Landscape Ecol (2008) 23:1119–1132
DOI 10.1007/s10980-008-9272-1

RESEARCH ARTICLE

# Modeling grain-size dependent bias in estimating forest area: a regional application

Daolan Zheng · Linda S. Heath · Mark J. Ducey

Received: 5 March 2008 / Accepted: 4 September 2008 / Published online: 26 September 2008


**Abstract** A better understanding of scaling-up effects on estimating important landscape characteristics (e.g. forest percentage) is critical for improving ecological applications over large areas. This study illustrated effects of changing grain sizes on regional forest estimates in Minnesota, Wisconsin, and Michigan of the USA using 30-m land-cover maps (1992 and 2001) produced by the National Land Cover Datasets. The maps were aggregated to two broad cover types (forest vs. non-forest) and scaled up to 1-km and 10-km resolutions. Empirical models were established from county-level observations using regression analysis to estimate scaling effects on area estimation. Forest percentages observed at 30-m and 1-km land-cover maps were highly correlated. This intrinsic relationship was tested spatially, temporally, and was shown to be invariant. Our models provide a practical way to calibrate forest percentages observed from coarse-resolution land-cover data. The models predicted mean scaling effects of 7.0 and 12.0% (in absolute value with standard deviations of 2.2 and 5.3%) on regional forest cover estimation (ranging from 2.3 and 2.5% to 11.1 and 23.7% at the county level) with standard errors of model estimation 3.1 and 7.1% between 30 m and 1 km, and 30 m and 10 km, respectively, within a 95% confidence interval. Our models improved accuracy of forest cover estimates (in terms of percent) by 63% (at 1-km resolution) and 57% (at 10-km resolution) at the county level relative to those without model adjustment and by 87 and 84% at the regional level in 2001. The model improved 1992 and 2001 regional forest estimation in terms of area for 1-km maps by 15,141 and 7,412 km$^2$ (after area weighting of all counties) respectively, compared to the corresponding estimates without calibration using 30 m-based regional forest areas as reference.

**Keywords** Aggregation · Confidence interval · Land-cover map · Pixel resolution · Standard errors · 3 Lake States of USA

D. Zheng (✉) · M. J. Ducey
Department of Natural Resources and the Environment, University of New Hampshire, 215 James Hall, Durham, NH03824, USA
e-mail: daolan.zheng@unh.edu

L. S. Heath
USDA Forest Service, Northern Research Station, 271 Mast Road, Durham, NH03824, USA

## Introduction

Although scaling and its effects on land cover identification is not a new topic, it is still a challenging and core issue in modern ecological studies across multiple scales (Turner 1989; Levin 1992; Goodchild and Quattrochi 1997; Cohen and Justice 1999; Running et al. 1999; Wu and Hobbs 2002). Landscapes are complex systems having a hierarchical structure where dominant patterns and processes exist at specific scales (O'Neill 1988; Wu and Marceau 2002; Hall et al. 2004). A more general and widely accepted definition of scaling in ecology and earth science is the translation of information between or across spatial or temporal scales or organizational levels (Turner et al. 1989; Bloschl and Sivapalan 1995; Wu 1999; Saura 2004; Wu and Li 2006). Thus, the scaling-up process (including changes in sensor spatial resolution, or grain size) inevitably alters representation or understanding of ecological patterns and processes (or both) 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). However, in some cases, investigators or decision makers are more interested in knowing how the scaling-up process affects the estimation of a given attribute across the landscape, such as forest area or percentage of coniferous forest, rather than changes in spatial arrangements of forest (vs. non-forest), especially for large area ecological applications often relying on satellite-derived products at coarser resolutions (e.g. 1-km or larger).

Comparisons between existing vegetation cover maps obtained from conventional methods suggest that the area estimates for major vegetation types vary substantially because of differences in classification methods, data sources, and the sample size of the specific parameters used to separate vegetation classes (even if the same classification approach has been adopted) (Townshend et al. 1991). For example, estimated areas of global forestland have varied from about 30 million km$^2$ to over 70 million km$^2$ for a similar time (Ajtay et al. 1979; Emanuel et al. 1985). Such variations can significantly affect many ecological analyses and conclusions related to total forest area over large areas, such as forest production, resource assessment, carbon storage, and greenhouse gas inventories (Heath et al. 1996; Smith and Heath 2007; USDA 2007). Discrepancies in area estimates also make any comparison attempts over time difficult (Smith et al. 2006; Zheng et al. 2007).

Rapid development of remote sensing techniques in recent decades provides alternative sources for land cover classification at various scales (Tucker et al. 1985; Cohen et al. 2001; Vogelmann et al. 2001; Friedl et al. 2002). Satellite-based remote sensing data have been shown to have considerable potential for monitoring land-cover change using relatively consistent methodology because satellites often cover large areas with high revisitation frequencies (Goetz et al. 2000; Running et al. 2000; Bresee et al. 2004). Even with the same methodology, estimates in forest area using satellite-derived land-cover maps can differ notably because of differences in sensor spatial resolution (Hansen et al. 2000; Vogelmann et al. 2001; Friedl et al. 2002; Homer et al. 2004), but also for other factors such as spectral, temporal, and radiometric characteristics of various sensors (Strahler et al. 1986; Woodcock and Strahler 1987).

No matter what method (traditional or remote sensing based) is used for producing land-cover maps, degree of detail in land-cover classification usually decreases while grain size of dataset increases as the study area sizes increase. While moderate resolution land-cover datasets (30-m Landsat TM and ETM+ data) are appropriate for local land use planning, coarse resolution datasets such as 1-km Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectrometer (MODIS) land-cover products are usually well-suited for ecological analysis over large areas (Vogelmann et al. 2001). Land-cover maps developed using moderate resolution are generally more accurate and reliable because the maps can be calibrated or verified using existing inventory data or field sampling, while training data are lacking for those developed using coarse resolution. However, coarse-resolution data are often preferable for large-scale ecological applications for three reasons. First, they are ideal for efforts that require complex computations and manipulations using much less memory, space, and computing time. For example, there are about 9 billion 30-m pixels over the conterminous U.S. (Homer et al. 2004) whereas the number of pixels reduces to about 7.8 million at 1-km resolution. Second, the accuracy and precision for a given ecological characteristic at a particular location is sometimes of less interest than the geographic patterns and trends (Zheng et al. 2003). Detection of large-scale trends in finer resolution data may require aggregation of those data after computationally-expensive processing. Finally, coarse-resolution data are more useful for examining relationships between environmental driving variables (e.g. temperature and precipitation) and the ecological patterns or properties of interest that are usually more realistic at coarse resolution (Lieth 1975; Gower et al. 2001; Zheng et al. 2004a). Using unnecessarily fine-resolution data may degrade evaluations of relationships (e.g. climate & vegetation) over large areas because of our lack of ability to accurately quantify driving variables at finer resolution.

A recent study suggests a new approach, weighted sampling net, for rescaling land-cover data (Gardner et al. 2008). Other studies indicated the estimation of land-cover percentages from coarse resolution maps could be improved using a double sampling with regression estimator approach (Mayaux and Lambin 1997) to retrieve the "true" percentages between a "controlling" factor, which could be measured over the entire population from coarse resolution data and the "target" factor (land-cover percentages at a finer resolution), known as inverse calibration model (Brown 1982; Moody and Woodcock 1996). The regression estimator approach relies on the fact that the estimation of land-cover percentages from coarse-resolution maps is associated with a systematical bias caused by scaling effects. The regression approach was proven more reliable than classical calibration to correct misclassifications in remote sensing (Czaplewski and Catts 1992; Walsh and Burk 1993; Moody and Woodcock 1995).

While previous studies have demonstrated that spectral, temporal, and radiometric characteristics of various remote sensing data, landscape patterns, and thematic resolution can affect land cover investigations (Strahler et al. 1986; Woodcock and Strahler 1987; Li and Reynolds 1993; Buyantuyev and Wu 2007), we focus on changes in grain size that play a substantially important role in estimation and interpretation of landscape attributes and patterns (Woodcock and Strahler 1987; Moody and Woodcock 1994; Turner et al. 2000; Saura 2004; Wu 2004). Whereas thorough discussions on various concepts of scale and scaling, as well as the method of describing images using models, have been illustrated (Strahler et al. 1986; Bierkens et al. 2000; Dungan et al. 2002; Wu and Li 2006), the hierarchical theory asserts that a useful way in which to deal with complex, multi-scaled systems is to focus on a single phenomenon (O'Neill 1988).

The overall goal of this study is to answer the question: what will be the difference between coarse resolution and moderate resolution based forest area estimates? In particular, this study illustrates and quantifies how changes in grain sizes from 30 m to 1 km and 10 km (focusing on 1 km) affect regional forest area estimation (vs. non-forest type) based on county level observations in the three Lake States of the USA using NLCD land-cover maps.

The specific objectives of this study include: (1) illustrating how changes in grain size affect forest area estimates at the regional scale; (2) testing whether such relationships of scaling effects are temporally and spatially invariant (although landscape patterns and configurations are consistently changing spatially and temporally); (3) evaluating whether scaling effects (in relative percent) are affected by different coordinate systems; and (4) quantifying the relationship so differences in forest area estimates associated with changes in grain size can be quickly estimated based on coarse-resolution maps using empirical models.

## Materials and methods

### Study area

The area Michigan (MI), Minnesota (MN), and Wisconsin (WI), covers approximately 493,800 $km^2$ and ranges from 41° N to 49° N in latitude and from 97° W to 83° W in longitude. The landscapes of the region include dynamic interactions between the grasslands of the Great Plains, the eastern deciduous forests, and the boreal forests of North America. Dominant forest species are aspen-birch (Populus tremuloides, Betula papyrifera), northern hardwoods (Acer saccharum, Acer rubrum, Quercus rubra), and a mixture of conifers (Pinus banksiana, Pinus resinosa, Thuja occidentalis, Picea mariana, Abies balsamea) (McWilliams et al. 2000) 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). The region contains 242 counties with sizes ranging from a few hundreds to about 17,600 $km^2$ with a mean size of about 2,020 $km^2$ (Fig. 1). Forest percentages of counties varied from less than 1% to over 82% with a county mean forest cover of 28% according to the 2001 NLCD 30-m map (MRLC n.d.) (Fig. 1), providing almost a full range of percentages to examine grain-size effects on estimating forest areas across the region.

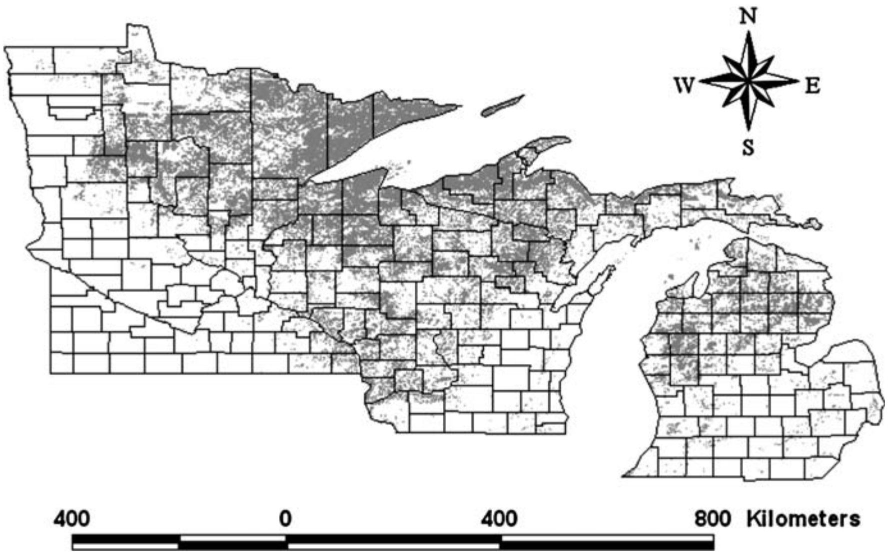


**Fig. 1** Spatial distribution of forest cover (in gray) at 1-km resolution (to reduce file size for presentation) overlaid with county boundaries in the 3 Lake States, USA, based on 2001 30-m data from the National Land Cover Dataset

Land-cover maps developed from 30-m TM and ETM+ data, and the county map

Designed to meet the broad requirements of federal agencies and scientific communities for a consistent national land-cover data set, NLCD was implemented in 1992 and 2001 using 30-m TM and ETM+ data (Vogelmann et al. 2001; Homer et al. 2004). We extracted the land-cover maps of 3 states (MN, WI, and MI) in the Great Lake region from the 1992 and 2001 NLCD maps to develop and test regional models, not to conduct any comparison or change detection between the 2 years. Although the classification methods and systems were not identical between the 2 years, such effects were minimal in this study (especially for the broad cover types we use) because one of the guiding principles in the NLCD 2001 map was to ensure that the second-generation land cover product maintained reasonable compatibility with NLCD 1992 map (Homer et al. 2004). We aggregated the cover types in both years into 2 broad categories to simplify the analysis (Buyantuyev and Wu 2007; Li and Reynolds 1993): (1) forest (e.g. land cover classes 41, 42, and 43), and (2) non-forest (all the other classes including inland water).

The 30-m land-cover maps were aggregated to 1-km and 10-km resolutions respectively using majority rule (ESRI n.d.) that finds the pixel value that appears most often within the specified windows (e.g. $1 \times 1$ km$^2$) and sends it to each of the corresponding cells as the output grid. This scheme, compared to other scaling schemes (random or nearest-neighbor), is more commonly used for scaling up distinct variables derived from remote sensing (e.g., land-cover data) in ecological studies (Stuckens et al. 2000; Ahl et al. 2005). Thus, our aggregation is a label based assignment by a classifier of choice to pixels at the finer spatial resolution whereas a remote sensing derived land-cover map at coarse spatial resolution is spectrally-based aggregation. The approach of label aggregation, however, is more widely used (Moody and Woodcock 1994; Wu and David 2002), likely because spectral aggregation requires that a classifier be trained at each scale, a non-trivial task (Ju et al. 2005). The county boundary map of the region was downloaded from the USA county map produced by Environmental Systems Research Institute (ESRI).

Model development and validation

All 2001 NLCD 30-m and the aggregated 1-km and 10-km land-cover maps were overlaid with the county map to obtain the forest percentages observed at different spatial resolutions for a given county. We plotted forest percentages observed at 1 km and 10 km spatial resolutions for all counties (as the independent variable) against the corresponding differences (in %) between 30 m- and 1 km- (or 10 km-) based forest percentages (as the dependent variable) to develop scaling-effect models using regression analysis (that is, forest percentages from coarse resolution as X and differences in percentages from coarse and finer resolutions as Y). The difference (%) in forest percentages ($\text{Percent}_{\text{diff}}$) calculated between 30 m (as reference) and 1 km based county observations was defined as: $\text{Percent}_{\text{diff}} = \text{F}_{\text{cover\%\_km}} - \text{F}_{\text{cover\%\_30 m}}$. The same calculations were conducted between 30-m and 10-km resolutions. Again, our goal was focused on answering the question: if we used coarse resolution land-cover maps (e.g. 1 km or 10 km) for large-scale applications, what would be the likely percentage of forest cover at 30-m resolution for the same landscape using forest percentages from coarse-resolution maps as the predictor? Although spectral, temporal, and radiometric characteristics of sensors could also affect prediction accuracy (Strahler et al. 1986; Woodcock and Strahler 1987).

Before the above models (predicting the difference in % obtained between the 2 spatial resolutions) were developed we examined the intrinsic relationship between forest percentages observed from 30-m and 1-km land-cover maps and tested whether the relationship was spatially and temporally variant in the region. First, we divided the 2001 observations for all counties into two groups systematically (i.e. odd ID numbers vs. even ID numbers). One group was used for establishing the relationship between 30 m- and 1 km-based forest percentages (not the difference) and the data in the other group was reserved for a spatial test of the relationship. Second, we used all counties' observations in 1992 for a temporal test of the relationship. Furthermore, we evaluated whether scaling effects (the difference in obtained forest percentages between 30 m- and 1 km-based cover maps) observed from different coordinate systems differed significantly. We examined the scaling effects at the county level between original NLCD observations in the Albers Equal Area projection and the observations after being reprojected to a geographic coordinate system. An intrinsic relationship and the three tests (spatial, temporal, and projection) would (1) provide a solid foundation for generating useful scaling-effect models and (2) increase the generalization of model applications because land-cover maps for large scale applications are usually given in the geographic coordinate system. Whenever there was a need to convert relative scaling effects (in %) to absolute forest areas under the geographic coordinate system, the same and "true" total areas for each counties as obtained under the Albers Equal Area projection were used because surface area for each grain cell varies with latitude due to convergence of the meridians of longitude towards the poles.

In all cases, standard errors ($\text{S}_\text{E}$) of model estimates were calculated as: $\text{S}_\text{E} = [(\sum(\text{Y}_{\text{iobs}} - \text{Y}_{\text{ipre}}))/(\text{n}-2)]^{0.5}$, where $\text{Y}_{\text{iobs}}$ and $\text{Y}_{\text{ipre}}$ were the observed and predicted differences in forest percentages between the two spatial resolutions for county i, respectively, and n was the total number of counties used in the analysis (Clark and Hosking 1986). We provided statistical summaries at different administrative levels to illustrate whether consistent patterns or trends existed as grain sizes increased from 30 m to 1 km and 10 km using 2001 observations.

## Results

### Intrinsic relationship between forest percentages observed for NLCD-based 30-m and 1-km resolutions and the related tests

The 2001 data indicated that strong relationships existed between county-level forest percentages observed at 30-m and 1-km resolutions (Fig. 2). The cubic model explained 98.1% of variance (defined as $r^2$ from regression analysis), suggesting that if forest percentage of the coarse resolution map is known, then the forest percentage at a finer resolution is predictable when other conditions are kept constant. For example, when observed forest percentage was zero on a 1-km resolution map, the corresponding forest percentages at 30-m resolution map could range from zero to 12% (Fig. 2).

The spatial test using 2001 data in the reserved group showed that there was a strong relationship (almost following the 1:1 lines at 1-km resolution) between observed and predicted forest percentages at 30-m resolution (Fig. 3a) with $R^2 = 0.979$, suggesting the relationship of scaling effect was reasonably invariant although the model tended to slightly overestimate forest areas at the low end (towards to 0%) and underestimate forest areas at the high end (toward 100%) at 30-m resolution. The mean difference between model predicted and observed 30-m forest percentages for all counties in the reserved

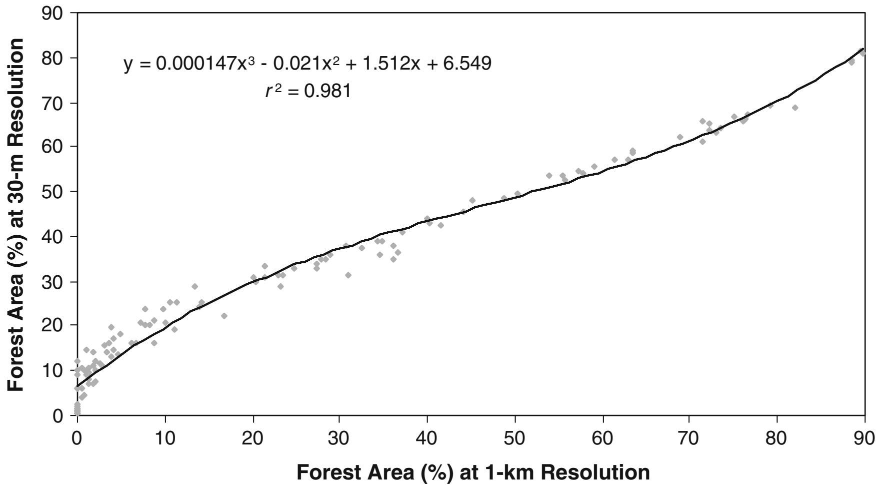


**Fig. 2** Observed relationship between forest percentages at 30-m and 1-km resolutions using 2001 county data in group one ($P < 0.001$). Each dot represents a county in the 3 Lake States region

group across the region was 2.5% (in absolute value) with standard deviation (Std.) of 1.8% and $S_E$ of 3.1% (Table 1). The temporal test of the relationship also showed a strong correlation between observed and predicted forest area percentages at 30-m resolution ($R^2 = 0.975$, Fig. 3b) in 1992, suggesting the relationship of scaling effect was temporally invariant as well. The temporal validation indicated that the mean difference between predicted and observed 30-m forest percentages across the region was 3.0% (in absolute value) with Std. of 2.2% and $S_E$ of 3.8% (Table 1). Our results suggested that different mapping projections had little impact on estimating scale effects on changes in forest area from 30-m to 1-km resolutions over large areas as expected with a slope close to 1 (Fig. 4). The mean difference of scaling effects for all counties detected between two coordinate systems was 0.6% (in absolute value) with Std. of 0.8% and $S_E$ of 0.6% (Table 1).

## Quantifying scaling effects on forest area estimates based on forest percentages from coarse resolutions

The highly correlated intrinsic relationship between forest percentages observed at coarse and fine resolutions provided the essential prerequisite for quantifying scaling effects (difference in forest %), thus, improving forest area estimates across the entire percentage profile (expressed as fractions from 0 to 1) using forest percentages obtained from coarse resolution maps (1 km and 10 km) as predictor (Fig. 5). Forest percentages from coarse resolutions alone could explain 78% of variance in predicting scaling effects on area estimation. The $S_E$ values of model estimates were 3.1 and 7.1% for 1-km and 10-km resolutions, respectively.

Our scaling-effect models indicated that the maximum underestimation of forest percentages, comparing to the 30-m based estimation, were 10.1% for 1-km and 15.7% for 10-km when forest area percentages obtained from the coarse resolutions were around 15% while the maximum overestimation of forest percentages were 9.9 and 27.1% respectively when forest area percentages obtained from the coarse resolutions were around 80 and 98% at 1-km and 10-km resolutions (Fig. 5).

Mean observed differences (in absolute value) in forest percentages between 30-m and 1-km resolutions were 6.5 and 2.4% at the county- and regional-level respectively (Table 2). For the calibrated forest percentages estimated using our model, the mean differences reduced to 2.4% (63% more accurate than without calibration) and 0.3% (87% more accurate) for the corresponding county- and regional-level estimates. Similar improvements were also achieved between 30-m and 10-km based estimates with the mean differences of 13.1 and 2.9% at the county- and regional-levels respectively (Table 2). After the calibration, mean forest percentages were 5.6% (i.e. improvement of 57% closer to the 30-m based observation) and 0.5% (84% closer) at the corresponding levels. Overall, 77% of counties improved their forest cover estimates using scaling-effect models at both 1-km (Fig. 6) and 10-km resolutions (data not shown).

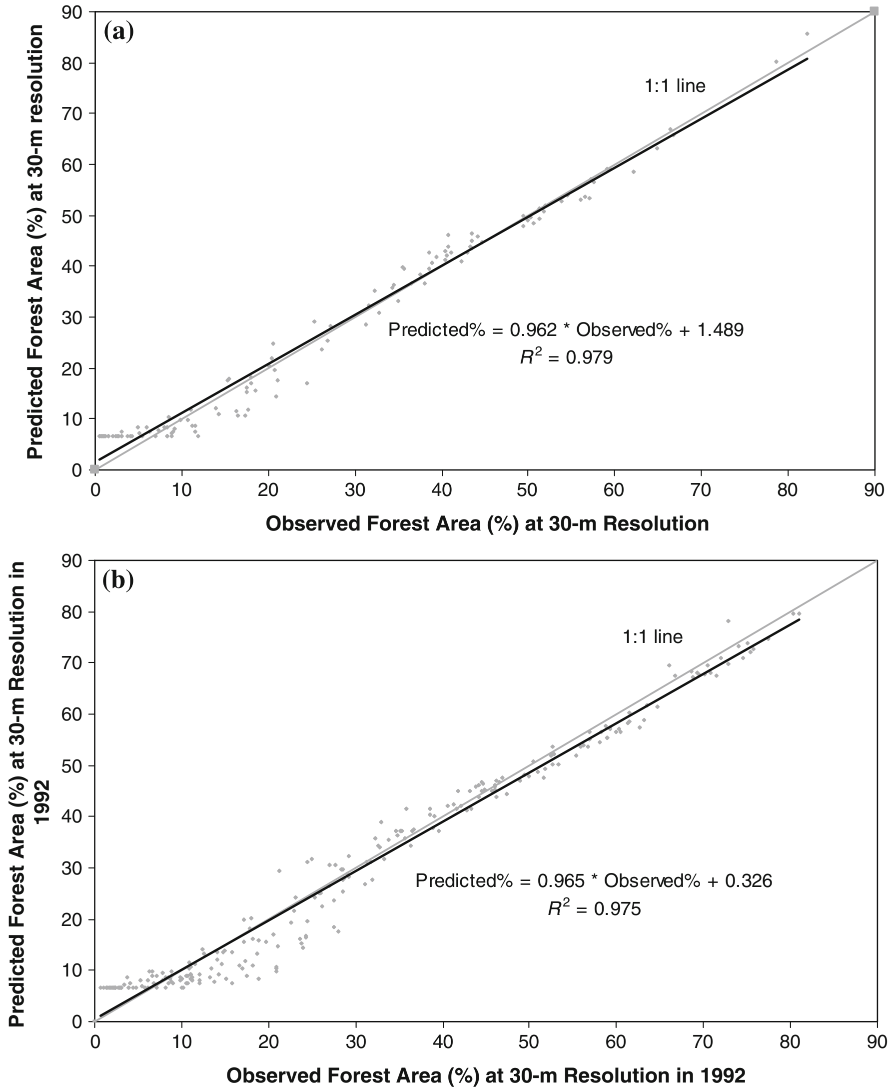


**Fig. 3** (**a**) A spatial validation of empirical model by comparing predicted and observed forest percentages at 30-km resolution using independent 2001 county data in the reserved group; and (**b**) a temporal validation of empirical model by comparing predicted and observed forest percentages at 30-km resolution using all county data in 1992. Each dot represents a county in the 3 Lake States region

Our study suggested that the errors and variations in forest cover estimates tended to increase as grain sizes increase (from 1 km to 10 km) when study extent is kept constant. If the grain size was held constant, mean differences in forest percentages caused by scaling effects tended to decrease with less variation as the study extent (at which the scaling effects were assembled) increased from county to region (Table 2).

In terms of total regional forest area, our 1-km scaling effect model improved 2001 estimation by 7,412 km$^2$ (or 60%), compared to the difference (in absolute value) between the 30-m and 1-km based estimates before calibration whereas the net improvement for 1992 was 15,141 km$^2$ (Table 3).

## Discussion

The above results suggest that strong correlations exist between forest-area percentages obtained from different spatial resolutions. The relationship between different resolutions appears to be spatially and temporally invariant, at least within our study area. Variation in coordinate systems seems to have little impact on identifying grain-size dependent errors in area estimates.

Our grain-size-effect models provide a simple and quick tool to improve forest-area estimates from coarse resolutions with reasonable reliability and accuracy. Although the best fits of models may vary

**Table 1** Statistics of observed and predicted county forest percentages (%) at 30-m resolution using forest percentages observed from the NLCD 1-km map as the driving variable for various tests

| Description | Mean (%) difference | $r^2$ | Standard deviation (%) | Standard error (%) | $P$ value |
|---|---|---|---|---|---|
| Empirical model[a] | 2.6 | 0.981 | 1.9 | 3.2 | <0.001 |
| Spatial test[b] | 2.5 | 0.979 | 1.8 | 3.1 | <0.001 |
| Temporal test[c] | 3.0 | 0.975 | 2.2 | 3.8 | <0.001 |
| Projection test[d] | 0.6 | 0.985 | 0.8 | 0.6 | <0.001 |

[a] The model was developed using half each county's data in 2001

[b] The model was tested spatially using a different half of the county's data of 2001 in the reserved group

[c] The model was tested temporally using all data for counties in 1992

[d] We calculated the differences in county forest percentages observed between 30-m and 1-km land-cover maps registered to the geographic coordinate system and Albers projection, respectively, and then examined the relationship of differences detected from the two coordinate systems

*Note*: The models presented in this table are not the same as the grain-size-effect models presented in Fig. 5. However, the high correlations illustrated between 30 m- and 1 km-based forest percentage observations provide a solid foundation to ensure significant relationships between grain-size effect and forest percentages observed from coarse resolution maps in Fig. 5

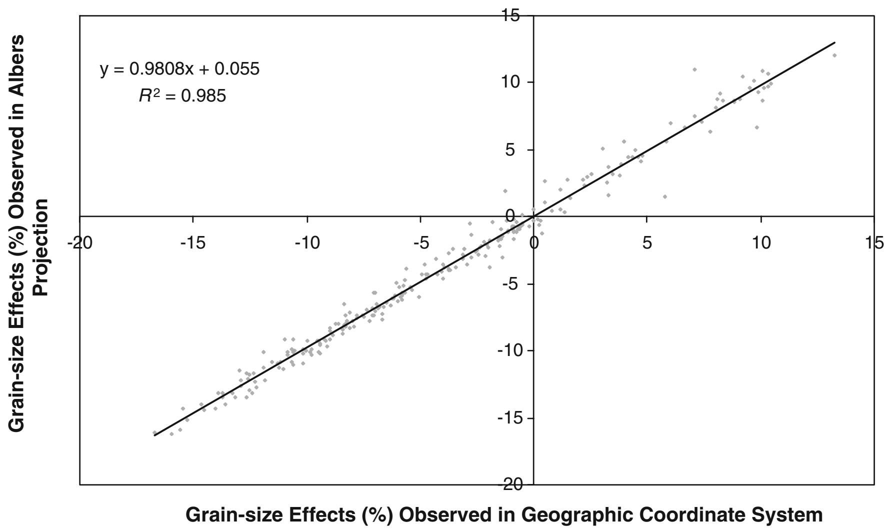


**Fig. 4** Comparison of scaling effects (difference in %) calculated as $F_{cover\%\_km} - F_{cover\%\_30\ m}$ between two different coordinate systems in the three Lake States. Each dot represents a county

if the data used for model development are observed at different scales (e.g. county vs. state), a theoretic model of scaling effect from a large sample size that includes 'all' possible variations in patch size distributions and spatial arrangements across the entire cover-percentage (0–100%) profile should show the smallest effect on forest area estimates at the 50% cover point. The scaling effect on area estimates (given 2 types) should increase as the area percentages at coarse resolutions diverged from 50% in either direction until reaching peak values (negative or positive) before declining in absolute value (Fig. 5). The theoretic curve is also expected to be symmetric because area gain in one type is equal to the loss in the other, which should be more suitable for general application. Our results suggested we could fairly quantify the grain-size dependent errors in area estimates using forest-cover percentages observed from coarse-resolution data alone. However, other landscape pattern characteristics (e.g. patch size distributions and spatial arrangements) and spectral and radiometric characteristics of various sensors could also function as secondary controlling factors.

The departure of our empirical curves from this conceptual ideal might be caused by (1) sample size or study region inadequate to include 'all' possible or reasonable combinations of landscape patch size distributions and spatial arrangements; and (2) biased

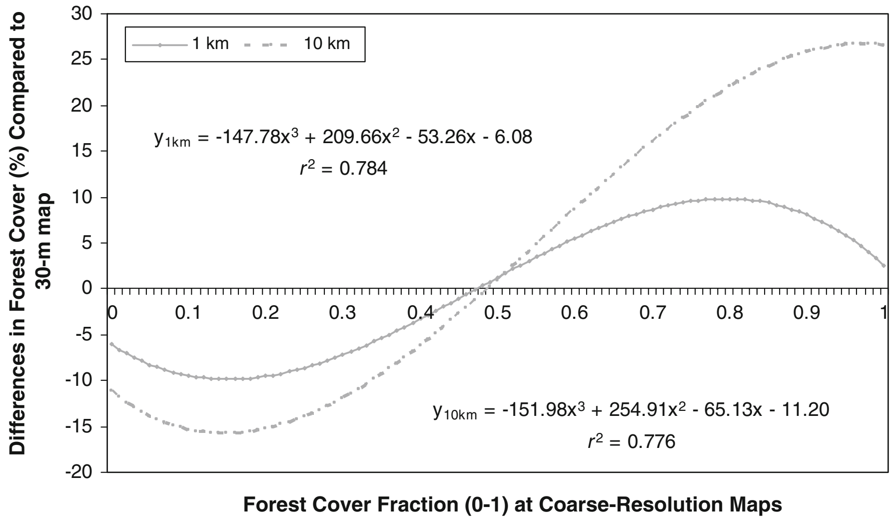


**Fig. 5** Comparison of regional empirical models ($P < 0.001$) using forest percentages observed from coarse resolutions (1 km and 10 km) as driving variable to predict scaling effects in terms of percentage differences comparing to the percentages observed from the 30-m map based on all counties' data in 2001

**Table 2** Comparisons of observed grain size effects on forest area estimates (percentage of total land) expressed as differences (%) between 30-m and 1-km resolutions (= % in 1-km map − % in 30-m map) and between 30-m and 10-km (=% in 10-km map − % in 30-m map, values in the parentheses) at various administrative levels at which the scaling effects were evaluated using the 2001 NLCD map

| Scale | Changes in grain size | Observed difference (%) | | | (%) |
|---|---|---|---|---|---|
| | | Min | Mean[a] | Max | Std.[a] |
| County | | | | | |
| | 30 m–1 km | −16.7 | 6.5 | 13.2 | 4.2 |
| | 30 m–10 km | −34.3 | 13.1 | 42.9 | 14.9 |
| State | | | | | |
| | 30 m–1 km | −1.2 | 2.6 | −4.2 | 1.5 |
| | 30 m–10 km | −1.7 | 3.1 | −4.4 | 1.4 |
| Region | | | | | |
| | 30 m–1 km | N/A | 2.4 | N/A | N/A |
| | 30 m–10 km | N/A | 2.9 | N/A | N/A |

[a] In absolute value

county-level forest cover composition across the percentage profile (i.e. more than half of counties across the region had forest percentages <50%). The increased asymmetry of the 10-km based curve relative to that of the 1-km based curve suggests that a larger bias be likely introduced as grain size increases.

One potential problem with our calibration models was that a county with forest cover of 0% at coarse resolution would result in some positive forest percentage after model calibration. Taking the 1-km model as an example, when forest percentage for a county was zero from the 1-km map and the actual forest percentage from the 30-m map was 2.0% (<half of the model intercept 3.04%, Fig. 5), then the model could enhance ($|6.08 - 2.0| = 4.08\%$) rather than reduce the original difference in absolute % ($|0 - 2| = 2\%$). In general, as spatial resolution of land-cover map increases it is rare for a county as a whole to have no forest cover at all except in places like deserts and bare ground. In our study area, about 18% of counties were observed with 0% forest cover at 1-km resolution in our study area, but none of them was 0% at 30-m resolution (minimum of 0.5% in both years). While the calibrated mean forest percentage for those zero-percent counties was 6.1% based on our 1-km model (Fig. 5), the observed mean forest percentage for the same counties was 3.2%. The difference of 2.9% was smaller than the $S_E$ of model estimates (3.1%). Furthermore, it would not be reasonable to use our models in regions where there is no forest cover or with a very small amount of forest for the entire region. When the model is applied to the sublevel of a given study where amount of forest cover is thought to be significant (e.g. the Great Lake Region contains about 30% forest cover), scaling effects estimated at the low end of forest cover profile could be offset by those at the high end of the profile at some degree because a symmetric curve is expected if the sample size is large enough, at least theoretically, due to the fact that for 2 cover types, a loss in one type indicates a gain in the other.

Our models in Fig. 5 reflect solely how changes in grain size affect forest percentage estimate across

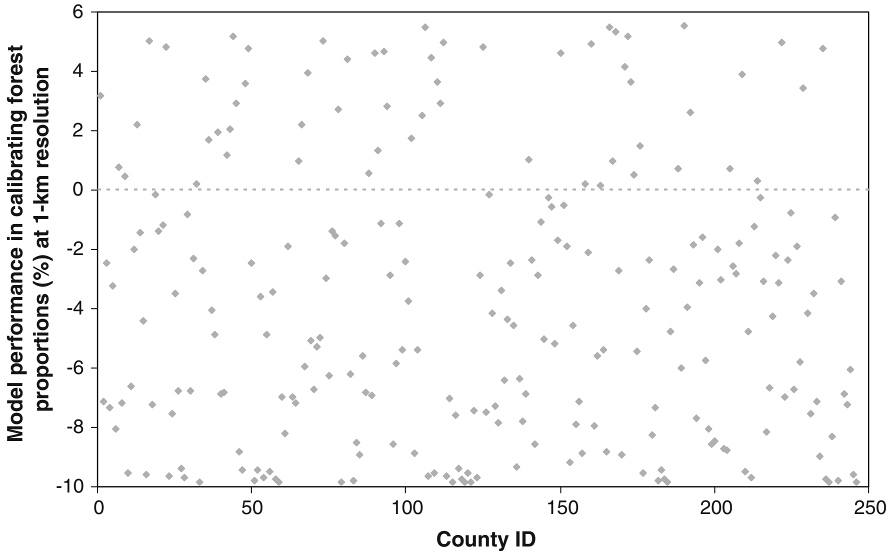


**Fig. 6** The percentages were calculated as $|CF_{\%\_km} - F_{\%\_30\ m}| - |OF_{\%\_km} - F_{\%\_30\ m}|$, where $CF_{\%\_km}$ was the calibrated forest percentage from 1-km map for a county, $OF_{\%\_km}$ was the original forest percentage observed from 1-km map, and $F_{\%\_30\ m}$ was the original forest percentage observed from 30-m map for the county. As a result, counties with negative % indicate improvements in estimating forest percentages while those counties with positive % suggest errors are being introduced. Each dot represents a county data in 2001

**Table 3** Regional forest areas ($km^2$) obtained before and after model calibration based on the 1992 and 2001 NLCD 1-km land-cover maps, compared to those obtained from the corresponding 30-m land-cover maps (as reference)

| Year | Reference area | 1-km before calibration | 1-km after calibration | Improvement (absolute value) |
|---|---|---|---|---|
| 2001 | 167,983 | 155,556 | 172,998 | 7,412 |
| 1992 | 166,650 | 149,973 | 165,114 | 15,141 |

The same scaling-effect model in Fig. 5 was applied to both years

landscapes because it was the only factor manipulated. Such an effect proves to be projection independent (Fig. 4), which is desired and useful information for future studies because land-cover and other necessary maps (or data) for ecological studies often come from various sources using different coordinate systems. For example, boundary maps at various levels from ESRI and many satellite derived land-cover products for larger areas are in geographic coordinate system, NLCD maps are in Albers Equal Area projection, and the MODIS land-cover maps are in Sinusoidal projection. The practical significance of this result is that such models can be used more generally regardless of coordinate systems and the results obtained from various projections are comparable.

Our results suggest when scaling difference (from 30 m to 1 km, or from 30 m to 10 km) is fixed, the effects (mean difference) and variations (Std.) tend to decrease at the level the scaling effects were evaluated (Table 1) as study extent increase. In general, scaling effects tended to be more predictable with changes in grain size than with changes in extent (Wu 2004). The overall effect of changes in grain size on forest estimation could vary from region to region because of variations in 1) composition of sub-level forest percentages, and 2) patch size distributions and spatial arrangements (Moody and Woodcock 1995), not because of changes in the relationship of scaling effects. In the other words, effect of changing grain sizes on area estimation is a universal phenomenon.

Previous studies have demonstrated that unmixing methods allow a user to estimate the subpixel coverage within each pixel category at coarse resolution using linear mixture models (Adams et al. 1986; Settle and Drake 1993; Huguenin et al. 1997). Compared to the unmixing methods, our approach is more practical and efficient because it is impossible to decompose the linear mixture models to calculate the category ratio within a mixed pixel unless the spectral radiance of a particular category is known, which is difficult to determine (Oki et al. 2004). Our models can improve our understanding and accuracy in ecological applications related to forest area estimates over large areas where coarse resolution data, such as 1-km MODIS and AVHRR derived land-cover products, are usually more appropriate for meaningful analyses and efficient processing. For example, it took more than 55 h (our computer is equipped with 4 GB RAM and a 200 GB hard drive) for processing data for the state of MN using ArcGis at 30-m resolution, but the same operation was completed in 5 s at 1-km resolution. If scaling effects can be incorporated quickly and reliably, there are considerable advantages for using coarse resolution data in large-scale ecological investigations.

The same concept and methodology from this study may also be applied to estimate other ecological attributes in a similar fashion. For example, changes in deciduous and coniferous forest composition caused by changes in grain size could also affect the outcome and conclusion for a given study if different models are necessary to distinguish ecological properties (e.g. leaf area index and forest biomass) between these 2 forest types (Fassnacht et al. 1997; Zheng et al. 2004b). We found that general forest species compositions (coniferous vs. deciduous) in 63% of the counties with forest cover at 1-km resolution could be improved using our empirical model established based on cover type observations. We expected further improvement if the samples used for model development are collected based on species composition.

Changes in spatial resolution of satellite sensors can affect estimation of landscape attributes or properties for both discrete (e.g. land-cover type) and continuous variables (e.g. percent tree cover, NPP, and forest biomass) (Hansen et al. 2003; Ahl et al. 2005; Zheng et al. 2007). Although the majority rule is commonly used for aggregating discrete variables, different aggregation methods may be applied for continuous variables. Furthermore, the continuous attributes may be rescaled with no effect on statistical means across geographic extents, although variance of these estimates does change (Alexandridis and Chemin 2002; Fang et al. 2004).

## Conclusions

Results from this study may have universal impact on quantifying scaling effects on forest area estimates at coarse resolutions because such relationships of scaling effects are likely temporally and spatially invariant and projection independent, although more studies on the subject are needed to see if the patterns would hold in other regions and/or data sets due to possible differences in composition of forest-percentage profile, definition of forest land, and configuration of forest non-forest patch distributions. The degree of effect increases as grain sizes increase as long as the study extent is fixed. The scaling effects at 10-km resolution even after adjustment (average 5.6% with $S_E$ of 7.1% at the county level) are much higher than an average 2.4% with $S_E$ of 6.0% at 1-km resolution. Incorporating scaling effects on forest area estimates can reduce uncertainties of any ecological analyses and studies requesting accurate forest-area estimation over large areas. Furthermore, efficiency of spatial computations is often polynomially, rather than linearly, related to the number of pixels over the study areas. For example, each individual file of a 1-km data set is approximately 0.09% the size of 30-m data but the computing time needed for data processing and analysis may be reduced at a disproportionally faster rate than that of reduction in data size.

Changes in grain size almost inevitably affect forest area estimation because land cover is a discrete variable. The issue deserves more attention as the study extent of applied ecology increases from local to globe. The change in forest area for a given entity (e.g. county, state, and region) at coarse resolution primarily depends on whether forest cover at the corresponding fine resolution (30 m) observations is larger or smaller than 50%. This study provides a simple and practical method to quantify grain-size effects on forest area estimates with reasonable accuracy when coarse-resolution land-cover data are used over large areas.

**Acknowledgements** This study was in part funded by the USDA Forest Service through grant 05-DG-11242343-074.

## References

Adams JB, Smith MO, Johnston PE (1986) Spectral mixture modeling: a new analysis of rock and soil types at the viking lander 1 site. J Geophys Res 91:8098–8112. doi:10.1029/JB091iB08p08098

Ahl DE, Gower ST, Mackay DS et al (2005) The effects of aggregated land cover data on estimating NPP in northern Wisconsin. Remote Sens Environ 97:1–14. doi:10.1016/j.rse.2005.02.016

Ajtay GL, Ketner P, Duvigneaud P (1979) Terrestrial primary production and phytomass. In: Bolin EDB, Kempe S, Ketner P (eds) The global carbon cycle. Wiley, New York, pp 129–182

Alexandridis T, Chemin Y (2002) Landsat ETM+, Terra MODIS and NOAA AVHRR: issues of scale and interdependency regarding land parameters. In: Proceedings of Asian Conference on Remote Sensing, 25–29 November, Kathmandu, Nepal

Bierkens MFP, Finke PA, Willigen PD (2000) Upscaling and downscaling methods for environmental research. Kluwer Academic Publisher, Dordrecht

Bloschl G, Sivapalan M (1995) Scale issues in hydrological modeling: a review. Hydrol Process 9:251–290. doi:10.1002/hyp.3360090305

Bresee MK, LeMoine JM, Mather S et al (2004) Disturbance and landscape dynamics in the Chequamegon National Forest, Wisconsin, USA, from 1972 to 2001. Landsc Ecol 19:291–309. doi:10.1023/B:LAND.0000030419.27883.40

Brown PJ (1982) Multivariate calibration. J R Stat Soc [Ser A] B44:287–321

Buyantuyev A, Wu J (2007) Effects of thematic resolution on landscape pattern analysis. Landsc Ecol 22:7–13. doi:10.1007/s10980-006-9010-5

Carleton TJ (2003) Old growth in the Great Lakes forest. Environ Rev 11:S115–S134. doi:10.1139/a03-009

Clark WAV, Hosking PL (1986) Statistical methods for geographers. John Wiley & Sons, New York, p 518

Cohen WB, Justice CO (1999) Validating MODIS terrestrial ecology products: linking in situ and satellite measurements. Remote Sens Environ 70:1–3. doi:10.1016/S0034-4257(99)00053-X

Cohen WB, Maiersperger TK, Spies TA et al (2001) Modelling forest cover attributes as continuous variables in a regional context with Thematic Mapper data. Int J Remote Sens 2:2279–2310. doi:10.1080/014311601300229827

Czaplewski RL, Catts GP (1992) Calibration of remotely sensed proportion or area estimates for misclassification error. Remote Sens Environ 39:29–43. doi:10.1016/0034-4257(92)90138-A

Dungan JL, Perry JN, Dale MRT et al (2002) A balanced view of scale in spatial statistical analysis. Ecography 25:626–640. doi:10.1034/j.1600-0587.2002.250510.x

ESRI (nd) (2006) Retrieved December 19, from http://webhelp esricom/arcgisdesktop/92/indexcfm?TopicName=Block Majority

Emanuel WR, Shugart HH, Stevenson MP (1985) Climatic change and the broad-scale distribution of terrestrial ecosystem complexes. Clim Change 7:29–43. doi:10.1007/BF00139439

Fang H, Liang S, Chen M et al (2004) Statistical comparison of MISR, ETM+ and MODIS land surface reflectance and albedo products of the BARC land validation core site, USA. Int J Remote Sens 25:409–422. doi:10.1080/01431 16031000101666

Fassnacht KS, Gower ST, MacKenzie MD et al (1997) Estimating the leaf area index of North Central Wisconsin forests using the Landsat Thematic Mapper. Remote Sens Environ 61:229–245. doi:10.1016/S0034-4257(97)00005-9

Friedl MA, McIver DK, Hodges JCF et al (2002) Global land cover from MODIS: algorithms and early results. Remote Sens Environ 83:135–148. doi:10.1016/S0034-4257(02)00078-0

Gardner RH, Lookingbill TR, Townsend PA, Ferrari J (2008) A new approach for rescaling land cover data. Landsc Ecol 23:513–526. doi:10.1007/s10980-008-9213-z

Goetz SJ, Prince SD, Small J et al (2000) Interannual variability of global terrestrial primary production: results of a model driven with satellite observations. J Geog Res 105:20077–20091. doi:10.1029/2000JD900274

Goodchild MF, Quattrochi DA (1997) Scale, multiscaling, remote sensing, and GIS. In: Quattrochi DA, Goodchild MF (eds) Scale in remote sensing and GIS. Lewis Publisher, Boca Raton, pp 1–11

Gower ST, Krankina ON, Olson RJ et al (2001) Net primary production and carbon allocation patterns of boreal forest ecosystems. Ecol Appl 11:1395–1411. doi:10.1890/1051-0761(2001)011[1395:NPPACA]2.0.CO;2

Hall O, Hay G, Bouchard A, Marceau D (2004) Detecting dominant landscape objects through multiple scales: an integration of object-specific methods and watershed segmentation. Landsc Ecol 19:59–76. doi:10.1023/B:LAND.0000018371.43447.1f

Hansen MC, DeFries RS, Townshend JR et al (2000) Global land cover classification at 1 km spatial resolution using a classification tree approach. Int J Remote Sens 21:1331–1364. doi:10.1080/014311600210209

Hansen MC, DeFries RS, Townshend JR et al (2003) Global percent tree cover at a spatial resolution of 500 meters: First results of the MODIS Vegetation Continuous Fields algorithm. Earth Interact 7:1–15. doi:10.1175/1087-3562(2003)007<0001:GPTCAA>2.0.CO;2

Heath LS, Birdsey RA, Row C (1996) Carbon pools and fluxes in US forest products. In: Apps MJ, Price DT, Price DT (eds) Forest ecosystems, forest management, and the global carbon cycle NATO ASI Series I: global environmental changes. Springer Verlag, NY, USA, pp 271–278

Homer C, Huang C, Yang L et al (2004) Development of a 2001 national land-cover database for the United States. Photogramm Eng Remote Sens 70:829–840

Huguenin RL, Karaska MA, Bralicom DV et al (1997) Subpixel classification of bald cypress and tupelo gum trees in thematic mapper imagery. Photogramm Eng Remote Sens 63:717–725

Jelinski D, Wu J (1996) The modifiable areal unit problem and implications for landscape ecology. Landsc Ecol 11:129–140. doi:10.1007/BF02447512

Ju J, Gopal S, Kolaczyk ED (2005) On the choice of spatial and categorical scale in remote sensing land cover classification. Remote Sens Environ 96:62–77. doi:10.1016/j.rse.2005.01.016

Katz RW (2002) Techniques for estimating uncertainty in climate change scenarios and impact studies. Clim Res 20:167–185. doi:10.3354/cr020167

Levin SA (1992) The problem of pattern and scale in ecology. Ecology 73:1943–1983. doi:10.2307/1941447

Li H, Reynolds F (1993) A new contagion index to quantify spatial patterns of landscapes. Landsc Ecol 8:155–162. doi:10.1007/BF00125347

Li H, Wu J (2006) Uncertainty analysis in ecological studies: an overview. In: Wu J, Jones KB, Li H, Loucks O (eds) Scaling and uncertainty analysis in ecology: methods and applications. Springer, Dordrect, Netherlands, pp 43–64

Lieth H (1975) Modelling the primary productivity of the world. In: Lieth H, Whittaker RH (eds) Primary productivity of the biosphere. Springer-Verlag, New York, pp 237–263

Mayaux P, Lambin EF (1997) Tropical forest area measured from global land-cover classifications: inverse calibration models based on spatial textures. Remote Sens Environ 59:29–43. doi:10.1016/S0034-4257(96)00077-6

McWilliams WH, Heath LS, Reese GC et al (2000) Forest resources and conditions. In: Mickler RA, Birdsey RA, Hom J (eds) Responses of northern US forests to environmental change. Springer-Verlag, New York, pp 3–26

Moody A, Woodcock CE (1994) Scale-dependent errors in the estimation of land-cover proportions: implications for global land-cover datasets. Photogramm Eng Remote Sens 60:585–596

Moody A, Woodcock CE (1995) The influence of scale and the spatial characteristics of landscapes on land-cover mapping using remote sensing. Landsc Ecol 10:363–379. doi:10.1007/BF00130213

Moody A, Woodcock CE (1996) Calibration-based methods for correction of area estimates derived from coarse resolution land-cover data. Remote Sens Environ 58:225–241. doi:10.1016/S0034-4257(96)00036-3

MRLC (nd) (2007) Retrieved May 14, from http://wwwmrlcgov/

Oki K, Uenishi TM, Omasa K (2004) Accuracy of land cover area estimated from coarse spatial resolution images using unmixing method. Int J Remote Sens 25:1673–1683. doi:10.1080/0143116031000139854

O'Neill RV (1988) Hierarchy theory and global change. In: Rosswall T, Woodmansee RG, Risser PG (eds) Scales and global change. Wiley, Melbourne, Australia, pp 29–46

Running SW, Baldocchi DD, Turner DP et al (1999) A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling and EOS satellite data. Remote Sens Environ 70:108–127. doi:10.1016/S0034-4257(99)00061-9

Running SW, Thornton PE, Nemani R et al (2000) Global terrestrial gross and net primary productivity from the earth observing system. In: Sala OE, Jackson R, Mooney HA, Hwarth R (eds) Methods in ecosystem science. Springer-Verlag, New York, pp 44–57

Saura S (2004) Effects of remote sensor spatial resolution and data aggregation on selected fragmentation indices. Landsc Ecol 19:197–209. doi:10.1023/B:LAND.0000021724.60785.65

Settle JJ, Drake NA (1993) Linear mixing and the estimation of ground cover proportions. Int J Remote Sens 14:1159–1177. doi:10.1080/01431169308904402

Smith JE, Heath LS (2007) US agriculture and forestry greenhouse gas inventory: 1990–2005. Tech Bull Wash DC (in press)

Smith JE, Heath LS, Skog KE (2006) Methods for calculating forest ecosystem and harvested carbon with standard estimates for forest types of the United States. Gen Tech Rep NE-343. USDA Forest Service, Northeastern Research Station, Newtown Square, PA, p 216

Strahler AH, Woodcock CE, Smith JA (1986) On the nature of models in remote sensing. Remote Sens Environ 20:121–139. doi:10.1016/0034-4257(86)90018-0

Stuckens J, Coppin PR, Bauer ME (2000) Integrating contextual information with per-pixel classification for improved land cover classification. Remote Sens Environ 71:282–296. doi:10.1016/S0034-4257(99)00083-8

Townshend J, Justice CO, Li W et al (1991) Global landcover classification by remote sensing: present capabilities and future possibilities. Remote Sens Environ 35:243–255. doi:10.1016/0034-4257(91)90016-Y

Tucker CJ, Townshend JRG, Goff TE (1985) African landcover classification using satellite data. Sci 227:369–375. doi:10.1126/science.227.4685.369

Turner MG (1989) Landscape Ecol: the effect of pattern on process. Annu Rev Ecol Syst 20:171–197. doi:10.1146/annurev.es.20.110189.001131

Turner MG, Dale VH, Gardner RH (1989) Predicting across scales: theory development and testing. Landscape Ecol 3:245–252. doi:10.1007/BF00131542

Turner DP, Cohen WB, Kennedy RE (2000) Alternative spatial resolutions and estimates of carbon flux over a managed forest landscape in Western Oregon. Landsc Ecol 15:441–452. doi:10.1023/A:1008116300063

USDA (2007) Natural Resources Conservation Service. http://wwwnrcsusdagov/TECHNICAL/land/nri03/statereports/2003summaryreportpdf

Vogelmann JE, Howard SM, Yang L et al (2001) Completion of the 1990s National Land Cover Dataset for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources. Photogramm Eng Remote Sens 67:650–652

Walsh TA, Burk TE (1993) Calibration of satellite classification of land area. Remote Sens Environ 46:281–290. doi:10.1016/0034-4257(93)90048-3

Woodcock CE, Strahler AH (1987) The factor of scale in remote sensing. Remote Sens Environ 21:311–332. doi:10.1016/0034-4257(87)90015-0

Wu J (1999) Hierarchy and scaling: extrapolating information along a scaling ladder. Can J Rem Sens 25:367–380

Wu J (2004) Effects of changing scale on landscape pattern analysis: scaling relations. Landscape Ecol 19:125–138. doi:10.1023/B:LAND.0000021711.40074.ae

Wu J, David JL (2002) Spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. Ecol Modell 153:7–26. doi:10.1016/S0304-3800(01)00499-9

Wu J, Hobbs R (2002) Key issues and research priorities in landscape ecology: an idiosyncratic synthesis. Landscape Ecol 17:355–365. doi:10.1023/A:1020561630963

Wu J, Li H (2006) Concepts of scale and scaling. In: Wu J, Jones B, Li H, Loucks OL (eds) Scaling and uncertainty analysis in ecology: methods and applications. Springer, Dordrecht, The Netherlands, pp 3–15

Wu J, Marceau DJ (2002) Modeling complex ecological systems: an introduction. Ecol Modell 153:1–6. doi:10.1016/S0304-3800(01)00498-7

Zheng D, Prince SD, Wright R (2003) Terrestrial net primary production estimates for $05^0$ grid cells from field observations—a contribution to global biogeochemical modeling. Glob Change Biol 9:46–64. doi:10.1046/j.1365-2486.2003.00534.x

Zheng D, Prince SD, Hame T (2004a) Estimating net primary production of boreal forests in Finland and Sweden from field data and remote sensing. J Veg Sci 15:161–170. doi:10.1658/1100-9233(2004)015[0161:ENPPOB]2.0.CO;2

Zheng D, Rademacher J, Chen J et al (2004b) Estimating aboveground biomass using Landsat 7 ETM+ data across a managed landscape in northern Wisconsin, USA. Remote Sens Environ 93:402–411. doi:10.1016/j.rse.2004.08.008

Zheng D, Heath LS, Ducey MJ (2007) Forest biomass estimated from MODIS and FIA data in the Lake States: MN, WI, and MI, USA. Forestry 80:265–278. doi:10.1093/forestry/cpm015