest growth–climate relationships in the Olympic Mountains, Washington. *Canadian Journal of Forest Research*, **36**, pp. 77–91.

NEMANI, R.R., KEELING, C.D., HASHIMOTO, H., JOLLY, W.M., PIPER, S.C., TUCKER, C.J., MYNENI, R.B. and RUNNING, S.W., 2003, Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science*, **300**, pp. 1560–1563.

NIGHTINGALE, J.M., COOPS, N.C., WARING, R.H. and HARGROVE, W.W., 2007, Comparison of MODIS Gross Primary Production estimates for forests across the U.S.A. with those generated by a simple process model, 3-PGS. *Remote Sensing of Environment*, **109**, pp. 500–509.

PHILLIPS, D.L., BROWN, S.L., SCHROEDER, P.E. and BIRDSEY, R.A., 2000, Toward error analysis of large-scale forest carbon budgets. *Global Ecology and Biogeography*, **9**, pp. 305–313.

POTTER, C., KLOOSTER, S., HUETE, A. and GENOVESE, V., 2007, Terrestrial carbon sinks for the United States predicted from MODIS satellite data and ecosystem modeling. *Earth Interactions*, **11**, pp. 1–21.

POTTER, C.S., RANDERSON, J.T., FIELD, C.B., MATSON, P.A., VITOUSEK, P.M., MOONEY, H.A. and KLOOSTER, S.A., 1993, Terrestrial ecosystem production: a process model based on global satellite and surface data. *Global Biogeochemical Cycles*, **7**, pp. 811–841.

POWELL, S.L., COHEN, W.B., HEALEY, S.P., KENNEDY, R.E., MOISEN, G.G., PIERCE, K.B. and OHMANN, J.L., 2010, Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: a comparison of empirical modeling approaches. *Remote Sensing of Environment*, **114**, pp. 1053–1068.

PRINCE, S.D. and GOWARD, S.N., 1995, Global primary production: a remote sensing approach. *Journal of Biogeography*, **22**, pp. 815–835.

REICH, P.B., TJOELKER, M.G., MACHADO, J.L. and OLEKSYN, J., 2006, Universal scaling of respiratory metabolism, size and nitrogen in plants. *Nature*, **441**, pp. 902–902.

RUNNING, S.W., THORNTON, P.E., NEMANI, R. and GLASSY, J.M., 2000, Global terrestrial gross and net primary productivity from the Earth Observing System. In *Methods in Ecosystem Science*, O. Sala, R. Jackson, H.A. Mooney and R.W. Howarth (Eds.), pp. 44–57 (New York: Springer-Verlag).

RYAN, M.G., LINDER, S., VOSE, J.M. and HUBBARD, R.H., 1994, Dark respiration of pines. *Ecological Bulletin*, **43**, pp. 50–63.

SCHWARZEL, K., FEGER, K.H., HANTZSCHEL, J., MENZER, A., SPANK, U., CLAUSNITZER, F., KOSTNER, B. and BERNHOFER, C., 2009, A novel approach in model-based mapping of soil water conditions at forest sites. *Forest Ecology and Management*, **258**, pp. 2163–2174.

STEINBERG, D.C. and GOETZ, S., 2009, Assessment and extension of the MODIS FPAR products in temperate forests of the eastern United States. *International Journal of Remote Sensing*, **30**, pp. 169–187.

TESKEY, R.O., SHERFF, D.W., HOLLINGER, D.Y. and THOMAS, R.B., 1995, External and internal factors regulating photosynthesis. In *Resource Physiology of Conifers*, W.K. Smith and T.M. Hinckley (Eds.), pp. 105–140 (New York: Academic Press).

TOMPPO, E., OLSSON, H., STAHL, G., NILSSON, M., HAGNER, O. and KATILA, M., 2008, Combining national forest inventory field plots and remote sensing data for forest databases. *Remote Sensing of Environment*, **112**, pp. 1982–1999.

TURNER, D.P., KOERPER, G.J., HARMON, M.E. and LEE, J.J., 1995, A carbon budget for forests of the conterminous United States. *Ecological Applications*, **5**, pp. 421–436.

TURNER, D.P., RITTS, W.D., COHEN, W.B., GOWER, S.T., ZHAO, M.S., RUNNING, S.W., WOFSY, S.C., URBANSKI, S., DUNN, A.L. and MUNGER, J.W., 2003, Scaling Gross Primary

Production (GPP) over boreal and deciduous forest landscapes in support of MODIS GPP product validation. *Remote Sensing of Environment*, **88**, pp. 256–270.

Turner, D.P., Ritts, W.D., Cohen, W.B., Maeirsperger, T.K., Gower, S.T., Kirschbaum, A.A., Running, S.W., Zhao, M.S., Wofsy, S.C., Dunn, A.L., Law, B.E., Campbell, J.L., Oechel, W.C., Kwon, H.J., Meyers, T.P., Small, E.E., Kurc, S.A. and Gamon, J.A., 2005, Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. *Global Change Biology*, **11**, pp. 666–684.

USDA Forest Service, 2003, *Land Areas of the National Forest System* (Washington, DC: USDA Forest Service). Available online at: http://www.fs.fed.us/land/staff/lar/LAR03/lar03index.htm

Waring, R.H., Landsberg, J.J. and Williams, M., 1998, Net primary production of forests: a constant fraction of gross primary production? *Tree Physiology*, **18**, pp. 129–134.

Xiao, C.W., Yuste, J.C., Janssens, I.A., Roskams, P., Nachtergale, L.C.A., Sanchez, B.Y. and Ceulemans, R., 2003, Above and belowground biomass and net primary production in a 73-year old Scots pine forest. *Tree Physiology*, **23**, pp. 505–516.

Xiao, J.F., Zhuang, Q.L., Baldocchi, D.D., Law, B.E., Richardson, A.D., Chen, J.Q., Oren, R., Starr, G., Noormets, A., Ma, S.Y., Verma, S.B., Wharton, S., Wofsy, S.C., Bolstad, P.V., Burns, S.P., Cook, D.R., Curtis, P.S., Drake, B.G., Falk, M., Fischer, M.L., Foster, D.R., Gu, L.H., Hadley, J.L., Hollinger, D.Y., Katul, G.G., Litvak, M., Martin, T.A., Matamala, R., McNulty, S., Meyers, T.P., Monson, R.K., Munger, J.W., Oechel, W.C., Paw, U.K.T., Schmid, H.P., Scott, R.L., Sun, G., Suyker, A.E. and Torn, M.S., 2008, Estimation of net ecosystem carbon exchange for the conterminous United States by combining MODIS and AmeriFlux data. *Agricultural and Forest Meteorology*, **148**, pp. 1827–1847.

Yang, F.H., Ichii, K., White, M.A., Hashimoto, H., Michaelis, A.R., Votava, P., Zhu, A.X., Huete, A., Running, S.W. and Nemani, R.R., 2007, Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach. *Remote Sensing of Environment*, **110**, pp. 109–122.

Yang, W.Z., Tan, B., Huang, D., Rautiainen, M., Shabanov, N.V., Wang, Y., Privette, J.L., Huemmrich, K.F., Fensholt, R., Sandholt, I., Weiss, M., Ahl, D.E., Gower, S.T., Nemani, R.R., Knyazikhin, Y. and Myneni, R.B., 2006, MODIS leaf area index products: from validation to algorithm improvement. *IEEE Transactions on Geoscience and Remote Sensing*, **44**, pp. 1885–1898.

Zhang, X. and Kondragunta, S., 2006, Estimating forest biomass in the USA using generalized allometric models and MODIS land products. *Geophysical Research Letters*, **33**, L09402, doi:10.1029/2006GL025879.

Zhao, M., Heinsch, R.A., Nemani, R.R. and Running, S.W., 2005, Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment*, **95**, pp. 164–176.

Zheng, D.L., Heath, L.S. and Ducey, M.J., 2007, Forest biomass estimated from MODIS and FIA data in the Lake States: MN, WI and MI, USA. *Forestry*, **80**, pp. 265–278.

Zheng, D.L., Heath, L.S. and Ducey, M.J., 2008, Spatial distribution of forest aboveground biomass estimated from remote sensing and forest inventory data in New England, USA. *Journal of Applied Remote Sensing*, **2**, 021502s, doi:10.1117/1.2940686.