Available online at www.sciencedirect.com

SCIENCE DIRECT®

Remote Sensing of Environment xx (2004) xxx–xxx

Remote Sensing of Environment

www.elsevier.com/locate/rse

Estimating aboveground biomass using Landsat 7 ETM+ data across a managed landscape in northern Wisconsin, USA

Daolan Zheng[a,*], John Rademacher[b], Jiquan Chen[a], Thomas Crow[c], Mary Bresee[a], James Le Moine[d], Soung-Ryoul Ryu[a]

[a]Department of Earth, Ecological, and Environmental Sciences, University of Toledo, Toledo, OH 43606, USA
[b]USDA Forest Service, WFWAR, Arlington, VA 22209, USA
[c]USDA, Forest Service Ruby Mtn./Jarbidge Ranger District, Wells, NV 89835, USA
[d]Department of Ecology and Evolutionary Biology, University of Michigan, Ann Arbor, MI 48108, USA

Received 7 January 2004; received in revised form 13 July 2004; accepted 5 August 2004

Abstract

Aboveground biomass (AGB; Mg/ha) is defined in this study as a biomass of growing stock trees greater than 2.5 cm in diameter at breast height (dbh) for stands >5 years and all trees taller than 1.3 m for stands <5 years. Although AGB is an important variable for evaluating ecosystem function and structure across the landscape, such estimates are difficult to generate without high-resolution satellite data. This study bridges the application of remote sensing techniques with various forest management practices in Chequamegon National Forest (CNF), Wisconsin, USA by producing a high-resolution stand age map and a spatially explicit AGB map. We coupled AGB values, calculated from field measurements of tree dbh, with various vegetation indices derived from Landsat 7 ETM+ data through multiple regression analyses to produce an initial biomass map. The initial biomass map was overlaid with a land-cover map to generate a stand age map. Biomass threshold values for each age category (e.g., young, intermediate, and mature) were determined through field observations and frequency analysis of initial biomass estimates by major cover types. We found that AGB estimates for hardwood forests were strongly related to stand age and near-infrared reflectance (r^2=0.95) while the AGB for pine forests was strongly related to the corrected normalized difference vegetation index (NDVIc; r^2=0.86). Separating hardwoods from pine forests improved the AGB estimates in the area substantially, compared to overall regression (r^2=0.82). Our AGB results are comparable to previously reported values in the area. The total amount of AGB in the study area for 2001 was estimated as 3.3 million metric tons (dry weight), 76.5% of which was in hardwood and mixed hardwood/pine forests. AGB ranged from 1 to 358 Mg/ha with an average of 70 and a standard deviation of 54 Mg/ha. The AGB class with the highest percentage (16.1%) was between 81 and 100 Mg/ha. Forests with biomass values >200 Mg/ha accounted for less than 3% of the study area and were usually associated with mature hardwood forests. Estimated AGB was validated using independent field measurements (R^2=0.67, p<0.001). The AGB and age maps can be used as baseline information for future landscape level studies such as quantifying the regional carbon budget, accumulating fuel, or monitoring management practices.

Keywords: Hardwood and pine forests; Stand age; Carbon pools; Biomass distribution; Fuel accumulation; Vegetation indices; Reflectance

1. Introduction

Estimation of aboveground biomass (AGB) is necessary for studying productivity, carbon cycles, nutrient allocation, and fuel accumulation in terrestrial ecosystems (Alban et al., 1978; Brown et al., 1999; Crow, 1978; Ryu et al., in press). Remote sensing techniques allow scientists to examine properties and processes of ecosystems and their interannual variability at multiple scales because satellite observations can be obtained over large areas of interest with high revisitation frequencies (Goetz et al., 2000; Prince & Goward, 1995; Running et al., 2000). Many studies have

* Corresponding author. Tel.: +1 419 530 5499; fax: +1 419 530 4421.
E-mail address: dzheng@utnet.utoledo.edu (D. Zheng).

0034-4257/$ - see front matter © 2004 Elsevier Inc. All rights reserved.
doi:10.1016/j.rse.2004.08.008

demonstrated that indices such as spectral vegetation index (SVI), simple ratio (SR), normalized difference vegetation index (NDVI), and corrected normalized difference vegetation index (NDVIc) obtained from satellite data are useful predictors of leaf area index (LAI), biomass, and productivity in grasslands and forests (Cheng & Zhao, 1990; Diallo et al., 1991; Fassnacht et al., 1997; Jakubauskas, 1996; Nemani et al., 1993; Paruelo & Lauenroth, 1998; Steininger, 2000; Tieszen et al., 1997).

Stand level biomass is frequently calculated from linear and nonlinear regression models established by species with field measurements (Crow & Schlaegel, 1988; Hahn, 1984; Ohmann & Grigal, 1985; Smith, 1985). Although estimates of AGB vary with species composition, tree height, basal area, and stand structure, bole diameter at breast height (dbh) is the most commonly used and widely available variable for calculating AGB (Crow & Schlaegel, 1988). Numerous regression models have been developed to estimate AGB in the Great Lakes Region (GLR; Hahn, 1984; Perala & Alban, 1994; Raile & Jakes, 1982; Steinhilb et al., 1983); while these models are accurate at tree, plot, and stand levels, they are limited when considering spatial pattern analysis of AGB across the landscape. In order to scale AGB estimates to the landscape level, the estimates have to be linked with various vegetation indices derived by remote sensing data.

Past studies have shown varying degrees of success in estimating forest biomass and primary production from remote sensing data in temperate and tropical forests worldwide (Brown et al., 1999; Gower et al., 1999; Jakubauskas, 1996; Lee & Nakane, 1997; Lefsky et al., 1999; Malcolm et al., 1998; Sader et al., 1989; Sannier et al., 2002; Steininger, 2000). Recent studies suggest that such relationships vary temporally and spatially; however, biomass estimates at the landscape level are necessary for understanding processes of the target landscapes and provide baseline data for future studies (Foody et al., 2003; Woodcock et al., 2001). Models derived from remote sensing need further calibration with ground data before they can be used appropriately to predict AGB for a given landscape.

To bridge the application of remote sensing techniques with various forest management practices in Chequamegon National Forest (CNF), Wisconsin, USA, we produced age and AGB maps using both remotely sensed and field-measured stand level data—one of the research priorities (e.g., combining carbon pool assessments from existing inventories with remotely sensed variables at the landscape level) identified in the North American Carbon Program (NACP; http://www.esig.ucar.edu/nacp/). Lack of a high-resolution stand age map is one of the research gaps preventing landscape level ecological analyses in the CNF. The existing stand age map in the area developed by the USDA Forest Service for other purposes has coarse spatial resolution and limited availability, and is infrequently updated (i.e., land-use changes between years cannot be reflected). Hence, it is unsuitable for landscape level studies, in conjunction with the Landsat data that have much higher spatial and temporal resolutions than the existing USDA age map.

The overall objectives of this study were to combine field observations and remotely sensed data to: (1) produce a high-resolution age map of the landscape; (2) generate a spatially explicit AGB map using our age map and various vegetation indices as driving variables; and (3) examine spatial patterns of AGB in an intensively managed landscape. We implemented three specific steps to meet our study objectives: (a) estimating initial AGB by coupling field measurements with solely remotely sensed data through stepwise regressions for hardwood forests, pine forests, and a combination (i.e., hardwood and pine); (b) obtaining a landscape age map by overlaying the initial AGB map with an existing land-cover map using biomass threshold values, determined by

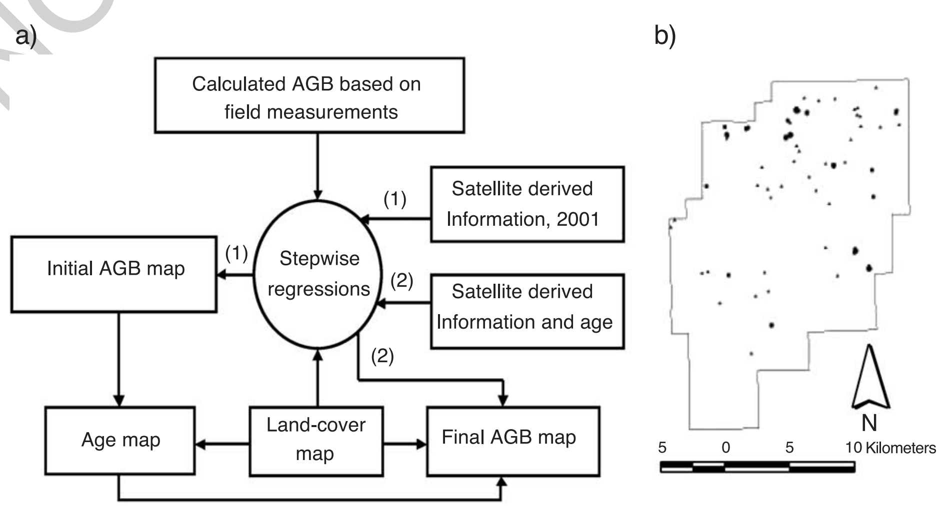

Fig. 1. (a) Framework of estimating AGB (Mg/ha) using Landsat 7 ETM+ data and field measurements in the CNF; and (b) spatial distributions of the plots used for model construction (circles) and validation (triangles).

frequency analysis and field observations, to separate young, intermediate, and mature hardwood and pine forests; and (c) refining the initial landscape AGB estimates using a combination of newly developed models incorporating age variable from field observations, other satellite-derived information, and our created age map (Fig. 1a).

2. Materials and methods

2.1. Study area

Our study area is located in the Washburn Ranger District of CNF in northern Wisconsin, USA, which has been extensively researched during the last decade (Bresee et al., 2004; Brosofske et al., 2001; Burrows et al., 2003; Chen et al., 1999; Euskirchen et al., 2003; Fassnacht & Gower, 1999; Fassnacht et al., 1997; Gustafson & Crow, 1996; He et al., 1998; Mackay et al., 2002; Mladenoff et al., 1993; Saunders et al., 1999; Zheng & Chen, 2000). The area is characterized by Precambrian shield bedrock and a late Wisconsin-age glaciated landscape. The topography is flat to rolling (elevations ranging from 232 to 459 m), with terrace and pitted outwash landforms composed of deep, coarse-textured soils. The climate is marked by a short/hot summer with a growing season of 120–140 days, and cold winters (−10 °C on average from December and February over a 30-year period (http://mcc.sws.uiuc.edu/Temp/WI/470349_tsum.html). Annual precipitation ranges from 660 to 700 mm (Albert, 1995). Six dominant cover types in the study area, basically following Bresee et al. (2004) with slight modifications, were: mixed northern hardwood, thereafter referred to hardwood (HW); jack pine (JP), red pine (RP), mixed hardwood/pine (MIX), regenerating forest/shrub (RFS; including pine barrens), and nonforested bare ground [NFBG; including clearcuts (CC)].

Stand level forest management has been the most dominant factor determining landscape structure in CNF. In recent decades, two major forest management periods have occurred: (1) maximization of timber production (e.g., pre- to mid-1980s), and (2) multiple use (i.e., wildlife habitat and plant diversity) by implementing a variety of silvicultural techniques (i.e., clearcutting, thinning, prescribed burning, etc.), which promote early- and mid-successional species (Bresee et al., 2004; Saunders et al., 1998). For example, the pine barrens (PB) landscape in Moquah Wildlife Area is currently being restored and maintained through the use of silvicultural treatments and prescribed burning every 5–10 years (Brosofske et al., 1999) because of its importance for plant and wildlife habitat (e.g., sharp-tail grouse) and recreation (e.g., berry pickers) (Vora, 1993). According to the current forest management plan, mature forests (i.e., pine and hardwoods) were harvested at an average age between 65 and 70 years (USDA, 1986), which resulted in more or less the even age forest structure across the landscape.

2.2. Field design and measurements of tree dbh

Fifty-five circular plots used in model construction were established and measured in the 2002 growing season. All were continuous even-aged stands: 2.6 km^2 for mature and intermediate aged stands and 1.3 km^2 for young and clearcut stands across cover types (i.e., RP, JP, and HW) and age groups. In each cover type, four age classes were sampled (i.e., 3–8, 15–20, 32–40, and 65–75 years) for a total of 12 stands. In each stand, four to five plots were set around its center at a distance of 150 m for the 32–40- and 65–75-year stands, and 60 m for the 3–8- and 15–20-year stands. The plot area for all cover types and age classes (except for young hardwood) was approximately 0.05 ha. Conversely, the young hardwood plots were approximately 0.01 ha due to high stem density. Within each 0.05-ha plot, the dbh of all trees (>2.5 cm dbh) and the average stand age of the plot were determined by tree ring analysis and recorded. In the young hardwood plot, the dbh of all trees with a height of >1.3 m was measured. Both the 0.05- and 0.01-ha areas were located in homogeneous cover types (even age management) within a minimum size of 60×60 m.

In addition to the initial 55 plots, 40 validation plots were selected randomly and measured in the 2003 growing season for model validation. The plot selection was based on similar criterion as stands used for model construction, which were: (1) stratified by management areas (i.e., small block pine, large block pine, and hardwood regions); (2) separated into four age classes; and (3) large enough to insure that the plot was not influenced by edges (i.e., the boundary between two contrasting communities), road, and/or pipeline. Once a suitable stand was found, a random number table was used to determine plot location (i.e., compass bearing and distance) (Fig. 1b) and dbh of the trees in each subarea (i.e., 0.05 or 0.01 ha) was measured. Field biomass calculated from the measured tree dbh in either 0.05- or 0.01-ha area of the 95 plots was adjusted to 1 ha before being used for model construction and validation.

2.3. Biomass estimation

AGB (Mg/ha) is defined in this study as biomass of growing stock trees greater than 2.5 cm dbh for stands >5 years and all trees taller than 1.3 m for stands <5 years, including tree foliage and branches. Previous studies have shown that amount of biomass from shrub and sapling is minimal in forested ecosystems of the region and that the AGB accounts for 92–99% of the total AGB depending on forest type and age (Alban et al., 1978; Crow, 1978; Ohman, 1984). For each sampled tree, AGB was calculated as a function of dbh [$AGB=a(dbh)^b$, where AGB is the oven dry weight, and a and b are regression parameters]. The parameter estimates used were from published literature in the closest geographical regions for red pine (*Pinus resinosa*) and jack pine (*Pinus banksiana*), paper birch (*Betula papyrifera*), big tooth aspen (*Populus grandidentata*), red oak (*Quercus rubra*), sugar maple (*Acer saccharum*), quaking aspen (*Populus tremuloides*), red maple (*Acer rubrum*) (Perala & Alban, 1994; Ter-Mikaelian & Kirzukhin, 1997), and choke cherry (*Prunus virginiana*) (Ter-Mikaelian & Kirzukhin, 1997; Young et al., 1980). Once AGB was calculated using the dbh of all trees species in each plot, we calculated the sum and converted to megagrams per hectare. In the young hardwood and pine plots, as tree diameter size violated the minimum diameter of the documented models, we used the models developed outside the GLR that were able to handle the smaller diameter size for *P. resinosa* and *P. banksiana* (Ker, 1980), *Q. rubra* (Hocker & Earley, 1983), *B. papyrifera*, *P. grandidentata*, *A. saccharum*, *P. tremuloides*, and *A. rubrum* (Freedman et al., 1982).

2.4. Remotely sensed indices

An ETM+ image of 2001 (June 12) in the study area (46°30′–46°45′N, 91°02′–91°22′W) was acquired to calculate various vegetation indices. The image was georectified to UTM projection and the raw satellite data in each ETM+ band (except thermal and panchromatic) were converted to reflectance using an exoatmospheric model (http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_htmls/chapter11/chapter11.html) prior to the calculation of vegetation indices. This study incorporated reflectance in six individual bands [blue, green, red, near-infrared (NIR), and two middle-infrared (MIR)] and five vegetation indices calculated from individual bands as independent variables including: (1) ratio of blue/red; (2) NDVI (NIR−red)/(NIR+red) (Rouse et al., 1973); (3) SR (NIR/red); (4) modified soil adjusted vegetation index (MSAVI), calculated as: MSAVI=$(\rho_{\mathrm{NIR}}-\rho_{\mathrm{red}})/(\rho_{\mathrm{NIR}}-\rho_{\mathrm{red}}+L)*(1+L)$, where ρ is reflectance in NIR or red band and L is a soil adjustment factor (Qi et al., 1994); and (5) NDVIc is calculated from NDVI*[1−(mIR−mIR$_{min}$)/(mIR$_{max}$−mIR$_{min}$)] (Nemani et al., 1993).

Table 1
The threshold values of AGB (Mg/ha) used to differentiate age classes for pine and hardwood forests in the CNF

Cover types	Young (4–15 years) [Mg/ha]	Intermediate (16–35[a] and 16–45[b] years) [Mg/ha]	Mature (36+[a] and 46+[b] years) [Mg/ha]
Pine	4–19	20–80	>80
Hardwood	4–39	40–100	>100

The values were determined from frequency analysis of initial AGB map and field observations. Clearcuts were assigned ages <3 years. Pine barrens were assigned ages of 5–25 years.
[a] For pine forests.
[b] For hardwood forests.

Table 2
Statistic models used for calculating AGB (Mg/ha)

Models	Description	n	r^2
AGB=48.8*(NIR/red)+2.3*Age-454*MASVI-38	Overall	55	0.82
AGB=111*(NDVIc$^{10.3}$/(NDVIc$^{10.3}$+0.35$^{10.3}$))	Pine	35	0.86
AGB=232.5*NIR+2.7*Age-71	Hardwood	20	0.95

The models were established from field measurements, Landsat ETM+ individual bands, and various vegetation indices developed from remote sensing data in CNF, WI, USA. Statistically, the model is generally expressed as $Y=\beta_0+\beta_1X_1\ldots\beta_iX_i+\varepsilon$, where Y=the dependent variable; X_i=the independent variable for the ith observation assumed to be measured without error; β_0, β_1, β_i=constant parameters of the system that need to be determined; and ε=error term (Clark & Hosking, 1986), and is usually simplified as above without the error term for practical application.

2.5. Relating ground data with the processed remote sensing indices to produce maps of initial AGB, age, and final AGB

The spatial location of each plot was acquired using a global positioning system (GPS). To develop the empirical models for hardwood, pine, and both combined, the 11 independent variables were linked to the AGB of the 55 selected plots. A conceptual framework was developed to demonstrate the major steps taken to produce the initial AGB map, age map, and final AGB map using field data and satellite-derived information (Fig. 1a).

To create the age map, we first determined the biomass threshold values (Table 1) based on our field observations of age distribution for hardwood and pine forests and the frequency analysis of initial AGB map (resulting solely from the remotely sensed independent variables and ground measurements; pathway 1 of Fig. 1a). Second, we applied these threshold values and overlaid the land-cover map with the initial AGB map to derive a landscape level age map of CNF. The age map was needed because our field observations suggested that the biomass accumulation for hardwood forests was linearly related to stand age due to heavy management practices (e.g., even age harvest). We then used field-observed age information plus the existing 11 independent variables for the 55 plots to establish new empirical

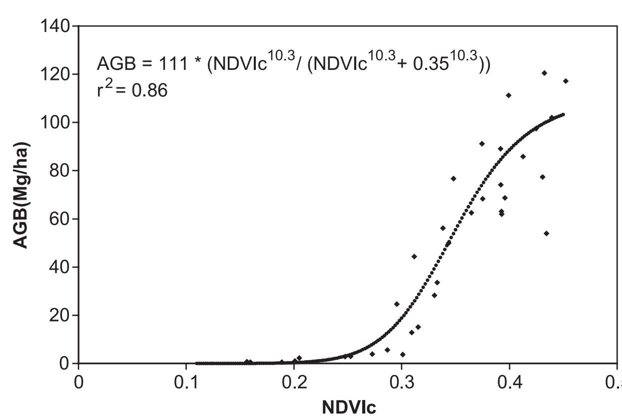

Fig. 2. Relationship between corrected NDVI (NDVIc) and AGB (Mg/ha) of pine forests in CNF (n=35, p<0.001).

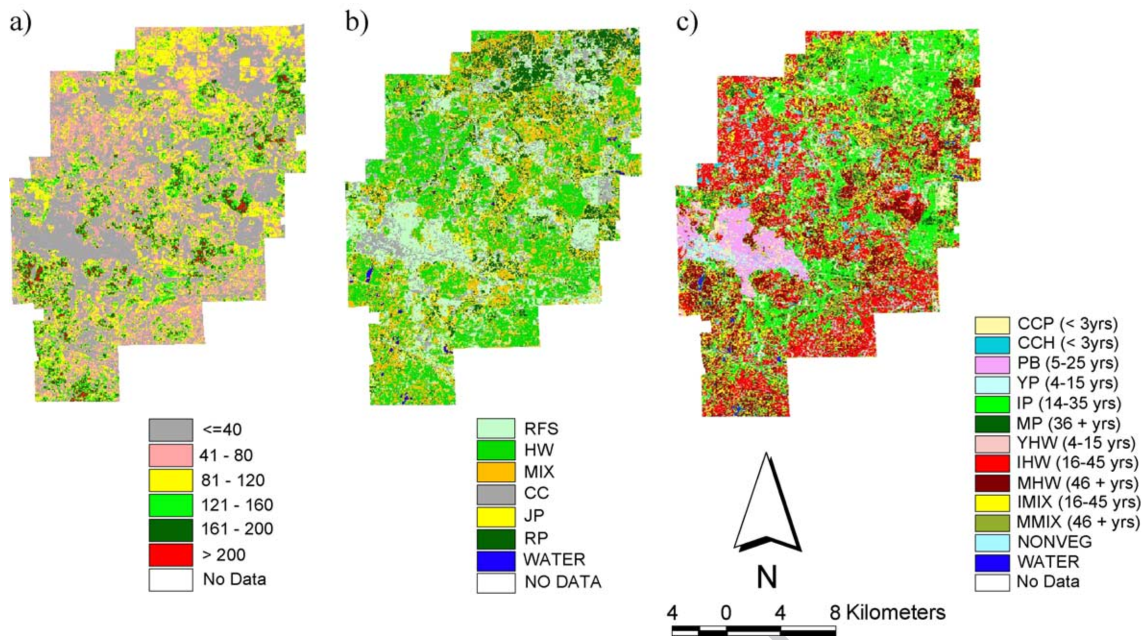

Fig. 3. Maps for (a) AGB (Mg/ha), (b) land cover, and (c) age map (recoded as a category map to increase the readability). All were derived from 2001 Landsat 7 ETM+ data for CNF.

models (Table 2) that were applied to create the final AGB map across the entire landscape using our created age map and the satellite derived land-cover map (pathway 2, Fig. 1a).

2.6. Model applications and validation

To improve the AGB estimates across the area, we modified the existing 2001 land-cover map slightly by further dividing RFS class into pine barrens, young pine (YP) forests, and young hardwood (YHW) forests according to the land-cover map in 1992 (or earlier, if necessary). While the AGBs for all pine and hardwood forests were estimated using pine and hardwood models, respectively. The AGB values for mixed forests were estimated using both models and weighted by their proportions of hardwood and pine species. According to our field observations, we estimated that the majority of mixed forests in the area has about 60% hardwood and 40% pine species. Additionally, we used the overall model for PB because it is a unique cover type characterized by a mixture of shrubs and sparse trees (pine dominated). For validation of the estimated AGB, we used 40 randomly selected independent field plots.

3. Results

Remote sensing derived variables including MSAVI, bands of red, NIR, and MIR were useful predictors of AGB (Table 2). The overall model explained 82% of variance

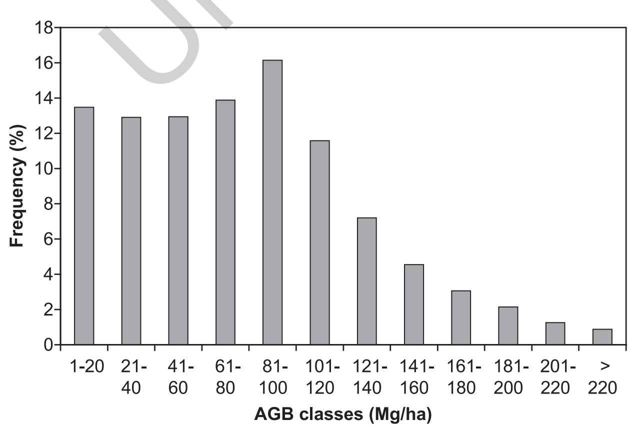

Fig. 4. Frequency distribution of AGB (Mg/ha) classes of forests excluding nonforested bare ground in CNF.

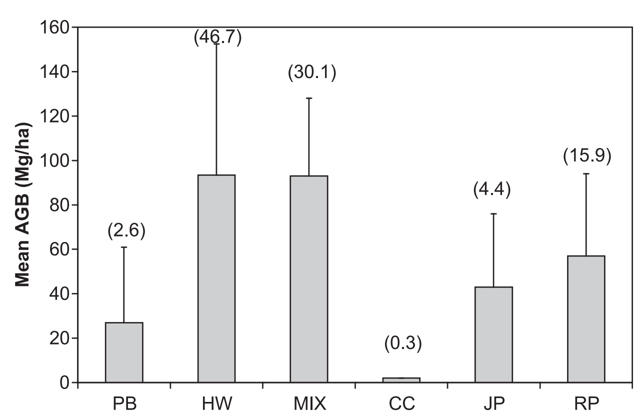

Fig. 5. Mean AGB (Mg/ha) plus 1 S.D. (vertical bar) by cover types (PB=pine barrens; HW=hardwood; MIX=mixed hardwood/pine; CC=clear-cuts; JP=jack pine; and RP=red pine). The numbers in parentheses indicate proportions of AGB (%) for each cover type in relation to the total AGB across the landscape.

(a=0.001). However, better models were achieved by separating the plots into hardwood and pine forests. Hardwood AGB was strongly related to stand age and NIR (r^2=0.95; Table 2) using a linear model, while AGB for pine forests was strongly related to NDVIc using a sigmoidal model(r^2=0.86; Fig. 2).

The final AGB map (Fig. 3a) resulted from the models incorporating age (Table 2). The predicted AGB values across the landscape ranged from 1 to 358 Mg/ha, with a mean value of 70 Mg/ha and standard deviation (S.D.) of 54 Mg/ha; consequently, the total AGB in the study area was estimated at 3.3 million metric tons (dry weight). The biomass class with the highest frequency (16.1%) was 80–100 Mg/ha (Fig. 4). The AGB class distribution was skewed toward lower AGB values. Less than 3% of the landscape had AGB >200 Mg/ha.

When separating the landscape by cover type, hardwood and mixed forests contained approximately 77% of the total AGB while PB stored less than 3%. Hardwood forests contained more AGB (47%) than mixed forests did (30%) in the area due to its high percentage of area occupancy (35%), although its mean was about the same as that of MIX forests (93 Mg/ha) because 19% of HW was classified as young forests. Pine forests comprised about 20% of the total AGB across the landscape (Fig. 5). Mean AGB value of red pine (57 Mg/ha) was about 33% higher than that of jack pine (43 Mg/ha). Clearcuts had the lowest values in terms of both mean AGB and proportion of total AGB (0.3%). Among the cover types, the AGB estimates for hardwood had the largest variation (S.D.=60 Mg/ha) while the estimates for jack pine had the smallest variation (S.D.=33 Mg/ha).

The final estimated AGB values compared reasonably with the independent field observations in the 40 validation plots (R^2=0.67; Fig. 6). Spatially, low AGB occurred in RFS and CC areas, while high AGB occurred in mature hardwood forests (Fig. 3a and b).

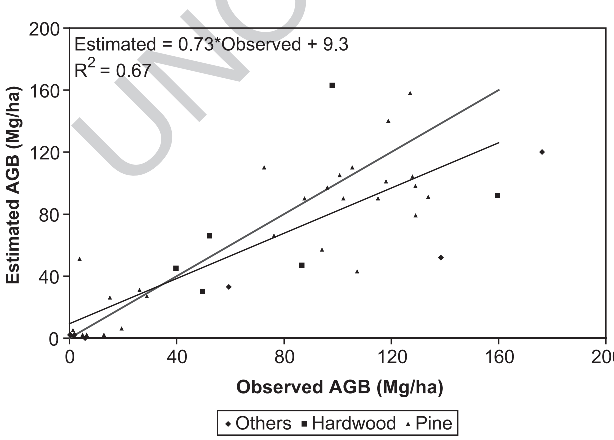

Fig. 6. Comparison between predicted AGB (Mg/ha) from the remote sensing-based models and the observed AGB calculated from field tree dbh measurements in CNF (n=40, p=0.001). Each point represents the AGB for one of the 40 plots and the AGB for the pixel that the plot falls in. Others include clearcuts and mixed forests.

4. Discussion

While AGB of hardwood forests was highly correlated to NIR reflectance and stand age (Table 2), NDVIc proved to be a good predictor in estimating the AGB of fine forests in the study area (Fig. 2). The variable is calculated from remotely sensed data in multiple bands including red, NIR, and MIR (Nemani et al., 1993). NDVIc can help account for understory effects and may be particularly useful in more open forest stands (Badhwar et al., 1986; Nemani et al., 1993, Spanner et al., 1990). The majority of pine forests in the study area was classified as young and intermediate ages, which were more likely to have open canopy structures at some degrees. A previous study found that both LAI and AGB were well correlated to red reflectance for a lodgepole pine forest in Yellowstone National Park (Jakubauskas, 1996). Furthermore, many studies have reported a high correlation between LAI and NDVI, or between LAI and SR of red and NIR bands in coniferous forests (Fassnacht et al., 1997; Herwitz et al., 1989; Peterson et al., 1987; Running et al., 1986; Spanner et al., 1990, 1994). Fassnacht et al. (1997) concluded that vegetation indices or individual bands containing one or more infrared bands required at least two regression lines to appropriately describe data for conifer and hardwood forests in the GLR. Separating hardwoods from pines improved AGB predictions because of a fundamental difference in NIR reflectance (hardwood canopies can reflect 50% more in NIR than that of pine canopies due to different canopy structures). Generally speaking, hardwoods have high canopy cover with horizontal expansion versus low canopy cover with cone shape vertical distribution for pines.

When category age map was presented for better visualization (Fig. 3c), the classification system was defined to be meaningful for future predictions of landscape fuel loading (Ryu et al., in press). For example, due to the differences in fuel accumulation, clearcuts (CC) were divided into pine forest clearcuts (CCP) and hardwood forest clearcuts (CCH) based on what the cover type was in earlier years. Management practices associated with natural regeneration of hardwood forests usually retained more available fuel on the floor, while the mechanical planting of pine required slash removal for site preparation. The differences in fuel loading could have significant impacts on fire behavior and spread.

Although our models tended to underestimate the AGB at high biomass values and overestimate the AGB at low values (Cohen et al., 2003) (Fig. 6), the estimated AGB values corresponded well in general with previously reported estimations in the region. Previously projected lower and upper bounds for AGB of mature forests in Northern Wisconsin ranged from 60 to 600 Mg/ha (Crow, 1978). Additionally, Crow (1978) reported that AGBs for three contiguous hardwood stands in the area ranged from 94 to 119 Mg/ha, which corresponds well with our estimated mean and S.D. for hardwood AGB (93±60 Mg/

ha; Fig. 5). The skewed AGB distribution toward lower values (Fig. 4) was caused by lack of old growth forests, high proportions of young growth, and PB in relation to total area (14%), which usually had low biomass.

Potential errors in our AGB estimates could be associated with the accuracy of land-cover map, sampling errors, confounding effects of soil moisture and soil color on reflectance (especially in open areas), species composition, and model utilization. For example, we assumed 60:40 compositions for mixed forests, suggesting fuzzy classification as possible means to further refine biomass estimates of mixed pixels. During model applications, if the grid cells had AGB estimates less than zero, the smallest positive integer (e.g., =1) was assigned because the cells more likely represented nonforested areas. Effects of soil background noise on remotely sensed reflectance could cause such errors and the truncation should have little impact on overall landscape biomass estimates and pattern analysis because such cells accounted for only less than 0.016% of the total study area and had small biomasses. For clearcut cells, a value of 2 was assigned based on field observations. It was realized that most biomass models or regressions were developed for specific locations; therefore, applications of these models at other locations rather than their originals could also generate errors in biomass estimates. However, because it is rarely feasible for managers or researchers to develop their own biomass models for various species in each specific study, it is commonly accepted to use existing models generalized by species (Crow & Schlaegel, 1988). Tritton and Hornbeck (1982) compiled biomass regressions developed at different locations in the northeast of the United States and found that, in most cases, regressions for a given species gave similar estimates. Others reported that such applications could be statistically valid for red maple biomass estimates for a wide range of conditions in the Lake States, or varied significantly for bigtooth aspen biomass estimates in northern Low Michigan only at the extremes: good site verse poor site (Crow, 1983; Koerper & Richardson, 1980). Most biomass models used in this study were developed from the upper GLR with a few exceptions due to model availability, so models developed outside the region had to be used. To illustrate the possible error ranges for such applications, we compared the biomass estimates between the models in the region and out of the region (i.e., Lower Great Lakes, Canada and USA, West Virginia, and New Hampshire) for six dominant species in our study area and found that the errors of estimation ranged from 3.2% for red oak to 20% for sugar maple, with an average error of 12.5%.

Spatial patterns of AGB were clearly related to landscape structure and composition. For example, places with higher AGB are usually associated with mature forests, especially the hardwoods. Low estimates of AGB were often associated with young forests and PB. The difference in mean AGB values between red pine (57 Mg/ha) and jack pine (43 Mg/ha) was potentially attributable to older mean age for red pines (26 years) versus jack pines (20 years). The age structure of these species likely differed because of the rotation age in CNF (40–60 years for red pine versus 35–40 years for jack pine) (Bresee et al., 2004).

Our AGB estimates corresponded well with Brown et al. (1999) biomass estimates in the region, but caution must be taken because they reported total biomass including both aboveground and belowground biomass, used coarse-resolution data at county level, and classified land cover into broader classes (hardwood versus softwood). As a result, cell-to-cell comparisons could not be conducted. However, it is likely that the AGB estimates resulting from high spatial resolution inputs are more suitable for landscape level analysis.

Although dbh is a primary variable commonly used for calculating aboveground tree biomass in the region (Burrows et al., 2003; Crow & Schlaegel, 1988; Perala & Alban, 1994), the AGB estimates across the landscape may be improved by incorporating tree height as an additional driving variable. Recent developments in light detection and ranging (lidar) remote sensing techniques provide a promising tool in estimating tree height, thus improving the accuracy of AGB estimation (Drake et al., 2002, 2003; Lefsky et al., 1999, 2002).

Stand age appeared to be a strong predictor in estimating AGB of HW forests in the area. For example, stand age alone explained 93% of variance in AGB estimates for HW forests (n=20). Our final estimates of AGB using models including stand age variable were improved substantially across the landscape based on the 40 plots reserved for validation (R^2=0.67; Fig. 6), compared to the initial estimates of AGB resulting from models without stand age variable (R^2=0.56; data not shown).

5. Conclusions

The AGB map may be used to refine the land-cover classification by differentiating young hardwood forests (with low AGB) from the mature ones. This study demonstrates separation, which is difficult through conventional classification schemes. For example, we classified 9.2% of hardwood forests as young when we used a criterion of AGB less than 40 Mg/ha (Table 2). Results from this study may also be used for examining differences in AGB between interior areas and in areas under edge influence, and how those differences may affect landscape level AGB.

Our AGB map can be a useful source for estimating aboveground net primary production (ANPP) across the landscape because stand ages in the area are relatively young (only about 3.1% of total CNF land area had forest stands with ages >70 years). A good relationship exists between AGB estimates and ANPP before forest stands reach old stage (Euskirchen et al., 2002).

Furthermore, there is a possibility that fuel accumulation in forest ecosystems, a necessary input for most fire models, can be theoretically determined by ANPP and decomposition rate (Ryu et al., in press). Therefore, the distribution of AGB across the landscape is necessary for quantifying landscape level fuel accumulation and its relationship to fire behavior and intensity (Anderson, 1982; Andrews & Rothermel, 1982; Finney, 1998). By combining our age map and the AGB map, fuel type and amount may be determined, which can be useful information for studying fire ignition and spread across the landscape. Such information could be helpful for resources managers to conduct fuel reduction plans to prevent catastrophic fire risk (Agee, 1993; Crow et al., 1999; Heinselman, 1973; Whitney, 1986). The fire-related issues, both natural and anthropogenic, have been an important historical factor for landscape structure in northern Wisconsin, as well as for carbon cycling changes under climate change (Heinselman, 1981). This study provides needed baseline information for landscape level analyses relating to regional carbon budget (i.e., monitoring changes of carbon pool over time).

6. Uncited reference

Johnson et al., 1994

Acknowledgements

This research is supported by the Joint Fire Science Project. We are grateful to Steve Mathers of LEES Laboratory at the University of Toledo for his assistance in image processing and data collection. We also thank John Erhardt and Amanda Mermer for their field assistance.

References

Agee, J. K. (1993). *Fire ecology of Pacific northwest forests*. Washington, DC: Island Press.

Alban, D. H., Perala, D. A., & Schlaegel, B. E. (1978). Biomass and nutrient distribution in aspen, pine, and spruce stands on the same soil type in Minnesota. *Canadian Journal of Forest Research*, *8*, 290–299.

Albert, D. A. (1995). *Regional landscape ecosystems of Michigan, Minnesota, and Wisconsin: A working map and classification.* USDA FS Gen. Tech. Rep. NC-178, St. Paul, MN.

Anderson, H. E. (1982). *Aids to determining fuel models for estimating fire behavior.* USDA FS Gen. Tech. Rep. INT-122, Ogden, UT, USA.

Andrews, P. L., & Rothermel, R. C. (1982). *Charts for interpreting wild fire behavior characteristics.* USDA FS Gen. Tech. Rep. INT-131, Ogden, UT, USA.

Badhwar, G. D., MacDonald, R. B., Hall, F. G., & Carnes, J. G. (1986). Spectral characterization of biophysical characteristics in a boreal forest: Relationship between Thematic Mapper band reflectance and leaf area index for aspen. *IEEE Transactions on Geoscience and Remote Sensing*, *GE-24*, 322–326.

Bresee, M. K., Le Moine, J. M., Mather, S., Brosofske, K. D., Chen, J., Crow, T. R., et al. (2004). Disturbance and landscape dynamics in the Chequamegon National Forest, Wisconsin, USA, from 1972 to 2001. *Landscape Ecology*, *19*, 291–309.

Brosofske, K. D., Chen, J., & Crow, T. R. (2001). Understory vegetation and site factors: Implications for a managed Wisconsin landscape. *Forest Ecology and Management*, *146*, 75–87.

Brown, S. L., Schroeder, P., & Kern, J. S. (1999). Spatial distribution of biomass in forests of the eastern USA. *Forest Ecology and Management*, *123*, 81–90.

Burrows, S. N., Gower, S. T., Norman, J. M., Diak, G., Mackay, D. S., Ahl, D. E., et al. (2003). Spatial variability of above ground net primary production for a forested landscape in northern Wisconsin. *Canadian Journal of Forest Research*, *33*, 2007–2018.

Chen, J., Saunders, S. D., Crow, T., Brosofske, K. D., Mroz, G., Naiman, R., et al. (1999). Microclimatic in forest ecosystems and landscapes. *BioScience*, *49*, 288–297.

Cheng, S., & Zhao, Y. (1990). *Remote sensing and geo-sciences analysis*. Beijing: Measuring Press.

Clark, W. A. V., & Hosking, P. L. (1986). *Statistical methods for geographers*. New York: John Wiley & Sons.

Cohen, W. B., Maiersperger, T. K., Gower, S. T., & Turner, D. P. (2003). An improved strategy for regression of biophysical variables and Landsat ETM+ data. *Remote Sensing of Environment*, *84*, 561–571.

Crow, T. R. (1978). Biomass and production in three contiguous forests in northern Wisconsin. *Ecology*, *59*, 265–273.

Crow, T. R. (1983). Comparing biomass regressions by site and stand age for red maple. *Canadian Journal of Forest Research*, *13*, 283–288.

Crow, T. R., Host, G. E., & Mlandenoff, D. G. (1999). Ownership and ecosystem as sources of spatial heterogeneity in forested landscape, Wisconsin USA. *Landscape Ecology*, *14*, 449–463.

Crow, T. R., & Schlaegel, B. E. (1988). A guide to using regression equations for estimating tree biomass. *Northern Journal of Applied Forestry*, *5*, 15–22.

Diallo, O., Diouf, A., Hanan, N. P., Ndiaye, A., & Prevost, Y. (1991). AVHRR monitoring of savanna primary production in Senegal, West Africa: 1987–1988. *International Journal of Remote Sensing*, *12*, 1259–1279.

Drake, J. B., Dubayah, R. O., Knox, R. G., Clark, D. B., & Blair, J. B. (2002). Sensitivity of large-footprint lidar to canopy structure and biomass in a neotropical rainforest. *Remote Sensing of Environment*, *81*, 378–392.

Drake, J. B., Knox, R. G., Dubayah, R. O., Clark, D. B., Condit, R., Blair, J. B., et al. (2003). Above-ground biomass estimation in closed canopy neotropical forests using lidar remote sensing: Factors affecting the generality of relationships. *Global Ecology and Biogeography*, *12*, 147–159.

Euskirchen, E. S., Chen, J., Gustafson, E. J., & Ma, S. (2003). Soil respiration at dominant patch types within a managed Northern Wisconsin Landscape. *Ecosystems*, *6*, 595–607.

Euskirchen, E. S., Chen, J., Li, H., Gustafson, E. J., & Crow, T. R. (2002). Modeling net carbon flows under alternative management regimes at a landscape level. *Ecological Modelling*, *154*, 75–91.

Fassnacht, K. S., & Gower, S. T. (1999). Comparison of the litterfall and forest floor organic matter and nitrogen dynamics of upland forest ecosystems in north central Wisconsin. *Biogeochemistry*, *45*, 265–284.

Fassnacht, K. S., Gower, S. T., MacKenzie, M. D., Nordheim, E. V., & Lillesand, T. M. (1997). Estimating the leaf area index of North Central Wisconsin forests using the Landsat Thematic Mapper. *Remote Sensing of Environment*, *61*, 229–245.

Finney, M. A. (1998). *FARSITE: Fire area simulator-model development and evaluation.* USDA FS Res. Pap. RMRS-RP-4, Fort Collins, CO, USA.

Foody, G. M., Boyd, D. S., & Culter, M. E. J. (2003). Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. *Remote Sensing of Environment*, *85*, 463–474.

Freedman, B., Duinker, P. N., Barclay, H., Morash, R., & Prager, U. (1982). Forest biomass and nutrient studies in central Nova Scotia. *Marit. For. Res. Cent. Inf., Can. For. Serv.* (pp. 126).

Goetz, S. J., Prince, S. D., Small, J., & Gleason, A. C. R. (2000). Interannual variability of global terrestrial primary production: Results of a model driven with satellite observations. *Journal of Geographic Research*, *105*, 20077–20091.

Gower, S. T., Kucharik, C. J., & Norman, J. M. (1999). Direct and indirect estimation of leaf area index, f_{apar}, and net primary production of terrestrial ecosystems. *Remote Sensing of Environment*, *70*, 29–51.

Gustafson, E. J., & Crow, T. R. (1996). Simulating the effects of alternative forest management strategies on landscape structure. *Journal of Environmental Management*, *46*, 77–94.

Hahn, J. T., (1984). *Tree volume and biomass equations for the Lake States.* St. Paul, MN, USDA FS Res. Pap. NC-250.

He, H. S., Mladenoff, D. J., Radeloff, V. C., & Crow, T. R. (1998). Integration of GIS data and classified satellite imagery for regional forest assessment. *Ecological Applications*, *8*, 1072–1083.

Heinselman, M. L. (1973). Fire in the virgin forests of the Boundary waters Canoe Area, Minnesota. *Quaternary Research*, *3*, 329–382.

Heinselman, M. L. (1981). Fire and succession in the conifer forests of northern North America. In D. C. West, H. H. Shugart, & D. B. Botkin (Eds.), *Forest succession: Concept and application* (pp. 374–406). New York, USA: Springer-Verlag.

Herwitz, S. R., Perterson, D. L., & Eastman, J. R. (1989). Thematic Mapper detection of change in the leaf area index of closed canopy pine plantations in central Massachusetts. *Remote Sensing of Environment*, *29*, 129–140.

Hocker, H. W. J., & Earley, D. J., (1983). *Biomass and leaf area equations for northern forest species.* N.H. Agric. Exp. Stn., Univ. NH Res. 102.

Jakubauskas, M. E. (1996). Thematic Mapper characterization of lodgepole pine serals in Yellowstone National Park, USA. *Remote Sensing of Environment*, *56*, 118–132.

Johnson, A., Miller, L., et al. (1994). Remote sensing of seasonal leaf area index across the Oregon Transect. *Ecological Applications*, *4*, 258–271.

Ker, M. F. (1980). *Tree biomass equations for ten major species in Cumberland County, Nova Scotia.* Can. For. Serv. Marit. For. Res. Cent. Inf. Rep., M-X-108: 26.

Koerper, G. J., & Richardson, C. J. (1980). Biomass and net primary production regressions for *Populus grandidentata* on 3 sites in northern Lower Michigan. *Canadian Journal of Forest Research*, *10*, 92–101.

Lee, N. J., & Nakane, K. (1997). Forest vegetation classification and biomass estimation based on Landsat TM data in mountainous region of west Japan. In H. L. Gholz, K. Nakane, & H. Shimoda (Eds.), *The use of remote sensing in the modeling of forest productivity* (pp. 159–171). Dordrecht: Kluwer.

Lefsky, M. A., Cohen, W. B., Harding, D. J., Parker, G. G., Acker, S. A., & Gower, S. T. (2002). Lidar remote sensing of above-ground biomass in three biomes. *Global Ecology and Biogeography*, *11*, 393–399.

Lefsky, M. A., Harding, D., Cohen, W. B., Parker, G., & Shugart, H. H. (1999). Surface lidar remote sensing of basal area and biomass in deciduous forests of eastern Maryland, USA. *Remote Sensing of Environment*, *67*, 83–98.

Mackay, D. S., Ahl, D. E., Ewers, B. E., Gower, S. T., & Burrows, S. N. (2002). Effects of aggregated classifications of forest composition on estimates of evapotranspiration in a northern Wisconsin forest. *Global Change Biology*, *8*, 1253–1265.

Malcolm, J. R., Zimmerman, B. L., Cavalcanti, R. B., Ahern, F. J., & Pietsch, R. W. (1998). Use of Radarsat SAR data for sustainable management of natural resources: A test case in the Kayopo indigenous area, Para, Brazil. *Canadian Journal of Remote Sensing*, *24*, 360–375.

Mladenoff, D. J., White, M. A., Pastor, J., & Crow, T. R. (1993). Comparing spatial pattern in unaltered old-growth and disturbed forest landscapes. *Ecological Applications*, *3*, 294–306.

Nemani, R., Pierce, L., Running, S. W., & Band, L. (1993). Forest ecosystem processes at the watershed scale: Sensitivity to remotely-sensed leaf area index estimates. *International Journal of Remote Sensing*, *14*, 2519–2534.

Ohmann, L. F., & Grigal, D. F. (1985). *Plant species biomass estimates for 13 upland community types of northeastern Minnesota.* St. Paul, MN, USDA FS Res. Bulle. RB-NC-88.

Paruelo, J. M., & Lauenroth, W. K. (1998). Interannual variability of NDVI and its relationship to climate for North American shrublands and grasslands. *Journal of Biogeography*, *25*, 721–733.

Perala, D. A., & Alban, D. H. (1994). *Allometric biomass estimations for aspen-dominated ecosystems in the Upper Great Lakes.* USDA FS Res. Pap. NC-134.

Peterson, D. L., Spanner, M. A., Running, S. W., & Teuber, K. B. (1987). Relationship of Thematic Mapper Simulator data to leaf area index of temperature coniferous forests. *Remote Sensing of Environment*, *22*, 323–341.

Prince, S. D., & Goward, S. N. (1995). Global primary production: A remote sensing approach. *Journal of Biogeography*, *22*, 815–835.

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). A modified soil adjusted vegetation index. *Remote Sensing of Environment*, *48*, 119–126.

Raile, G. K., & Jakes, P. J. (1982). *Tree biomass in the North Central Region.* USDA FS Res. Pap. NC-220.

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). Monitoring vegetation systems in the Great Plains with ERTS. *Third ERTS Symposium*, *1*, 48–62.

Running, S. W., Peterson, D. L., Spanner, M. A., & Teuber, K. B. (1986). Remote sensing of coniferous forest leaf area. *Ecology*, *67*, 273–276.

Running, S. W., Thornton, P. E., Nemani, R., & Glassy, J. M. (2000). Global terrestrial gross and net primary productivity from the earth observing system. In O. E. Sala, R. Jackson, H. A. Mooney, & R. Hwarth (Eds.), *Methods in ecosystem science* (pp. 44–57). New York: Springer-Verlag.

Ryu, S. -R., Chen, J., Crow, T. R., & Saunders, S. C. (2003). Available fuel dynamics in nine contrasting forest ecosystems in north America. *Environmental Management*, (in press).

Sader, S. A., Waide, R. B., Lawrence, W. T., & Joyce, A. T. (1989). Tropical forest biomass and successional age class relationships to a vegetation index derived from Landsat TM data. *Remote Sensing of Environment*, *28*, 143–156.

Sannier, C. A. D., Taylor, J. C., & Plessis, W. D. (2002). Real-time monitoring of vegetation biomass with NOAA-AVHRR in Etosha National Park, Namibia, for a fire risk assessment. *International Journal of Remote Sensing*, *23*, 71–89.

Saunders, S. C., Chen, J., Crow, T. R., & Brosofske, K. D. (1998). Hierarchical relationships between landscape structure and temperature in a managed forest landscape. *Landscape Ecology*, *13*, 381–395.

Saunders, S. C., Chen, J., Drummer, T. D., & Crow, T. R. (1999). Modeling temperature gradients across edges over time in a managed landscape. *Forest Ecology and Management*, *117*, 17–31.

Smith, W. B., (1985). *Factors and equations to estimate forest biomass in the North Central Region.* St. Paul, MN, USDA FS Res. Pap. NC-268.

Spanner, M. A., Pierce, L. L., Peterson, D. L., & Running, S. W. (1990). Remote sensing of temperate coniferous forest leaf area index: The influence of canopy closure, understory vegetation, and background reflectance. *International Journal of Remote Sensing*, *11*, 95–111.

Steininger, M. K. (2000). Satellite estimation of tropical secondary forest above-ground biomass: Data from Brazil and Bolivia. *International Journal of Remote Sensing*, *21*, 1139–1157.

Ter-Mikaelian, M. T., & Kirzukhin, M. D. (1997). Biomass equations for sixty-five North American tree species. *Forest Ecology and Management*, *97*, 1–24.

Tieszen, L., Reed, B. C., & Dejong, D. D. (1997). NDVI, C3 and C4 production, and distributions in the Great Plains grassland cover classes. *Ecological Applications*, *7*, 59–78.

Tritton, L. M., & Hornbeck, J. W. (1982). *Biomass equations for major tree species of the Northeast.* USDA FS Gen. Tech. Rep. NC-20.

USDA Forest Service (1986). *Chequamegon forest plan*. Washburn, WI: Washburn Range District, Chequamegon National Forest.

Vora, R. S. (1993). Moquah barrens: Pine barrens restoration experiment initiated in Chequamegon National Forest. *Restoration & Management Notes*, *11*, 39–44.

Whitney, G. G. (1986). Relation of Michigan's presettlement pine forests to substrate and disturbance history. *Ecology*, *67*, 1548–1559.

Woodcock, C. E., Macomber, S. A., Pax-Lenney, M., & Cohen, W. B. (2001). Monitoring large areas for forest change using Landsat: Generalization across space, time and Landsat sensors. *Remote Sensing of Environment*, *78*, 194–203.

Young, H. E., Ribe, J. H., & Wainwright, K. (1980). *Weight tables for tree and shrub species in Maine.* Orono, Life Science and Agriculture Experimental Station, University of Maine, Miscellaneous Report 230, pp. 84.

Zheng, D., & Chen, J. (2000). Edge effects in fragmented landscapes: A generic model for delineating area of edge influences (D-AEI). *Ecological Modelling*, *132*, 175–190.