Environ Monit Assess (2008) 144:67–79
DOI 10.1007/s10661-007-9946-1

Satellite detection of land-use change and effects on regional forest aboveground biomass estimates

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Received: 1 April 2007 / Accepted: 28 August 2007 / Published online: 20 September 2007

Abstract We used remote-sensing-driven models to detect land-cover change effects on forest aboveground biomass (AGB) density (Mg·ha^{-1}, dry weight) and total AGB (Tg) in Minnesota, Wisconsin, and Michigan USA, between the years 1992–2001, and conducted an evaluation of the approach. Inputs included remotely-sensed 1992 reflectance data and land-cover map (University of Maryland) from Advanced Very High Resolution Radiometer (AVHRR) and 2001 products from Moderate Resolution Imaging Spectroradiometer (MODIS) at 1-km resolution for the region; and 30-m resolution land-cover maps from the National Land Cover Data (NLCD) for a subarea to conduct nine simulations to address our questions. Sensitivity analysis showed that (1) AVHRR data tended to underestimate AGB density by 11%, on average, compared to that estimated using MODIS data; (2) regional mean AGB density increased slightly from 124 (1992) to 126 Mg ha^{-1} (2001) by 1.6%; (3) a substantial decrease in total forest AGB across the region was detected, from 2,507 (1992) to 1,961 Tg (2001), an annual rate of −2.4%; and (4) in the subarea, while NLCD-based estimates suggested a 26% decrease in total AGB from 1992 to 2001, AVHRR/MODIS-based estimates indicated a 36% increase. The major source of uncertainty in change detection of total forest AGB over large areas was due to area differences from using land-cover maps produced by different sources. Scaling up 30-m land-cover map to 1-km resolution caused a mean difference of 8% (in absolute value) in forest area estimates at the county-level ranging from 0 to 17% within a 95% confidence interval.

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Keywords Biomass density · Change detection · Land-cover map · Remote sensing · Total biomass

Introduction

Forest biomass is an important component for studying ecosystems' carbon cycles and is one of key indicators of forest health (Heath and Birdsey 1993; Houghton 1995; Schimel 1995; Sannier et al. 2002; Zheng et al. 2004; Bechtold and Patterson 2005). Quantifying changes of forest aboveground biomass density over time at large scales is a necessary step for developing long-term resources management strategies at regional- and national-levels. For example, forests can provide a reliable supply of wood for bioenergy production and wood products businesses and reduce human reliance on non-renewable energy. Fuels reduction in forests through harvesting and appropriate forest management can also reduce wildfire threats and the staggering costs of fighting those fires (National Association of Conservation Districts 2007).

Natural and human disturbances or forest management practices alter landscape structure, composition, and configuration all of which affect forest biomass in terms of both biomass density (Mg ha^{-1}, dry weight per unit area), and total biomass (Tg, 10^{12} gram, density multiplied by forest area for the area of interest). A change in forest density, even at constant land area, translates into a change in total forest biomass. A change in forest area means a change in total forest biomass even when the forest features the same biomass density. Therefore, it is important to quantify and monitor spatial and temporal changes of land cover, as well as forest ecosystem characteristics such as forest biomass, for sustainable management of our natural resources and environment. Moreover, methodology and scaling-related issues on land-cover change studies are critical not only for ecological applications but also for economic and political implications. Such studies in some cases require using cover maps generated from different sources due to data availability.

In recent centuries, land-use change has had much greater effect on ecological variables of ecosystems than has climate change (Dale 1997). For instance, the world's total forested area decreased from $6{,}042\times10^6$ ha in 1700 (Houghton et al. 1983) to $4{,}165\times10^6$ in the 1980s (Dixon et al. 1994), suggesting that at least 30% of the world's forests have been cleared since 1700 (not including areas that were cleared and grew back to forests). In North America, the most important cause of forest loss from 1850 to 1992 is cultivation (Ramankutty and Foley 1999). Richards (1990) estimated that cropland area had increased fourfold in the last 150 years, from roughly 50 million hectares in 1850 to 200 million hectares in 1980. Another study indicated the area of forestland in the Great Lakes region declined by over 40% in the last 150 years, and much of the remaining area was converted to early successional forest types as a result of extensive logging (Cole et al. 2003). However, much area also remains relatively undisturbed in wildlife reserves, undeveloped wetlands, national forests, and national parks. Documenting the extent and timing of the historical ecological change in such a diverse region presents a scientific challenge.

The rapid deployment of remote sensing (RS) satellites and development of RS analysis techniques in the past three decades has provided a reliable, effective, and practical way to characterize terrestrial ecosystem properties (e.g., biomass and production) and to monitor land-cover changes over large scales (Tucker et al. 1985; Sader et al. 1989; Turner et al. 1993; Running et al. 1994; Prince and Goward 1995; Hame et al. 1997; Hansen et al. 2000; Steininger 2000; Friedl et al. 2002). However, quantifying effects of land-cover change on forest aboveground biomass density estimates at the regional-level over time using optical RS inputs are still in the rudimentary stage. For example, saturation phenomenon in optical signal obscures biomass density estimates in mature forests. Although LIDAR (Light Detection and Ranging) and laser RS methods work well for biomass estimates (Lefsky et al. 1999, 2002; Drake et al. 2002), they are currently too expensive to be applied over large scales. Nevertheless, a RS approach provides an additional tool to monitor forest carbon dynamics and forest health at regional and national scales.

In this study, we will: (1) quantify the forest aboveground biomass (AGB) dynamics associated with land-cover change from 1992 to 2001 in the three Lake States (Michigan (MI), Minnesota (MN), and Wisconsin (WI)) of the USA; (2) determine effects of the scaling process (e.g. from 30-m to 1-km resolution) on AGB; and (3) illustrate how land-cover data from different sources affect AGB estimates. Objectives 2 and 3 were conducted in a smaller subarea because of data availability constraints.

Methodology

Study areas

The landscapes of the Great Lakes region include the grasslands of the Great Plains, the eastern deciduous forests, and the boreal forests of North America, whose boundaries interact and shift over time. The area, comprised of MI, MN, and WI, covers approximately 493,800 km^2 and ranges from 41 to 49°N in latitude and from 97 to 83°W in longitude. Climate in the region is characterized by warm summers (mean 14.8°C); and cold winters (mean −13.0°C) with mean annual temperature 1.5°C. Mean annual precipitation ranges from 500 mm in the west to 800 mm in the east (Chaplin et al. 2001). Dominant forest species are aspen–birch (*Populus tremuloides*, *Betula papyrifera*) and northern hardwood deciduous with a mixture of needle-leaved evergreens (*Pinus banksiana*, *Pinus resinosa*, *Picea glauca*, *Picea mariana*, *Abies balsamea*) extending from east of the prairie borderlands in MN, through northern WI, northern MI, and the northernmost two-thirds of the southern MI peninsula (Carleton 2003).

Stand age data from the last three USDA Forest Service Forest Inventory and Analysis (FIA) surveys suggest that the region is still dominated by relatively young forests with most stands between 30 and 60 years of age (Schulte et al. 2003). In general, the region experienced a decrease in forestland and corresponding increases in non-forest and urban uses, based on 1-km 1992 land-cover map from University of Maryland (UMD, Hansen et al. 2000), derived from Advanced Very High Resolution Radiometer (AVHRR, Hansen et al. 2000), and 2001 land-cover map, derived from Moderate Resolution Imaging Spectroradiometer (MOD12Q1, USGS-NASA 2006; Fig. 1a,b).

A subarea covering about 32,700 km^2 and crossing the MN and WI border was chosen (Fig. 1a) to test how scaling processes of land-cover maps could affect regional AGB estimates (objective 2) and to evaluate how different land-cover classification systems (AVHRR/MODIS land-cover maps vs the National Land Cover Data (NLCD) land-cover maps) could affect the change detection (objective 3).

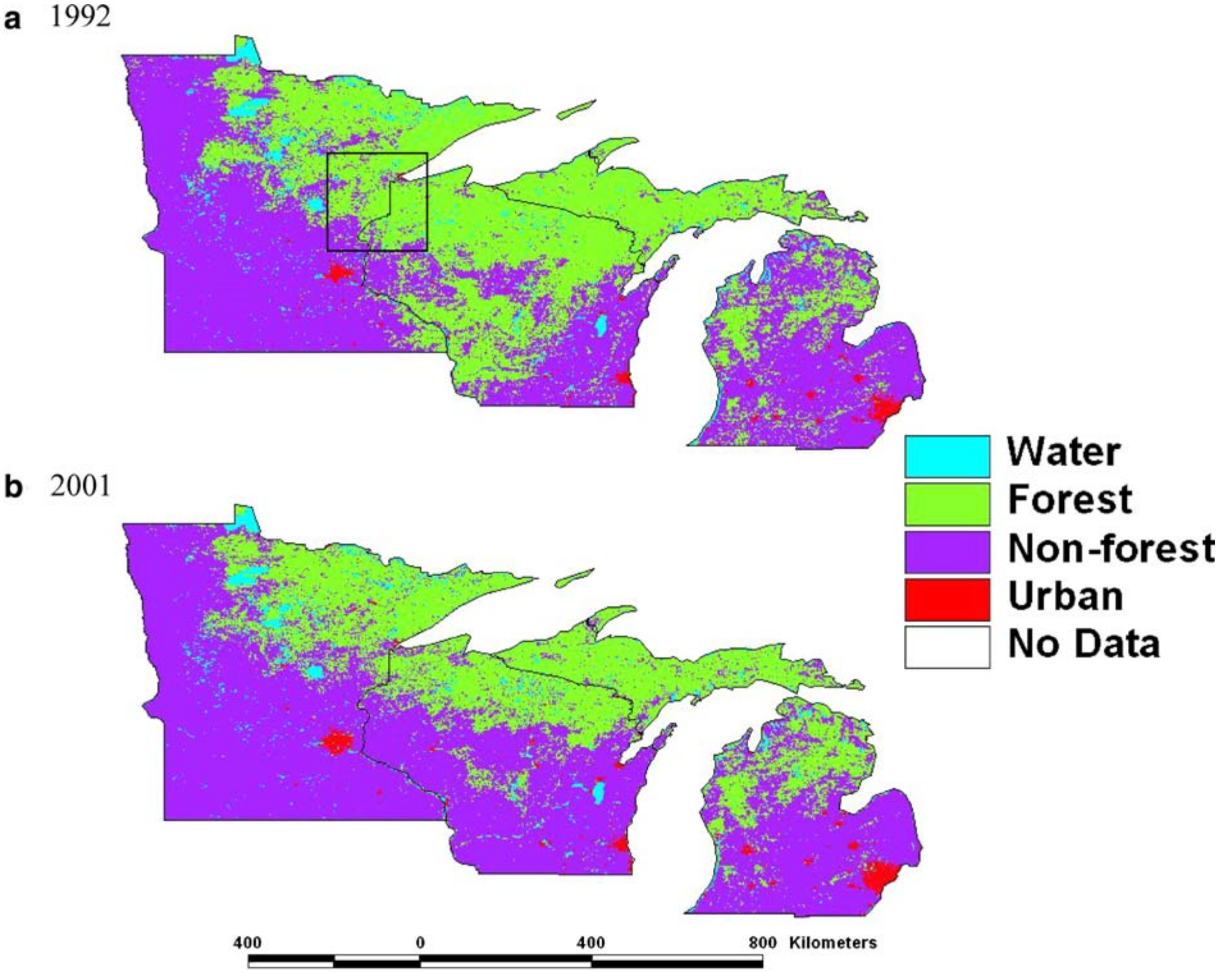

Fig. 1 Regional land-cover maps for1992 (**a**) and 2001 (**b**) extracted from the global 1-km AVHRR-based land-cover maps (generated by University of Maryland) and the MODIS land-cover team, respectively. The original cover types were aggregated to broad cover types. The *square box* indicates the subarea. Other *solid lines* represent state boundaries

Land-cover maps and RS data for the entire area

Identifying the effects of sensor differences on ecological properties of interest and using comparable land-cover maps are necessary first steps toward estimating meaningful changes associated with land-cover dynamics. MODIS observations (1999) are probably one of the most reliable, consistent, and appropriate RS data sources for terrestrial ecosystems studies at large-scales for several reasons: (1) the MODIS project funded by NASA provides various land products (including land-cover maps and surface reflectance data) to the public for free, (2) the MODIS project provides new products annually since 2000 using consistent methodologies and is likely to be continuing, and (3) MODIS data have higher spectral and radiometric resolutions than AVHRR data, which are required for improvements in atmospheric corrections to remove haze, aerosols and clouds from land surface images (King et al. 1992; Running et al. 1994).

We downloaded two kind of MODIS data for the study area from the Land Processes Distributed Active Archive Center (USGS-NASA, 2006): (1) surface reflectance of bands 1, 2, and 6 corresponding to spectral channels of red, near infrared, and middle infrared, respectively, at resolution of 500 m (MOD09A1); and (2) land-cover map of 2001 (MOD12Q1, type 2 classification) at resolution of 1 km. The reflectance data were used directly or indirectly for calculating various indices requested as model inputs. The land-cover map at 1-km spatial resolution was used to identify forest area and species in the region. All reflectance data were resampled to 1-km resolution to match the land-cover map.

An AVHRR-based 1992 land-cover map produced by the UMD was also used for detecting the cover change effects on forest AGB because AVHRR data best matches the spatial resolution of 1-km MODIS terrestrial products and because MODIS was not available in the early 1990s. In addition, AVHRR data have been successfully applied to many terrestrial ecosystem studies over large scales since 1980s before the MODIS products were available (Tucker et al. 1984; Townshend et al. 1987; Justice et al. 1986; Malingreau et al. 1985; Nemani and Running 1989; DeFries and Townshend 1994).

We obtained 1992 AVHRR reflectance data online from the U.S. Geological Survey (USGS, 2006). The regional land-cover map of 1992 was a subset from the 1-km global land-cover map generated from AVHRR by UMD (Hansen et al. 2000). There are five classification systems in the 2001 MODIS land-cover map but we follow the type 2 that most closely matches the classification system of UMD 1992 AVHRR-based land-cover map. Furthermore, we only used the five forest classes (1–5 of Table 1) that were identical in both 1992 and 2001 maps to mask out the forest areas for conducting AGB change analyses. Note that identical classes do not mean that the different sensors necessarily registered each land area as the same class. The five forest types were further merged to three broad classes and used in this study: (1) evergreen, (2) deciduous, and (3) mixed forests. All the remaining classes across the region were classified to either urban development or non-forest category (Fig. 1), excluding water.

Land-cover maps and RS data for the subarea

To study the scaling up effects on regional AGB estimates, high-resolution (e.g. 30 m) land-cover

Table 1 Comparison of global land-cover types between 1992 University of Maryland (UMD) AVHRR-derived product and 2001 MODIS-derived product at 1-km resolution

Class	1992 UMD[a]	2001 MODIS[b]
0	Water	Water
1	Evergreen needleleaf forest	Evergreen needleleaf forest
2	Evergreen broadleaf forest	Evergreen broadleaf forest
3	Deciduous needleleaf forest	Deciduous needleleaf forest
4	Deciduous broadleaf forest	Deciduous broadleaf forest
5	Mixed forests	Mixed forests
6	Woodlands	Closed shrublands
7	Wooded grasslands/ shrublands	Open shrublands
8	Closed bushlands or shrublands	Woody savannas
9	Open shrublands	Savannas
10	Grasslands	Grasslands
11	Croplands	–
12	Bare ground or sparse vegetation	Croplands
13	Urban and built-up	Urban and built-up
14		–
15		–
16		Bare ground or sparse vegetation

[a] Hansen et al. 2000.

[b] (LP DAAC, 2006)—using type 2 classification.

maps are needed. The NLCD has been compiled across the USA including Puerto Rico in 1992, and is currently being compiled for 2001 as a cooperative mapping effort of the Multi-Resolution Land Characteristics Consortium (MRLC, 2006). However, the 2001 NLCD map for the three Lake States was not completed when this study was conducted. As a result, only land-cover maps in a subarea were available in both 1992 and 2001. We downloaded the 1992 and 2001 land-cover maps for the subarea from NLCD (MRLC, 2006). The subarea was selected based on what were commonly available in both years for two reasons: (1) the subarea covered two states rather than one, and (2) a mixture of forest and non-forest land cover mosaic was included, which is typical across the region for detecting land cover scaling effects on AGB estimates. We scaled 30-m resolution land cover maps up to 1-km resolution maps using the majority rule (ESRI, 2006), an aggregate function that finds the value that appears most often within the specified windows (e.g. 1×1 km^2 cells) and sends it to each of the corresponding cells as the output grid. For AGB simulations at 30-m resolution in the subarea, we used the same values of the driving variables that were used for the simulations at 1-km resolution but disaggregated to 30-m resolution. We did this purposely so that comparison between AGB simulations conducted at different spatial resolutions within the same area would reflect solely the effects of the scaling up process.

Aboveground biomass equations

AGB was estimated using empirical models developed in northern Wisconsin and applied across the region (Zheng et al. 2004, 2007) using corrected NDVI (NDVIc) as driving predictor of AGB for evergreen ($_{ev}$) forests, and stand age and reflectance in the near infrared channel (ρ_{nir}) for deciduous ($_{de}$) forests. All driving variables were parameterized from remotely sensed information, either from high-resolution (30 m) Landsat 7 ETM+ or MODIS data in 2001 (Eqs. 1 and 2, Zheng et al. 2004, 2007). The models are as follows:

$$AGB_{ev} = 111*\left(NDVIc^{10.3}/\left(NDVIc^{10.3}+0.35^{10.3}\right)\right) r^2 = 0.86 \quad (1)$$

$$AGB_{de} = 233*\rho_{nir} + 2.7*AGE - 71\, r^2 = 0.95 \quad (2)$$

where NDVIc is calculated from NDVI*$[1-(mIR-mIR_{min})/(mIR_{max}-mIR_{min})]$. mIR represents middle infrared reflectance centered at 1,640 nm. Equation 2 was also applied to mixed forests because in this region mixed forests are dominated by deciduous species.

For regional application, we used 1-km MODIS data for parameterization after conducting spectral calibrations between the two sensors ((MODIS & ETM+, Zheng et al. 2007). A spatially-explicit regional age map was generated using RS input and inventory data (Zheng et al. 2007). The same equations were applied in both years of 1992 and 2001 with comparable regional land-cover maps and satellite data to detect change effects of land-cover patterns and spectral characteristics on AGB estimates.

Forest inventory-based area and biomass density estimates

Survey data for early 1990s and 2000s for the three states were downloaded from USDA Forest Service (2006). Standard procedures were followed to calculate forest area and AGB density from the FIA data except we used models in Jenkins et al. (2004) for estimating AGB density, instead of using region-specific biomass estimates available in the FIA data.

Evaluating land-use-change effects on AGB estimates

We tested how land-use changes under different scenarios affect AGB estimates by conducting a sensitivity analysis in which we varied only one factor at a time while keeping other factors consistent. All simulated AGB reported in this study were derived from RS-driven models.

While all listed simulations (Table 2) are necessary for addressing the stated objectives and each of them can stand alone, each scenario consists of two simulations for comparison (Fig. 2). Table 2 also provides a summary of the relationships between the simulations and scenarios, and the issues addressed. We quantified the sensor effects on AGB estimates in 2001 (when both MODIS and AVHRR satellite data are available covering the same area and acquired during the same time period) by applying the same models (driven by reflectance or vegetation index) and the age map, but varying the satellite data sources (comparison between simulations 1 and 2, scenario 1).

Table 2 Detecting the effect of land-cover change on AGB estimates (Mg ha^{-1}, dry weight) by comparing the simulations (S)

S	Description	LC[a] source	RS[b] source	Mean AGB (standard[c])	Forest area (km^2)	Total AGB (Tg, 10^{12})	S to compare	Numbered scenario[d]	Issue addressed
1	Entire region, 2001 (1-km)[e]	MODIS[f]	MODIS	126 (126)	155,650	1,961	2	1	Sensor effect
2	Entire region, 2001 (1-km)	MODIS	AVHRR[g]	112 (123)	155,650	1,743			
3	Entire region, 1992 (1-km)	UMD[h]	AVHRR	124 (78)[i]	202,840	2,507	1	2	Change detection[j]
4	Subarea, 1992 (30-m)	NLCD[k]	AVHRR[l]	115 (63)	14,900	171	5	3	Scaling effect, 92
5	Subarea, 1992 (1-km)	NLCD	AVHRR	119 (65)	14,220	169			
6	Subarea, 2001 (30-m)	NLCD	MODIS[l]	121 (85)	16,990	206	7	4	Scaling effect, 01
7	Subarea, 2001 (1-km)	NLCD	MODIS	125 (88)	18,380	229	5	5	Change detection[m]
8	Subarea of number 1, 01 (1-km)	MODIS	MODIS	139 (91)	14,990	208			
9	Subarea of number 3, 92 (1-km)	UMD	AVHRR	125 (72)[i]	22,380	281	8	6	Change detection[n]

[a] Land cover

[b] Remote sensing

[c] Standard deviation

[d] See Fig. 2.

[e] Measure in parentheses indicates pixel resolution.

[f] Moderate Resolution Imaging Spectroradiometer

[g] Advanced Very High Resolution Radiometer

[h] University of Maryland

[i] The numbers have been adjusted by sensor difference.

[j] Regional change detection after being adjusted by sensor effects

[k] National Land Cover Data at 30-m pixel resolution and aggregated to 1-km resolution using majority rule for comparison purposes

[l] 1-km reflectance data were disaggregated to 30-m resolution to keep these inputs constant for comparison purpose.

[m] Detected AGB changes from 1992 to 2001 based on NLCD land-cover maps at 1-km resolution in the subarea

[n] Detected AGB changes from 1992 to 2001 based on AVHRR/MODIS land-cover maps at 1-km resolution in the subarea

Comparison between simulations 1 and 3 (scenario 2) illustrate how land-cover changes from 1992 to 2001 affected the AGB estimates after the detected sensor effects were considered. Although the land-cover maps were produced by different groups (UMD & MODIS, respectively), both maps are RS-based products with identical classes for forestlands (Table 1). To reduce the uncertainty, we detected the land-cover-change effects on AGB estimates at broader categories (e.g., forest, non-forest, and urban) because specific land-cover classifications from multiple sources with different resolutions may differ. For example, land-cover classification systems used in the NLCD are at 30-m resolution and contain 21 and 29 classes for 1992 and 2001, respectively. Both AVHRR (1992) and MODIS (2001) land-cover maps at 1-km resolution contain 13 classes (excluding water; Table 1). That is, all forest classes in both 1992 AVHRR and 2001 MODIS land-cover maps are identical (Table 1). Forestland is further differentiated as evergreen or deciduous forest, which is needed for this analysis because AGB estimates for these two types used separate equations. Classification on urban development areas is relatively consistent and reliable in both years.

Comparison between simulations 4 and 5 (scenario 3) and between simulations 6 and 7 (scenario 4) could reflect the effects of scaling 30-m land-cover maps to 1-km resolution on AGB estimates, given the changed

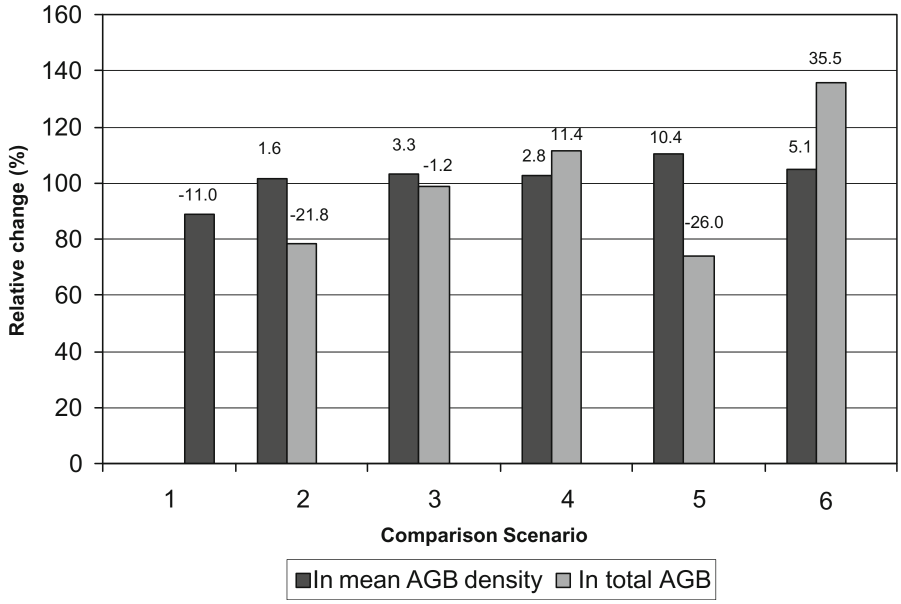

Fig. 2 Relative changes in forest AGB estimates under different scenarios: *1* difference in regional mean AGB density estimates resulted from using AVHRR and MODIS (as reference) data in 2001; *2* changes in regional AGB estimates between AVHRR based 1992 (as reference) results (adjusted by the sensor difference resulting from scenario 1) and MODIS based 2001 results; *3* changes in AGB estimates caused by scaling up land-cover map from 30-m (as reference) to 1-km resolution in the subarea given 1992 landscape configuration; *4* the same detections as in scenario 3 but given 2001 landscape configuration; *5* change detections in AGB estimates based on AVHRR/MODIS land-cover maps of 1992 (as reference) and 2001 at 1-km resolution in the subarea; and *6* similar detections to those in scenario 5 but based on NLCD land-cover maps of 1992 (as reference) and 2001 at 1-km resolution. See Table 2 for details of comparison scenarios.

land cover between 1992 and 2001 (Table 2). Comparison of changes in AGB estimates of subarea from 1992 to 2001 at 1-km resolution between NLCD (simulations 5 and 7 and scenario 5) and AVHRR/MODIS (simulations 8 and 9 and scenario 6) could demonstrate effects of different land-cover classification systems on AGB change detection (Table 2).

Quantifying landscape structure

We used FRAGSTATS (McGarical and Marks 1995), a spatial pattern analysis program, for quantifying landscape structures of 1992 and 2001 in the subarea at the land-cover type level (forest vs non-forest). We further linked these landscape characteristics to the scaling process (30 m to 1 km) to demonstrate how landscape configurations could affect the scaled outputs. The scaling process can modify area estimates substantially, compared to relatively small effect on biomass density by changing forest composition (deciduous vs coniferous forests), and this could significantly affect the total AGB estimates.

Results and discussion

Sensor effects

Our study suggests that the AVHRR sensor tends to have lower NDVI and reflectance values with smaller variances than those observed from MODIS sensor for the same period and region (Table 3). This agrees with previous work reported in Central China (Alexandridis and Chemin 2002; Zhan et al. 2002). Quantifying sensor differences is a necessary step to achieve any meaningful results involving change detection when satellite data from these two sensors are used. The mean NDVI value in the three Lake States obtained from the AVHRR in early June of 2001 was 1.4% lower than that from MODIS while mean reflectance in the near infrared band was 23% lower than that from MODIS (Table 3). Such sensor-caused differences resulted in an 11% lower estimate of regional mean AGB (Fig. 2, the most left bar) and must be considered before comparing 1992 AVHRR-driven AGB estimates to 2001 MODIS-driven AGB estimates.

Table 3 Comparison of NDVI values and near infrared (Nir) reflectance detected from different sensors in early June, 2001 in the three Lake States

Sensor	Mean NDVI	Variance	Mean Nir	Variance
MODIS	0.656	0.0384	0.334	0.0111
AVHRR	0.647	0.0207	0.257	0.0033

We did not adjust these estimates with ground-based plots because our objective was to compare the different sources of land-cover information, and adjustment would have masked the differences. While these relative estimates are valid and informative, the AGB density and total AGB values reported in absolute terms should be used with extreme caution. Although preliminary results suggested that the regional mean AGB density estimated from the RS-driven models was on average 31% higher than that of FIA plot-based calculations (Table 4), they have limited impact on change detections evaluated in relative numbers.

Regional land-cover change effects

Regional mean AGB density increased slightly from 124 Mg ha^{-1} in 1992 to 126 Mg ha^{-1} in 2001 (simulations 1 and 3, Table 2), by 1.6% (Fig. 2, scenario 2). This agrees well with FIA plot-based calculations that mean AGB density increased by 1.4% (Table 4) between the 1990s and 2000s surveys in the region. Several factors can affect the mean AGB density estimates in either a positive or negative way. These factors include: (1) changes in forest canopy cover—mean NDVI value is higher in 2001 than 1992, which is a positive effect; (2) changes in forest age structure—mean stand age in the region increased from 39 year old in 1992 to 46 years old in 2001 (based on our RS-based regional estimates (Zheng et al. 2007), positive effect); (3) changes in mean forested area portion of FIA plots—the mean forested proportion of plots in 2001 was 10% less than in 1992 based on field data from 20,000+ plots in each of the corresponding surveys across the region (negative effect); and (4) changes in broad forest type —deciduous forests, on average, tend to have higher AGB value than coniferous forests in the region and the area of deciduous forests increased from 89.9% in 1992 to 96.6% in 2001 (positive effect, data not shown). Variations in biomass estimation tend to be larger in RS outputs than in FIA datasets probably because the RS-based forested pixels may also include all ground conditions (Table 4). Although there are obvious increases (in North Central MN) and decreases (in Upper Peninsula of MI, northeastern part of MN and northwestern part of WI along Lake Superior) of AGB density (from one AGB class to another) in the region (Fig. 3), actual changes in AGB density for a given pixel could be much smaller than what may be interpreted from the figure because the AGB classes were presented at a 40 Mg ha^{-1} interval (Fig. 3).

Although the general patterns of frequency distributions in AGB density at broad classes in both 1992 and 2001 were similar (Fig. 3), we clearly show that distributions of regional AGB densities were more concentrated in the three categories ranging from 41 to 160 Mg ha^{-1} in 2001 (66%) than those in 1992 (57%), while the frequencies in both low and high AGB density categories were reduced (Fig. 3).

A 21.8% decrease in total forest AGB across the region was detected, from 2,507 Tg in 1992 to 1,961 Tg in 2001 (simulations 1 and 3, Table 2; Fig. 2, scenario 2), which is a mean annual rate of −2.4%. This was primarily caused by land-cover changes from forests to non-forest (including cropland) and urban development. Although gains in forestland were observed in some areas, such as the northern part of the MI Lower Peninsula, overall regional forest area decreased from 202,840 km^2 in 1992 to 155,650 km^2 in 2001, a 23.3% reduction, especially in Southern WI (Fig. 1a,b). Simultaneously, non-forest area increased from 267,590 in 1992 to 316,430 km^2 in 2001 by 18.3%, with a 19.2% increase in urban area from 5,880 in 1992 to 7,010 km^2 in 2001 across the region (Fig. 4).

Table 4 Remote sensing based (RS) and USDA Forest Service, Forest Inventory and Analysis (FIA) based estimates of AGB density [Mg ha^{-1}, mean and standard deviation (Std.)] and total forest area in the region

	AGB density		Forest area (km^2)	
	FIA	RS	FIA	RS
1992	94.2 (63)	123.6 (78)	208,023	202,840
2001	95.5 (66)	125.6 (126)	204,212	155,560

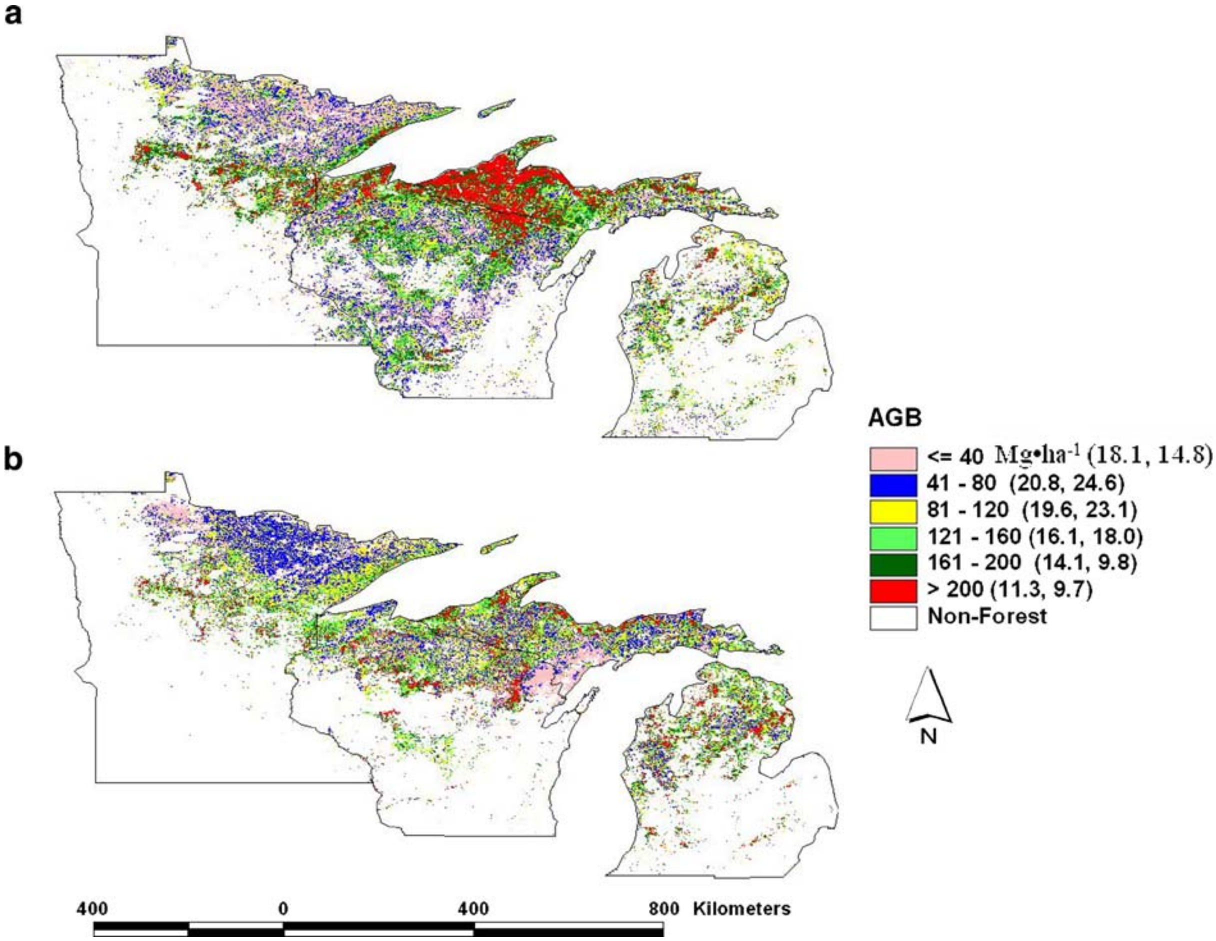

Fig. 3 Spatial patterns of forest aboveground biomass (AGB, Mg ha^{-1}, dry weight) in the three Lake States: **a** based on the 1992 AVHRR-derived land-cover map and reflectance data (the results have been adjusted by sensor difference); and **b** based on 2001 MODIS derived land-cover map and reflectance data. The *numbers in parentheses* represent the frequency distribution for a given biomass class in percent, for 1992 and 2001 respectively

Scaling effects

Scaling tended to have relatively consistent effects on mean AGB estimates, with fairly minor variation. However, the impacts of scaling could vary substantially on total AGB estimates for different years. The scaling process (using majority rule) from 30-m to 1-km pixel resolution resulted in a 3.3% increase of mean AGB density in the subarea for the1992 land-cover configuration (Fig. 2, scenario 3), and a 2.8% increase for the 2001 land-cover configuration based on the NLCD data (Fig. 2, scenario 4). Aggregation of land-cover maps from 30-m to 1-km resolution generated a slight decrease of total AGB by −1.2% (Fig. 2, scenario 3 shows a small gain in mean AGB density (3.3%) but this is counterbalanced by a 4.5% loss in forest area from 14,900 to 14,220 km^2 in 1992 (Table 2, simulations 4 and 5, Fig. 5a,b)). In 2001, both increases of mean AGB density (2.8%) and a substantial gain in forest area through the scaling process from 16,990 to 18,380 km^2 (8.2%, Table 2, simulations 6 and 7) resulted in a 11.4% increase in total AGB estimates (Fig. 2, scenario 4). Partitioning effects of multiple components on ecological properties of interest can improve our understanding on the subjects and simplify the analysis (Zheng et al. 2005).

The changes of direction and quantity in forest area caused by scaling process are largely dependent on whether forest or non-forest land is the prevailing type across the area and landscape configuration. FRAGSTATS analyses revealed that forest area of 1992 (at 1-km resolution) accounted for 44% of total

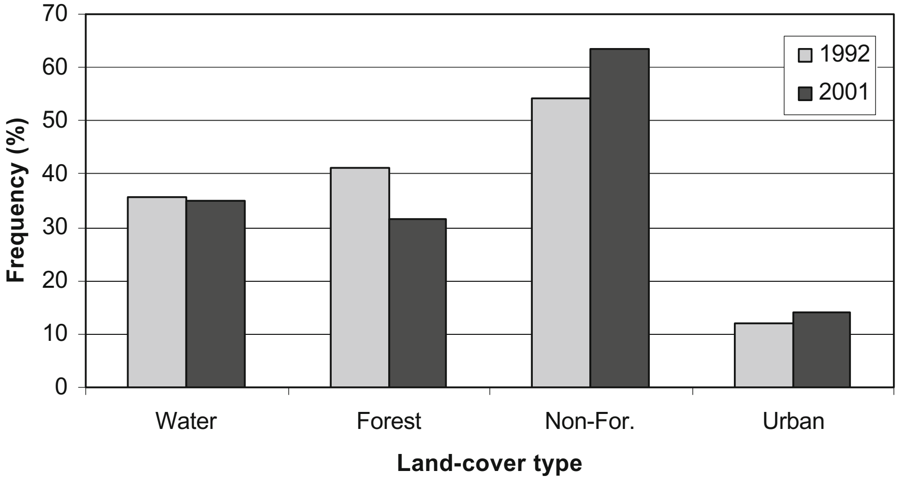

Fig. 4 Comparisons of area occurrence among the broad cover types in the three Lake States between 1992 and 2001. Because frequency changes in water and urban categories between the years are much smaller in absolute values than changes in forest and non-forest categories, we multiply the actual change values by 10 to make them visible

subarea with more fragmented patch distribution (a total of 1,375 forest patches in the area, Fig. 5b) while the 2001 forest area occupied 56% of the subarea with less fragmented patch distribution (a total of 993 forest patches in the area, a 28% decrease from the 1992 number, Fig. 5e). A scaling process using majority rule generally expands the area occupancy for the prevailing cover type (e.g. forest or non-forest). The degree of such area gain or loss for a given type (or species) depends on the degree of its dominance or non-dominance within the landscape.

Across the region, scaling up land-cover map from 30-m to 1-km resolution resulted in a mean difference of 8% (in absolute value) in county-level forest area estimates with a range from 0 to 17% differences within a 95% confidence interval.

Effects of land-cover maps from different sources on change detection

This study indicated that variations (both in forest area estimates and broad forest type identification) in land-cover maps generated using different methodologies was the primary source of uncertainty in detecting temporal changes on total forest AGB over large areas, even though all maps are RS-based products. For example, using land-cover maps of 1992 and 2001 developed from AVHRR/MODIS and NLCD lead to different conclusions about total forest AGB dynamics within the subarea. The AVHRR/MODIS based land-cover maps, derived with an original resolution of 1 km and a classification tree approach (Hansen et al. 2000), suggested a 26% decrease in total forest AGB between 1992 and 2001 (Fig. 2, scenario 5); the NLCD land-cover maps, primarily based on the unsupervised classification of Landsat TM (Thematic Mapper) 30-m imagery and other ancillary data (MRLC, 2006), produced a 36% increase in total forest AGB during the same period after being scaled up to 1-km resolution (Fig. 2, scenario 6). The discrepancy was mainly caused by a difference in estimation of forest area, plus positive or negative effects of forest type identification because in this study separate equations were used for estimating forest AGB for coniferous and deciduous (including mixed) forests. In the subarea, forest area was shown to increase 29% from 14,220 km^2 in 1992 to 18,380 km^2 in 2001 according to the NLCD land-cover maps (simulations 5 and 7, Table 2; Fig. 5b,e); conversely, according to the AVHRR/MODIS land-cover maps, forest area decreased by 33% from 22,380 km^2 in 1992 to 14,990 km^2 in 2001 (simulations 8 and 9, Table 2; Fig. 5c,f). Such a difference could be caused by variations in spatial resolution and classification method used in map generation. In terms of mean AGB density, both temporal comparisons showed the same trend—increasing from 125 and 119 Mg ha^{-1} in 1992 to 139 and 125 Mg ha^{-1} in 2001 (simulations 8 and 9 and simulations 5 and 7, Table 2) by 10 and 5%, respectively (scenarios 5 and 6, Fig. 2). Another uncertainty source complicating landscape AGB estimates in this study is the difference in forest type identification given different sources. For example, the AVHRR/MODIS 1-km land-cover maps identified 8.5% conifer forests in 1992 and only 1.5% in 2001

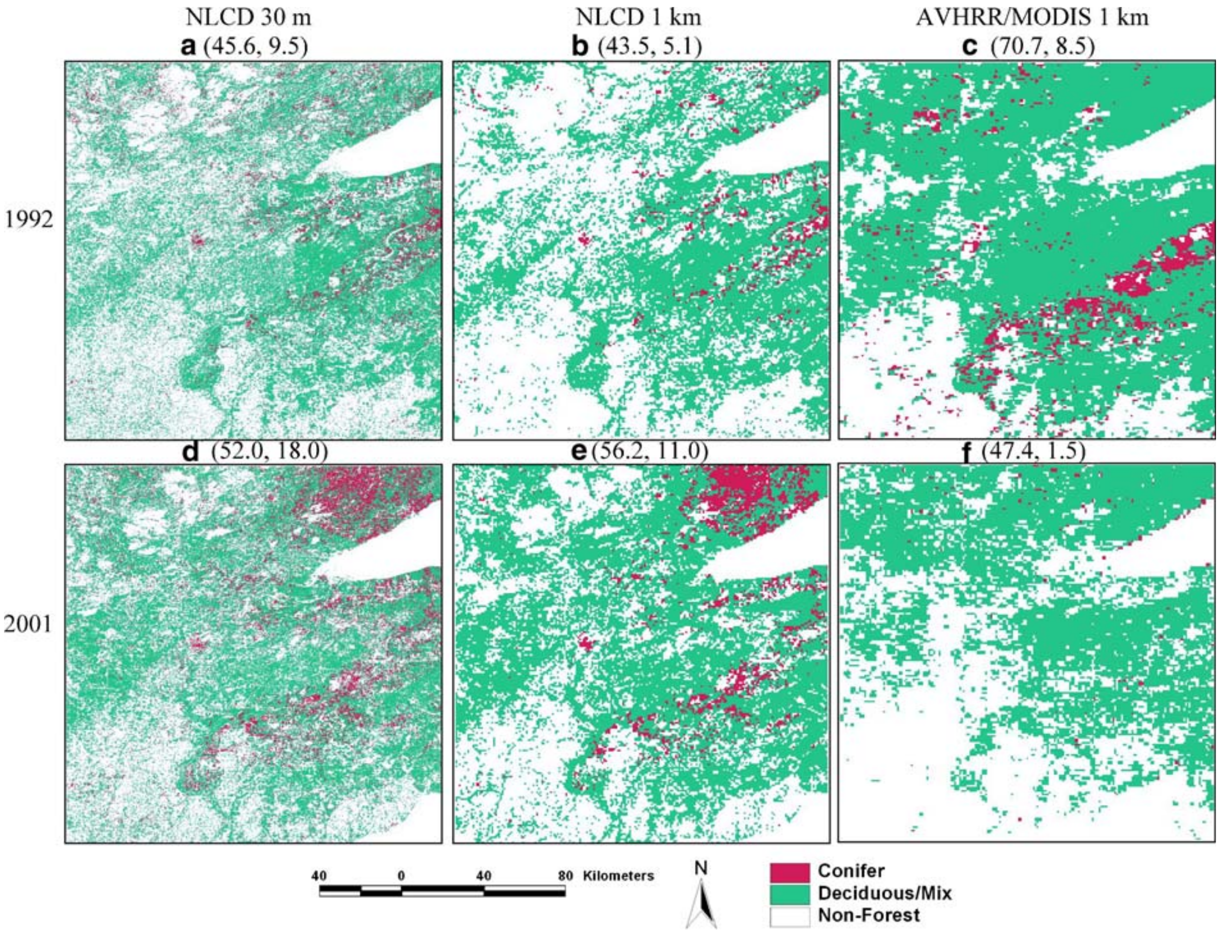

Fig. 5 Effects of the scaling-up process and applying land-cover maps from different data sources on general cover type composition (forest vs non-forest including water) and forest type composition (conifer vs deciduous/mix) in 1992 and 2001 for the subarea: **a** 1992 National Land Cover Data (NLCD) at 30-m resolution; **b** 1992 NLCD map after being scaled to 1-km resolution; **c** 1992 land-cover map produced by University of Maryland at 1-km resolution; **d** 2001 NLCD map at 30-m resolution; **e** 2001 NLCD map after being scaled to 1-km resolution; and **f** 2001 MODIS land-cover map at 1-km resolution. *Numbers in parentheses* represent percentages of forestland to total land area and coniferous forest to total forestland, respectively

(Fig. 5c,f) within the subarea, while the NLCD 1-km land-cover maps contained 5.1% coniferous forests in 1992 which increased to 11.0% in 2001. The differences affected the calculations of both AGB density and total AGB because separate models were used for coniferous and deciduous forests.

Conclusions

AVHRR data and products observed in early years before 2000 (1980s and 1990s) and the MODIS data and products observed after 2000 can be useful data sources for carbon related change studies in terrestrial ecosystems over large scales. However, effects of sensor difference on estimates of ecosystems' properties or characteristics need to be quantified for making meaningful comparisons or evaluations.

Scaling up land cover maps to coarser resolution is an important step in mapping forest biomass and its rates of change over large areas. The scaling-up process on land cover maps has relatively consistent and small effects on forest mean AGB density estimates. The resulting estimates of forest area through the scaling-up process can vary significantly, even from gaining forest area to losing forest area, depending on whether the forestland is the prevailing cover type within the landscape. Thus, forest area differences have much more impact on estimating total AGB across the landscape, introducing great uncertainty in change estimation. We estimated that the mean difference in forest area estimates caused by scaling 30 m land-cover map to 1-km resolution was 8% ranging from 0 to up to 17% at a 95% confidence level at the county-level across the region.

Dynamic changes of AGB estimates across the landscape through time are affected by: (1) changes in forest type (because AGB models based on forest type were used), (2) landscape configuration (which affects scaling results when finer resolution pixels were scaled up to coarser resolution), and (3) variation in forest area estimates and forest type identification from different sources. The third source of variation is especially problematic. This study demonstrate that land-cover maps derived from different data sources and with different classification schemes can have a substantial impact on estimates of terrestrial biomass. Accurate land-cover maps with a consistent classification scheme over time, commonly accepted by governmental agencies as well as the broader scientific community, are much needed for reducing uncertainty in monitoring carbon dynamics within terrestrial ecosystems associated with disturbances and global climate change.

Acknowledgements This study was in part funded by the USDA Forest Service, RWU4104, through grant 05-DG-11242343–074. We thank Michael Nichols for providing the FIA data for analyses. We are grateful to Asko Noormets and another anonymous reviewer for their critical and valuable comments on the manuscript.

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