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Quantifying scaling effects on satellite-derived forest area estimates for the conterminous USA

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We quantified the scaling effects on forest area estimates for the conterminous USA using regression analysis and the National Land Cover Dataset 30 m satellite-derived maps in 2001 and 1992. The original data were aggregated to: (1) broad cover types (forest vs. non-forest); and (2) coarser resolutions (1 km and 10 km). Standard errors of the model estimates were 2.3% and 4.9% at 1 km and 10 km resolutions, respectively. Our model improved the accuracies for 1 km by 0.6% (12 556 km^2) in 2001 and 1.9% (43 198 km^2) in 1992, compared to the forest estimates before the adjustments. Forest area observed from Moderate Resolution Imaging Spectroradiometer (MODIS) 2001 1 km land-cover map for the conterminous USA might differ by 80 811 km^2 from what would be observed if MODIS was available at 30 m. Of this difference, 58% (46 870 km^2) could be a relatively small net improvement, equivalent to 1444 Tg (or 1.5%) of total non-soil forest CO_2 stocks. With increasing attention to accurate monitoring and evaluation of forest area changes for different regions of the globe, our results could facilitate the removal of bias from large-scale estimates based on remote sensors with coarse resolutions.

1. Introduction

Understanding the consequences of management of spatial and temporal homogeneity of land surfaces on both processes and management is a primary focus in landscape ecology and environmental sciences (Risser *et al.* 1984). The emergence and widespread use of geographical information systems and remote sensing in recent decades has provided an effective tool for data analyses, resources monitoring and modelling from local to global scales (DeFries *et al.* 1997, Goodchild and Quattrochi 1997). Such applications have prompted interest in scale as a generic issue. The widespread use of remotely sensed data requires development and implementation of methods for dealing explicitly with scale because those data have a wide range of spatial resolutions (pixel resolution or pixel size) from 1 m resolution IKONOS to the 1 km Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) to even coarser resolutions of many meteorological sensors.

Reliable information on land cover is necessary to improve our ability to address a wide range of place-based environmental and ecological problems, such as climate change, quantifying or understanding carbon cycles, and resource management over large areas (Townshend *et al.* 1991, Heath and Birdsey 1993, Running *et al.* 1994, Gibbard *et al.* 2005, USEPA 2007, Zheng *et al.* 2008). As spatial resolutions of the

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mapping units increase, commensurate with the needs of ecological studies at various scales from local to global, it becomes more difficult to verify the accuracy of data inputs or to validate model outputs using ground-based observations or measurements, such as land-cover classification and net primary production (NPP).

Previous studies have demonstrated that changes in spatial resolution, thematic resolution and observation scale, together with other factors, can affect attribute estimates and pattern analyses (Li and Reynolds 1993, Turner *et al.* 2000, Saura 2004, Wu 2004, Wu and Li 2006, Buyantuyev and Wu 2007). While more complete reviews on the scaling issue have been conducted (Bierkens *et al.* 2000, Dungan *et al.* 2002, Wu and Li 2006), hierarchical theory asserts that a useful way to deal with complex, multi scaled systems is to focus on a single phenomenon (O'Neill 1988). In this study, we focus on changes in pixel resolution. The spatial resolution is the minimum size of mapping unit, and can be aggregated or disaggregated to pixel sizes that are larger or smaller than the original one depending on study purposes and the extent of the study area. Thematic resolution is the number of land-cover types used for land-cover classification across the landscape. The observation scale is the level at which the samples are measured.

While the satellite-derived 30 m National Land Cover Dataset (NLCD) is preferred by many users, others working at the national scale may find the number of pixels in the original map to be computationally challenging for their applications. Although it is reasonable to assume that maps or datasets obtained at fine resolutions are more accurate and verifiable than those obtained at coarse resolutions, coarser-resolution data are more manageable for efforts over large areas that require complex computations and manipulations (Vogelmann *et al.* 2001). An appropriate resolution should be used for a particular project, that is, the resolution should be applicable to the scale of the object being studied and the geographical area being observed. For example, MODIS data would often be preferred over the 30 m Thematic Mapper (TM) data for mapping a given attribute of interest at the national level. More importantly, the NLCD is updated approximately every 10 years, while many forest attributes (e.g. land-cover change and forest area) need to be evaluated or monitored at a finer temporal scale (Liknes *et al.* 2004); thus, the annualized MODIS land-cover maps at coarse resolution (1 km) are more useful to meet such a need at state or national level, although other remote sensing-derived land-cover maps at finer spatial resolutions are more appropriate for local land-use planning (Vogelmann *et al.* 2001).

Consequently, we want to know how increases in pixel size can affect area estimation for a given cover type of interest, compared to its area estimated at 30 m resolution. Previous studies compared US forest area estimates between inventory data and satellite-derived land-cover datasets with different classification schemes (Turner *et al.* 1993, Nelson *et al.* 2005). Nelson *et al.* (2002) and Liknes *et al.* (2004) evaluated how classified NLCD and MODIS products could be used as stratification tools in the Lake States of the USA, but these studies did not discuss scaling effects. Zheng *et al.* (2008) suggested that forest area estimation varies with pixel size, with differences in forest cover percentages based on maps of 30 m and 1 km resolutions ranging from 0% to 17% within a 95% confidence interval using county-level data for several US states. Ahl *et al.* (2005) reported a difference of up to 7% on NPP estimates as land-cover data were aggregated from 15 m to 1 km resolution. These studies, however, did not quantify the scaling effects on forest area estimates through a full range of forest cover at the national level. It is important to understand and quantify the impacts of using coarse resolution (1 km)-based land-cover data, compared to fine resolution-based data, for improving ecological applications over large areas.

Scaling effects, including changes in sensor spatial resolution, inevitably alter representation or understanding of ecological patterns and processes within a given entity of interest (Jelinski and Wu 1996, Buyantuyev and Wu 2007) and can bring errors or uncertainties in discovering the 'true' conditions observed at finer scales (Katz 2002, Li and Wu 2006). A complete exposition of the errors in forest cover estimates would also need to address bias and variance arising from misclassification error. In this study, we do not seek to provide a comprehensive accounting for all errors in forest cover estimates, which could be helpful for specific applications (McRoberts *et al.* 2002). Rather, our focus is on the changes in pixel resolution that play a substantially important role in estimation and interpretation of landscape attributes and patterns (Woodcock and Strahler 1987, Turner *et al.* 2000, Wu 2004).

It is not our intention to compare forest area estimates among maps from different sources with different methodologies in land-cover classification, nor to evaluate the accuracy of existing land-cover maps. Our general goal is to determine how estimates of forest area in remote sensing-derived land-cover products can be affected for broad cover types (forest vs. non-forest) by changes in pixel resolution (from 30 m to 1 km and 10 km resolutions focusing on 1 km analyses) at state and national levels. We focus on administrative levels because, in the USA, land-use planning and resource management strategies are usually implemented at administrative levels, including data collection at county and state levels. This research has three specific objectives. The first is to develop empirical models, given our study purpose and extent, using state-level observations to quantify the average scaling effect and its variability for forest cover percentage at 1 km resolution in comparison with 30 m resolution. This approach eliminates all other possible error sources, but the scaling on forest area estimates, such as differences in classification methods and criteria used for aggregating detailed land-cover classes into broader cover types (e.g. forest vs. non-forest), because we always compare the 'same' map but at different spatial resolutions (e.g. 30 m, 1 km and 10 km). The second objective is to evaluate expected scaling-effect differences between the MODIS land-cover map and its hypothetically equivalent 30 m map at the state and national levels using our developed models. The third objective is to show the general trend in forest area estimates as 30 m pixel size increases to 1 km and 10 km. Finally, the fourth objective is to compare the scaling effects on forest area estimates between the state level-based observations and county level-based observations.

2. Material and methods

2.1 *Study area and NLCD land-cover data*

The conterminous USA comprises 48 states with a total area of about 7.8 million km^2, including inland water. Forest cover, categorized as deciduous, evergreen and mixed, accounted for about 29% and 27% respectively for 1992 and 2001 based on the 30 m NLCD maps (Vogelmann *et al.* 2001, Homer *et al.* 2004). The states range in size from 2820 km^2 for Rhode Island to 685 610 km^2 for Texas, with forest cover percentages ranging from 0.4% in North Dakota to 90.3% in West Virginia based on the aggregated 2001 1 km NLCD map, covering virtually the entire profile of possible cover percentages. The digital NLCD maps were downloaded from the US Geological Survey Multi-Resolution Land Characteristics (MRLC) Consortium website (MRLC 2007). We do not conduct any land-use change detection between the years because that was not our focus. Instead, we use 2001 NLCD data for model development and the other 1992 data for model validation (figure 1).

While the NLCD 2001 map was developed from Landsat 7 imagery with 29 classes, the 1992 map with 21 classes was completed primarily based on 1992 vintage Landsat 5 TM imagery purchased and pre-processed through MLRC (Loveland and Shaw 1996). Although there were slight adjustments in agriculture, urban and barren classes, the 2001 map featured definitions of water, forest, shrub and others nearly identical to those of NLCD 1992 for the continental USA (Homer *et al.* 2004). Therefore, our approach using the 1992 data to validate the scaling-effect model on forest area estimation established from the 2001 data was appropriate, especially at two broad categories (forest vs. non-forest).

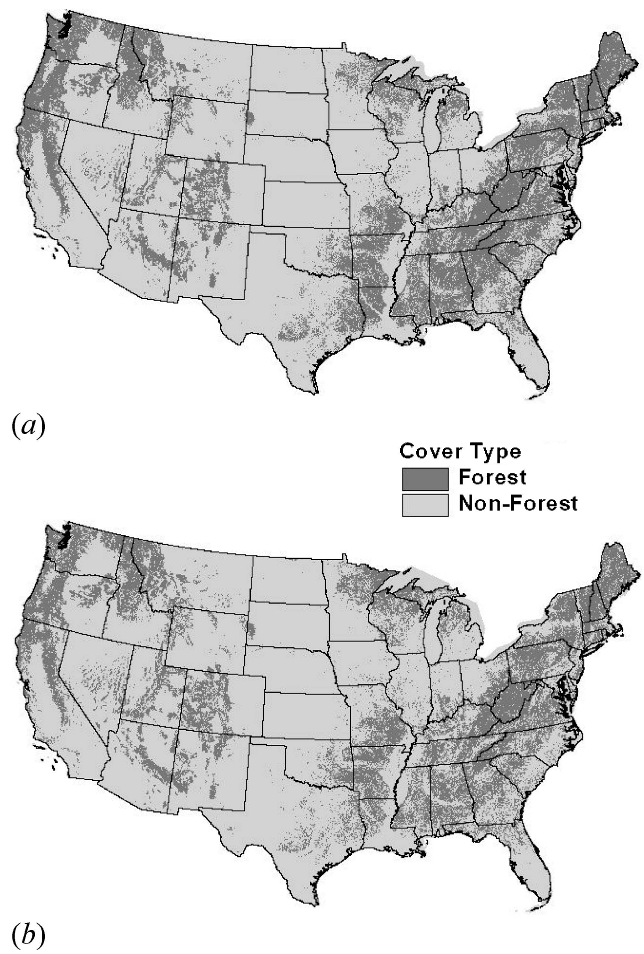

Figure 1. General distributions of forest vs. non-forest in the 48 states of the conterminous USA based on the NLCD 1992(*a*) and 2001(*b*) 30 m maps. The 2001 data were used for model development and the 1992 data were used for evaluating the model performance.

We do not assume that the NLCD map is completely accurate. Previous accuracy assessments of the NLCD data have been reported (Vogelmann *et al.* 2001, Homer *et al.* 2004). The NLCD map may not even be the 'best possible' map for our study, but it is easily available and is likely to be used widely for a range of applications. Therefore, it serves as a useful reference standard for comparison with maps generated from data obtained at or aggregated to coarser resolutions. Were one to compare the NLCD map with a hypothetical 'best possible' map, there would certainly be differences in classification for many individual pixels, and some differences in forest cover percentages as those data were aggregated to county, state and national extent. It is not necessary for the purposes of this study to assume that those two maps would be identical, or to attempt an accounting of the errors associated with differences between them.

2.2 *Data processing and model development*

Both 30 m maps were registered to Albers Equal Area projection. We aggregated the general classes into two broad cover types: (1) forest (classes 41 – deciduous forest, 42 – evergreen forest and 43 – mixed forest) and (2) non-forest (all the other classes including inland water). Such aggregation could reduce errors in estimating forest area over large areas (McRoberts *et al.* 2002). The boundary map for the 48 states was obtained from the Environmental Systems Research Institute (ESRI).

The 30 m NLCD 2001 map was aggregated to 1 km and 10 km pixel sizes, respectively, using majority rule (ESRI n.d.), a commonly used aggregation scheme in scaling-up processes, which finds the pixel value that appears most often within the specified windows, such as $1 \times 1\,\text{km}^2$ and $10 \times 10\,\text{km}^2$, and assigns it to corresponding cells as the output grid. The majority rule is much more widely used than other schemes (such as random or nearest-neighbour) for scaling up discrete variables derived from remotely sensed data in ecological studies (Stuckens *et al.* 2000, Ahl *et al.* 2005). Majority rule aggregation can be viewed as a label-based assignment by a classifier, while actual remote sensing-derived land-cover maps with coarse spatial resolution involve spectral aggregation before classification. Label aggregation is more widely used, however, because spectral aggregation requires training a classifier at each spatial scale, a non-trivial work (Moody and Woodcock 1994, Wu and David 2002, Ju *et al.* 2005). All three land-cover maps at different resolutions were overlaid with the states' boundary map. For each of the 48 states, areas of forest and non-forest lands were extracted and forest cover percentages were calculated at the three resolutions. For the purposes of this study, the scaling effect for any subdomain of the study area is defined as the difference between forest proportions observed from coarse resolution maps and those observed from the 30 m map as reference. This effect is attributable solely to changes in pixel size, because that is the only thing that has been manipulated.

Using regression analyses, we developed models to predict scaling effects (defined in equation (1)) for the 48 states on area estimation based on forest proportions from coarse resolutions, 1 km and 10 km, respectively. We consider the 2001 NLCD 30 m data as 'observations' – indeed, they are the remote sensing observations at the 30 m resolution. Our analyses, however, focus on the 1 km resolution. This is the finest resolution that is most often used for ecological applications at national and continental scales.

$$\text{Percent}_{\text{diff}} = F_{\text{cover\%\_coarse}} - F_{\text{cover\%\_30m}} \tag{1}$$

The standard error (S_E) of the model estimate was calculated as: $S_E = \left[\left(\sum \left(Y_{i\text{obs}} - Y_{i\text{pre}}\right)\right)/(n-2)\right]^{0.5}$, where $Y_{i\text{obs}}$ and $Y_{i\text{pre}}$ were the observed and predicted differences in forest percentages between two spatial resolutions for state *i*, and *n* was the total number of states used in the analysis (Clark and Hosking 1986).

2.3 *Model validation*

We tested the performance of models developed from the NLCD 2001 data using the independent NLCD 1992 data in two ways. First, we compared forest cover percentages in each of the 48 states observed at the NLCD 1992 30 m map with the predicted percentages using the models at both 1 km and 10 km resolutions. This should illustrate how changes in pixel size could affect error identifications in area estimation as range of the change increases from 30 m to 1 km and from 30 m to 10 km. Secondly, we used the 1 km model to test whether the relationship of scaling effect is the same for different years using state and conterminous US data because 1 km remote sensing products are most commonly used for large-scale ecological applications.

2.4 *Model application using the MODIS data*

We used the MODIS 2001 1 km land-cover map to illustrate how and how much forest area estimates at the state and national levels could be improved using our model. Although the AVHRR data have also been used successfully for various terrestrial ecosystem studies over large scales (Tucker *et al.* 1984, DeFries and Townshend 1994), the MODIS products have become the most commonly used remote sensing data for terrestrial ecosystems studies at large scales since 2000. This is because MODIS data have higher spectral and radiometric resolutions, 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 the MODIS 2001 land-cover data (MOD12Q1, type 2 University of Maryland (UMD) classification) for the conterminous USA from the Land Processes Distributed Active Archive Center (USGS-NASA n.d.). For the model application, we aggregated the 13 land-cover classes of the MODIS map into two broad cover types: (1) forest including evergreen needleleaf forest, evergreen broadleaf forest, deciduous needleleaf forest, deciduous broadleaf forest, and mixed forest; and (2) non-forest, which includes all the other classes. Finally, we compared the scaling-effect models developed from the different observation scales of state vs. county for 1 km and 30 m only to illustrate some important ecological implications of using these different resolutions.

3. Results and discussion

Significant correlations between forest area estimates, in decimal fraction at fine pixel resolution (30 m) and coarse resolutions (e.g. 1 km and 10 km) were observed with R^2 values of 0.984 and 0.938 ($P<0.001$), respectively (figures 2(*a*, *b*)). These strong relationships provided solid background information to examine quantitatively the scaling effects on forest area estimates between different resolutions.

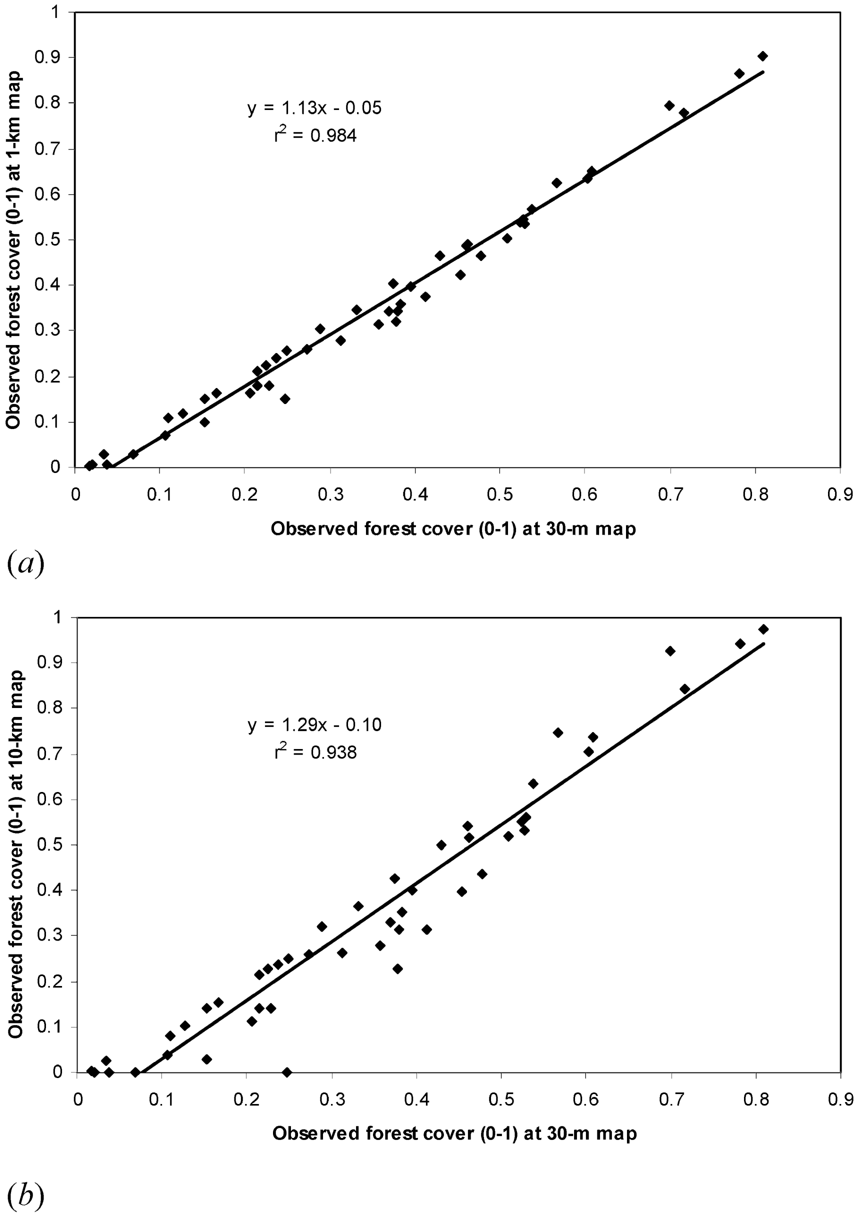

Figure 2. (*a*) Relationship between forest area estimates (in decimal fraction) of the NLCD 2001 30 m and 1 km maps. The latter was aggregated from the former using majority rule. (*b*) Relationship between forest area estimates of the NLCD 2001 30 m and 10 km maps. Each dot represents a state.

Cubic models allowed us to reasonably and quickly quantify the scaling effects on forest area estimates if forest area percentage for a given entity at 1 km or 10 km resolution was known, compared to what it would be for the corresponding hypothetical 30 m map (figure 3). The S_E of scaling effects was 2.3% and 4.9% for 1 km and 10 km resolutions, respectively (table 1). With all other conditions kept constant, increasing pixel size resulted in a larger difference and variation of forest

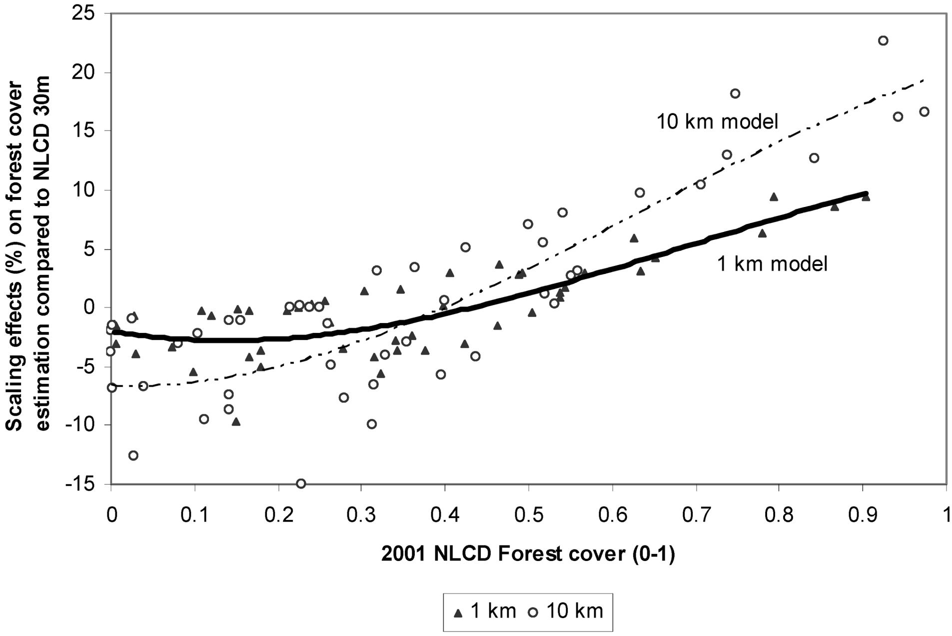

Figure 3. Empirical models developed from the NLCD 2001 maps for quantifying scaling effects on forest area estimates (%) between 30 m and 1 km and between 30 m and 10 km for the conterminous USA. Both models have P values <0.001. Each dot or empty square represents a state. For the 1 km model, $\begin{array}{l} y_{1\mathrm{km}} = -12.6x^3 + 35.5x^2 - 8.7x - 1.8 \\ r^2 = 0.704 \end{array}$ and for the 10 km model, $\begin{array}{l} y_{10\mathrm{km}} = -33.1x^3 + 62.9x^2 - 3.4x - 6.6 \\ r^2 = 0.706 \end{array}$.

area estimates (table 1). Mean observed scaling effect of the 48 states in absolute value without area weighting increased from 3.0% to 6.5% when pixel resolution increased from 1 km to 10 km. Taking the conterminous USA as a whole, after area weighting for each of the 48 individual states, the scaling effect increased from 2.2% to 3.3% for 1 km and 10 km pixel resolutions, respectively. The predicted scaling effects were smaller than observed ones in terms of both mean values and variations

Table 1. Statistics of observed and predicted scaling effects on forest area estimates as differences in percentage (%) of total land area between 30 m and 1 km resolutions (1km%–30m%) and between 30 m and 10 km (10km%–30m%, values in the parentheses) at state and national levels for the US 48 conterminous states based on the 2001 NLCD map.

	Observed, Predicted scaling effects in %				
Scale	Min.	Mean*	Max.	SD*	Error**
State	−9.7, −2.3 (−24.7, −6.3)	3.0, 2.3 (6.5, 6.4)	9.4, 10.1 (22.6, 16.1)	2.5, 2.1 (6.0, 3.6)	2.3% (4.9%)
USA	N/A	2.2 (3.3)	N/A	N/A	N/A

*Mean and standard deviation in absolute value.
**Standard errors of model estimates.

at 1 km and 10 km resolutions (table 1). Differences in and variability of forest area estimates caused by the scaling process increased in general as pixel size increased, especially as forestland becomes less prevalent across landscapes (figure 3). The scaling effects tended to be smaller when forest cover percentages at coarser resolutions approached medium values.

Our empirical models improved the forest area estimates observed on coarse resolution maps. Examining the 1 km model, for example, we improved forest area estimates in 32 of the 48 states in 2001, compared to the area estimates obtained on the NLCD 2001 30 m map (table 2). Ten of the 16 states that did not show improvement were in the western USA. This was not unexpected due to larger state sizes in the western USA with large areas of non-forest. A previous study indicated that in general the suggested precision for area estimates in the western USA was three times less than that in the eastern USA (Bechtold and Patterson 2005). The 30 m based forest area estimates at state and national level were in general less than those reported by the USDA Forest Service Forest Inventory and Analysis (FIA, data not shown) because the percentage land cover for the conterminous USA averaged around 30%, which was on the lower end. This phenomenon was also found in the Brazilian Amazon, where estimates of deforested areas were generally larger based on ground surveys than estimates from satellite data (Andersen *et al.* 2002, Ometto *et al.* 2005). However, this issue is outside the scope of this study. Pursuing that issue would make the analysis more complicated because (1) FIA estimates are point-based observations using statistically derived expansion factors, while the satellite-derived estimates are spatially explicit, and (2) definitions of forest land differ between FIA and NLCD datasets. Therefore, we compared the coarse-resolution forest area estimates with the fine-resolution estimates to make our analyses simpler and more consistent, although using the FIA estimates as reference numbers could raise the accuracy of our model predictions. Within the conterminous USA, forest area of 2 029 086 km^2 observed from the NLCD 1 km map was 44 693 km^2 less than that observed from the NLCD 30 m map (table 2), while our model overestimated forest area by 32 138 km^2. As a result, the model brought a net improvement of 12 555 km^2 on forest area estimation across the conterminous USA. The improvement accounted for 16% of the difference between the total simulated forest area of 2 105 917 km^2 and the observed 2 029 086 km^2 forest areas for the conterminous USA (table 2).

According to the NLCD 2001 maps, the top six states gaining forest area during the scaling-up process from 30 m to 1 km were Maine, Oregon, Washington, West Virginia, Virginia and Alabama, with average forest cover of 58% on the 30 m NLCD map and average gaining area per state of 5986 km^2. The top six states losing forest area during the process were Texas, Illinois, Oklahoma, Kansas, Michigan and Florida, with average forest cover of 18% on the 30 m NLCD map and average losing area of 9474 km^2 (table 2). Our adjusted forest cover (%) estimates at state and national levels incorporating scaling effects could provide more accurate and useful information for research concerning forest carbon sequestration, resources monitoring and management at the corresponding scales.

Forty-two of the 48 states showed consistent patterns of scaling effect on changes in forest area estimates, that is, either continually increasing or decreasing, as pixel sizes increased from 30 m to 1 km and 10 km (table 2). Whether area was increased or decreased primarily depended on whether forestland for a given state was the dominant type or not, given two cover types. California, Louisiana, Massachusetts and Mississippi, four of the six states with an inconsistent scaling-effect trend, were

Table 2. Comparisons of 2001 1 km NLCD and MODIS forest area estimates (km^2) before and after scaling effects adjustment for the conterminous 48 states of the USA.

State	NLCD30	NLCDkm	NLCDkm*	MODIS	MODIS*	NLCD10 km
Alabama	71 842	75 716	72 507	59 817	59 391	84 100
Arizona†	44 960	44 493	51 329	16 172	22 498	41 600
Arkansas‡	63 337	67 208	65 858	52 565	53 409	74 000
California†§	97 347	98 422	106 535	92 081	100 562	97 200
Colorado†	77 925	81 780	85 790	45 754	51 908	85 800
Connecticut	7303	8055	7593	10 045	9135	9500
Delaware	1281	781	900	795	915	0
Florida	30 288	24 189	27 551	41 039	43 524	16 300
Georgia†‡	72 883	70 616	69 733	54 191	55 613	66 000
Idaho†	71 618	74 844	77 118	71 957	74 544	78 700
Illinois	22 330	14 458	17 809	3752	6630	4000
Indiana	21 486	16 763	18 879	8387	10 517	13 200
Iowa	10 111	4364	7279	332	2944	200
Kansas	7915	1280	5166	1351	5242	0
Kentucky‡	54 843	56 226	54 280	41 785	42 181	57 000
Louisiana†‡§	25 914	25 595	28 181	55 983	55 302	25 900
Maine	58 932	66 859	60 619	76 903	68 227	77 700
Maryland	9803	8352	8692	9160	9410	5800
Massachusetts§	11 085	11 434	11 018	16 666	15 115	11 200
Michigan‡	53 678	47 312	49 386	67 086	66 635	41 800
Minnesota	59 776	57 050	61 077	58 398	62 320	56 500
Mississippi†§	48 723	49 002	49 503	49 525	49 960	48 900
Missouri	66 609	61 644	63 611	34 775	38 774	59 300
Montana†	85 630	85 803	93 675	76 738	85 044	86 100
Nebraska	4028	1050	4690	354	3935	0
Nevada†	31 606	30 813	37 428	6209	11 776	22 800
New Hampshire	18 751	20 796	18 604	22 496	19 881	23 100
New Jersey	7420	6704	6915	8150	8176	6000
New Mexico†	52 558	51 841	59 064	19 237	26 077	48 800
New York†	66 560	67 580	65 258	69 890	67 130	70 100
North Carolina	57 995	54 072	54 132	53 963	54 036	50 400
North Dakota	3174	702	4008	418	3699	300
Ohio	33 467	29 735	31 560	22 908	25 177	28 100
Oklahoma	38 984	32 346	36 432	8224	12 015	25 400
Oregon†	94 199	101 714	102 465	105 147	105 412	106 500
Pennsylvania	70 672	74 271	69 858	67 063	64 116	82 300
Rhode Island	1302	1382	1356	2206	2005	1500
South Carolina	33 098	30 161	30 707	30 578	31 071	24 900
South Dakota†	6949	5509	9473	3886	7737	5000
Tennessee†‡§	55 490	54 986	53 624	42 207	42 804	56 300
Texas	72 547	49 314	64 514	30 822	45 161	26 500
Utah†§	54 933	56 216	60 350	15 392	20 250	54 700
Vermont	17 842	19 442	17 667	20 252	18 293	21 000
Virginia	63 024	67 404	63 112	57 953	55 591	76 400
Washington	75 097	81 380	80 341	93 386	90 253	87 500
West Virginia	50 747	56 685	50 367	53 955	48 312	60 800
Wisconsin	55 641	52 293	53 573	43 045	45 298	50 900
Wyoming†	32 076	30 444	36 330	24 596	30 400	26 200
Total	2 073 779	2 029 086	2 105 917	1 747 594	1 828 405	

The 2001 30 m NLCD estimates were used as references to compare with those observed at 1 km and 10 km resolutions and to evaluate the model performance among the NLCD products at state level only, not for cross-comparison between the NLCD and MODIS estimates. NLCD estimates from Homer *et al.* (2004) and MODIS estimates from MOD12Q1, adjacent to oceans where the accuracy in calculation of land areas and the trend detection could be affected as pixel size increased to 10 km. The state of Tennessee had the most balanced forest and non-forest proportions (50.8% vs. 49.2%), so its estimated changes may be due to the second level of controlling factors, such as landscape configuration and patch size distributions (Moody and Woodcock 1995). The average difference in forest area estimates between 1 km and 10 km among the six states was 1.6%, with the maximum of 2.7% in Utah.

Model validation indicated there were strong relationships between the observed forest cover percentages from the NLCD 1992 30 m map and the predicted forest percentages at 30 m using both the 1 km and 10 km models. For instance, the slope (0.99) of the relationship between observed and predicted percentages using the 1 km model was very close to 1 (figure 4(*a*)). Although the slope between observed and predicted percentages using the 10 km model was slightly lower (0.92) than that for the 1 km model, it was still statistically significant ($P<0.001$) (figure 4(*b*)). Compared to the observed scaling effects between 30 m and 1 km at the state level based on the NLCD 1992 maps, 33 of the 48 states, or 69%, had adjusted 1 km forest area estimates closer to their corresponding estimates from the 30 m map (table 3). For the continent, the total forest area observed on the 1 km cover map, 2 232 587 km^2, was 45 614 km^2 less than that observed from the 30 m cover map. Our adjusted total forest area, 2 275 785 km^2, was 2416 km^2 less than that observed for the 30 m map, suggesting a net improvement of 43 198 km^2, or 100% of the difference between the 1992 1 km estimates before and after the adjustment (table 3).

We applied our 1 km model to examine possible scaling effects on forest area estimates in the MODIS 2001 1 km land-cover map across the conterminous USA. Our modelling results suggested there was about a 80 811 km^2 difference between unadjusted (1 747 594 km^2) and adjusted (1 828 405 km^2) forest area estimates based on the MODIS 2001 map (table 2). Since 'true' 30 m MODIS did not exist, we used the mean percentage 58% of the improvements achieved in the NLCD 1992 (100%) and 2001 (16%) maps to calculate the potential net forest area improvement in the MODIS 1 km land-cover map. Using the mean improvement rate of 58%, our model improved the forest area estimation in the MODIS 2001 1 km map for the conterminous USA by 46 870 km^2, that is, 80 811 km$^2 \times 0.58$. At the state level, 88% or 42 of the 48 states, showed the same scaling-effect trends on forest area estimates between the MODIS 1 km numbers before and after adjustment as those observed between the NLCD 1 km before and after adjustment (table 2). Our scaling-effect models always identify the difference in forest area estimates of an equivalent base map but at different spatial resolutions so that there is no cross-comparison issues between maps from different sources with possibly different classification schemes. However, it is valid to compare the trends of area changes caused by scaling effects detected from different datasets.

←

UMD classification system (http://lpdaac.usgs.gov/main.asp).
*Adjusted estimates using the scaling-effect model.
†The states without improvement after adjustments based on the NLCD data.
‡The states with detected trends of scaling effects before and after adjustment on the MODIS 2001 1 km map were in the opposite direction to the trends detected from the NLCD 2001 1 km map before and after adjustment.
§The states with inconsistent trends of scaling effects on forest area estimates as pixel resolution increases from 30 m to 1 km and 10 km.

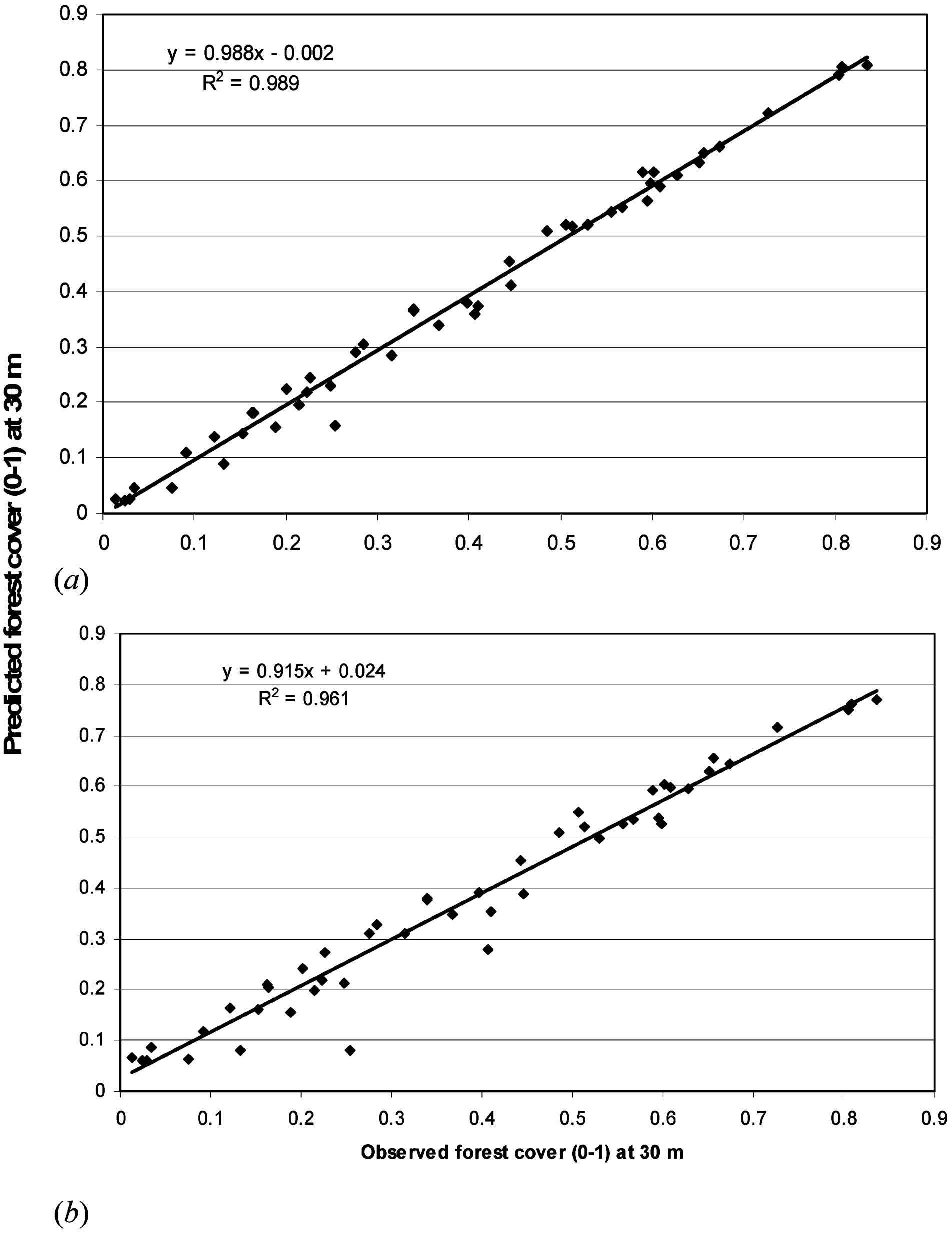

Figure 4. Comparisons of observed and predicted forest area estimates (in decimal fraction) at 30 m resolution based on the NLCD 1992 map: (*a*) predicted using the 1 km model $\left(\begin{matrix} y=1.13x-0.05 \\ r^2=0.984 \end{matrix}\right)$; and (*b*) using the 10 km model $\left(\begin{matrix} y=1.29x+0.10 \\ r^2=0.938 \end{matrix}\right)$ presented in figure 2. Each dot represents a state in the conterminous USA.

The net improvement of 46 870 km^2, about 2.7%, of the MODIS 2001 1 km forest estimation was equivalent to 1444 Tg, or 1.5% of total non-soil forest CO_2 stocks in the conterminous USA (after area weighting) based on values of unit CO_2 per square kilometre reported by the US EPA (2007).

Table 3. Validating the 2001 NLCD-based model using the 1992 NLCD observations for forest area estimation (km^2) for the 48 states of the conterminous USA.

	NLCD30 m	NLCDkm	NLCDkm*
State	1992	1992	1992
Alabama	90 045	95 947	88 441
Arizona†	48 496	46 268	53 081
Arkansas	70 701	73 869	71 334
California†	112 925	111 371	118 575
Colorado†	76 612	78 039	82 390
Connecticut	7587	8457	7908
Delaware	1321	696	817
Florida	36 403	30 368	33 531
Georgia	84 637	86 550	82 828
Idaho†	73 619	77 805	79 728
Illinois	19 310	9892	13 103
Indiana	17 632	12 338	14 519
Iowa	11 014	3951	6839
Kansas	6224	1545	5452
Kentucky†	62 298	62 102	59 021
Louisiana†	41 049	42 944	44 086
Maine	67 748	74 658	66 533
Maryland	10 555	9023	9289
Massachusetts	12 638	13 790	12 896
Michigan	61 670	54 727	55 986
Minnesota	48 573	42 628	47 449
Mississippi	62 459	66 548	64 213
Missouri	66 339	59 079	61 336
Montana†	86 108	84 868	92 793
Nebraska	4828	921	4550
Nevada†	26 241	24 738	31 222
New Hampshire	19 381	21 776	19 338
New Jersey	8713	7989	8038
New Mexico†	51 214	49 343	56 610
New York	79 087	81 832	76 643
North Carolina†	72 487	73 977	70 589
North Dakota†	2473	1101	4440
Ohio	33 624	28 351	30 284
Oklahoma	38 891	31 272	35 392
Oregon	111 326	115 244	113 976
Pennsylvania	76 424	79 634	74 062
Rhode Island	1683	1779	1674
South Carolina	42 460	43 276	41 749
South Dakota†	6920	5298	9248
Tennessee†	66 445	68 125	64 223
Texas	104 099	81 963	97 888
Utah†	44 243	44 195	48 995
Vermont	18 084	19 843	17 982
Virginia	67 939	72 645	67 201
Washington	84 926	91 586	88 783
West Virginia	52 440	57 170	50 739
Wisconsin	57 631	53 990	55 061
Wyoming†	30 679	29 076	34 950
Total	2 278 201	2 232 587	2 275 785

*Estimates were adjusted using the 2001 NLCD-based model.
†The states without improvement.

We hypothesize that when forest proportions of a given entity observed from coarse resolution maps were less (more) than 50%, the actual forest proportions at finer resolutions will likely increase (decrease) if forest and non-forest patch sizes and spatial arrangement are evenly and uniformly distributed across the landscape. In reality, such a landscape is probably rare. Our modelled results demonstrated that some states with forest cover smaller than 50% at fine resolution could still gain area while some states with forest cover larger than 50% at fine resolution could still lose area through the scaling process (figure 3). This suggests the configuration of forest and non-forest patches and patch size distributions across the landscapes could be the secondary factor affecting forest area estimates (the primary factor was forest cover percentages on coarse resolution maps). Possible error sources of our models included: (1) relatively small sample size (48 states), that is, relative to the entire profile of forest-cover percentages ranging from 0 to 100 after being binned to the nearest whole number; (2) uneven sample distribution across the entire profile – 77% of the 48 states had forest proportions <50% based on the 2001 NLCD 1 km map (figure 3); and (3) our simplified models did not include a secondary level of controlling factors, such as patch size distributions and arrangement. Our models predicted there were 'no' scaling effects where forest proportions were about 43% and 40%, respectively, from 1 km and 10 km maps, rather than at 50% as expected. This difference could be reduced with an increase in sample size (see later discussion for figure 5). Despite these less-than-ideal situations, our models are a simple tool with reasonable accuracy that can be used to assess quickly the scaling effects on forest area estimates on coarse resolution maps. Using these models, we demonstrated that forest cover percentages from the coarse-resolution map alone could explain more than 70% of the variance of scaling effects across the landscape (figure 3).

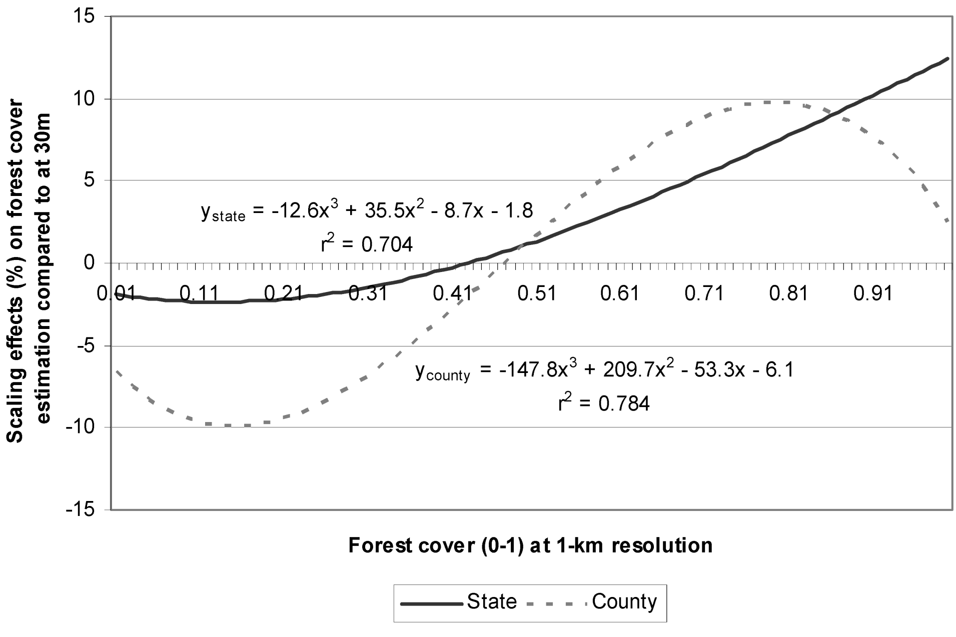

Figure 5. Comparison of 1 km scaling-effect models developed using state-level observations in this study and the county-level observations from three Lake States of the USA (Zheng *et al.* 2008).

We compared the 1 km model developed in this study, using observations at the state level, with the model from another study that used observations at the county level within the Lake States region of the USA (Zheng *et al.* 2008). Both models are statistically significant (figure 5, $p<0.001$) and provide the best fits for their corresponding scales of study. However, the relationship between forest cover and scaling effect are quite different because of difference in sample sizes (or the observation levels at which the models were developed). These two terms are negatively correlated only if the study extent is fixed. For example, the sample size for the conterminous USA is over 3000 with the county-level observations, while the sample size is 48 with the state-level observations. The county level-based model ($n=242$) had larger variation but was more symmetrical than the state level-based model ($n=48$). The mean predicted scaling effect using the county level model was 4.0%, ranging from −9.8% to 9.8% with SD of 5.9%, while the mean predicted scaling effect using the state level model was 2.3%, ranging from −2.3% to 10.1% with SD of 2.1% (table 1). Our findings agree well with previous studies that effective scale investigation required the scale of analysis be commensurate with the intrinsic scale of the phenomenon under study and that multiple observation sets at different scales usually are necessary (Allen *et al.* 1984, Bloschl and Sivapalan 1995, Wu 1999). The model developed from county-level observations showed that the division percentage was closer to 50% and somewhat symmetrical, as compared to the state level-based model. This is expected because the area gaining in one type translates to the area losing in the other type (and vice versa) given two broad types across a landscape.

The difference between models developed using data from various observation scales suggests that (1) scaling-effect models should be applied to the corresponding scales from which the observational data are obtained for model development to minimize possible model bias; (2) although these resulting regression models can best represent the ecological conditions of the study areas at a given observation scale, models obtained from smaller sample sizes tend to have less value for general applications; and (3) scaling-effect models derived from larger sample sizes that include ‘all’ possible variations in patch size distributions and spatial arrangements across the entire 0–100% cover percentage profile are desirable. With adequate samples, variability of scaling effects on area estimates within each whole percentage bin can be examined. In addition to forest percentage observed from coarse resolution land-cover maps, which is the primary model predictor, landscape pattern characteristics, such as patch size distributions and spatial arrangements, can also affect the accuracy of pixel size-dependent error identifications in area estimation across landscapes (Moody and Woodcock 1995). A theoretic model of scaling effect from an ‘ideal’ sample size should show the smallest effect on forest area estimates at 50% cover point; or no effect when size and arrangement of forest and non-forest patches are distributed perfectly evenly and uniformly across a landscape. The scaling effect on area estimates, given two types, should increase as the area percentages at coarse resolutions diverged from 50% in either direction until reaching peak values, either negative or positive, before declining in absolute value (see figure 5). The theoretical curve is expected to be symmetrical because area gain in one type is equal to the loss in the other. A symmetrical curve is also more feasible for general application (Zheng *et al.* 2008).

4. Conclusions

The effect of various satellite sensors with different spatial resolutions on forest area estimation deserves more attention on ecological applications over large areas because of their complexity and multi-scale nature. We provided meaningful and practical models to improve forest area estimates observed from coarse-resolution maps (e.g. 1 km or 10 km) that are more appropriate and commonly used for continental and global applications. We recommend that empirical models be applied on a scale similar to the scale of observations from which the models were developed. Our results provide useful implications for a range of resource and environmental monitoring, modelling, carbon studies and management activities.

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