Evaluating Ecoregions for Sampling and Mapping Land-cover Patterns

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Abstract

Ecoregional stratification has been proposed for sampling and mapping land-cover composition and pattern over time. Using a wall-to-wall land-cover map of the United States, we evaluated geographic scales of variance for nine landscape-level and eight forest pattern indices, and compared stratification by ecoregions, administrative units, and watersheds. Ecoregions accounted for 65 percent to 75 percent of the total variance of percent agriculture and percent forest because dominant land-cover is included in ecoregional definitions. In contrast, ecoregions explained only 13 percent to 34 percent of the variance of the other seven landscape-level pattern indices. After accounting for differences in amount of forest, ecoregions explained less than 5 percent of the variance of the eight forest pattern indices. None of the stratifications tested would be effective mapping units for land-cover pattern because within-unit variance of land-cover pattern is typically two to four times larger than between-unit variance.

Introduction

Tradeoffs between wall-to-wall mapping and sampling to estimate tropical deforestation rates have been the topic of recent discussion. Tucker and Townshend (2000) showed that a 10 percent sample of Landsat sensor scenes was inadequate to estimate deforestation rates for individual countries in South America, and recommended wall-to-wall coverage to capture localized land-cover dynamics. In response, Czaplewski (2003) showed that despite localized dynamics, a 10 percent sample was adequate for larger geographic areas (biomes, continents) because the sample size was larger for a fixed sampling intensity. Clearly, a sampling approach can estimate deforestation for a given geographic area, to any specified degree of precision, if the sample size is large enough. A wall-to-wall map is simply a 100 percent sample that provides measurements for all geographic areas.

The discussion of sampling versus wall-to-wall mapping should consider the type of information that is expected to come from remote sensing. Whereas a focus on *estimating* deforestation rates leads naturally to a statistical sampling approach, a focus on *managing* deforestation leads to a geographical mapping approach. It is one thing to know the deforestation rate, and another to know where to act on that information. Places that are not sampled still need to be managed, and an accurate map is required to decide actions for specific places. Sampling is obviated by wall-to-wall mapping. At issue is whether a map prepared from a sample is accurate for a small area, and thus useful for local land management.

There are several ways to produce a wall-to-wall map from a sample of locations. For example, geostatistical methods fit spatial surface models to sample measurements, which then provide interpolated estimates for the non-sampled locations. Local accuracy depends on a low "nugget" variance, which in turn requires a sufficiently dense sample in relation to the spatial correlation of the mapped attribute. A second approach uses geographically defined stratification whereby stratum-level estimates from sampling are mapped. In this case, local accuracy depends on spatial uniformity, that is, low within-stratum variance. Neither of these approaches is likely to solve the problem of mapping spatially concentrated deforestation rates from a small sample.

In the United States, the cost and difficulty of developing wall-to-wall temporal land-cover data have led to a proposal for sampling and mapping based on ecoregional stratification (Loveland *et al.*, 2002). Stehman *et al.* (2003a) demonstrated that the proposed stratified one-stage cluster design is effective for estimating population and ecoregion-level changes in land-cover composition. Stratification is effective when strata are defined with respect to the quantity that is to be estimated (Cochran, 1977), and land-cover composition is one of the components used to distinguish the Omernik (1987) ecoregions employed in the study. At the same time, substantial within-sample and within-ecoregion variance (see Figure 6 in Gallant *et al.*, 2004) led to recommendations to consider larger sample sizes, smaller sample units, post-stratification, and regression estimators to incorporate ancillary information (Stehman *et al.*, 2003a).

In contrast to land-cover composition, ecoregional stratification may be less effective for estimating changes in land-cover spatial pattern. Spatial patterns result from both local (e.g., urban expansion, parcelization) and regional (e.g., fire suppression, abandonment of agriculture) management regimes. Even if the ecoregional environment determines if there can be a farm at all (composition), individual humans decide the size and shape (pattern) of farms. These decisions are made in a local context that also includes the history of a landscape, local traditions, and economic and regulatory criteria (Masek *et al.*, 2000; McDonald and Urban, 2004). Thus, while ecoregional stratification is effective for estimating land-cover composition, more work is needed to prove its utility for sampling and mapping land-cover patterns.

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Hunsaker *et al*. (1994) showed that regional patterns are difficult to characterize by sampling, and Riitters and Coulston (2005) found that forest spatial patterns were only partly associated with Bailey's (1995) ecological regions. Loveland *et al*. (2002) recommended further evaluation of ecoregional stratification for estimating changes in land-cover patterns.

As a part of the evaluations, Loveland *et al*. (2002) suggested that significant differences in rates of composition change among six ecoregions indicated that ecoregions are appropriate strata for capturing unique patterns of land-cover change. Griffith *et al*. (2003a) reported statistically significant trends in six land-cover pattern indices for 11 sample units in one ecoregion over a 20-year period. Later, using an expanded set of five ecoregions in the eastern United States, Griffith *et al*. (2003b) evaluated trends in 10 indices of land-cover composition and pattern. In most cases, the temporal trend for each index was statistically significant within each ecoregion, and for five of the ten indices tested, the linear component of trend was statistically different between ecoregions. Griffith *et al*. (2003b) suggested that these results support the use of ecoregions as a geographically coherent way to regionalize national land-use and land-cover change. In a later summary, Gallant *et al*. (2004) concluded that ecoregion boundaries correspond well with land-cover patterns, and, furthermore, that ecoregion-level information developed from sampling met the needs of land managers.

These conclusions endorse ecoregional stratification for mapping changes in land-cover composition and pattern. However, the demonstrated effectiveness of ecoregional stratification for sampling does not imply that ecoregion-level maps will be accurate for the purpose of managing land-cover changes. Stratification yields gains in sampling precision even if there is only a weak correlation between ecoregion boundaries and the quantity of interest (Cochran, 1977), but the management utility of an ecoregion-level map depends critically on a very high correlation, that is, on very low within-ecoregion variance. If within-ecoregion variance is large, then management actions decided at the ecoregion level will likely be applied at inappropriate places within an ecoregion. Demonstrating that ecoregions are statistically different provides little basis for evaluating ecoregions as a mapping tool for land managers.

In this paper, we present another evaluation of ecoregions as a stratification tool for sampling and mapping land-cover patterns. We use the 1992 National Land Cover Data (NLCD; Vogelmann *et al*., 2001) that has been used in many studies of land-cover patterns. We address several generalized land-cover types (agriculture, urban, and forest) but focus on forest because the NLCD has been used to assess forest patterns at a national scale (e.g., Heilman *et al*., 2002; Riitters *et al*., 2002 and 2004a), and because detecting forest changes was one of the first applications of remote sensing (e.g., Skole and Tucker, 1993) that remains a relevant global question today (e.g., Tucker and Townshend, 2000; Achard *et al*., 2001; Czaplewski, 2003; Foody, 2003; Rogan *et al*., 2003). Although the map is only a snapshot in time, it can be used to estimate various statistical parameters that are useful for evaluating alternate multi-temporal sampling designs, for example within- and between-strata variance of landscape pattern indices.

As noted by Gustafson (1998) among many others, land-cover composition and pattern are conceptually different, referring respectively to the amount and spatial arrangement of land-cover. But composition is a fundamental aspect of pattern, if only because it places physical constraints on the types of patterns that can be realized. For example, forests cannot be fragmented in fully-forested landscapes. Among 50 pattern indices tested by Neel *et al*. (2004), 15 were strongly related to composition, 28 were related to both pattern and composition, and only seven were unrelated to composition. Thus, most pattern indices cannot be interpreted independently of composition. Considering the set of ten indices used by Griffith *et al*. (2003b), three are specifically composition indices, and six of the remaining seven are related to composition (Neel *et al*., 2004). If ecoregions are effective for estimating composition, it follows that they will also be effective for estimating pattern indices that are related to composition. Tests of ecoregion stratification for estimating and mapping land-cover pattern should recognize differences in composition among ecoregions.

Many alternate stratification schemes potentially satisfy the criterion that ecoregions are useful because they work (Griffith *et al*., 2003b). In this paper, we compare stratifications based on Omernik (1987) ecoregions, Bailey (1995) ecological regions (provinces and sections), administrative units (states and counties), and hydrologic units (watersheds). Administrative and hydrologic units are often dismissed because they are based on non-ecological criteria (e.g., Gallant *et al*. 2004). But if land-cover patterns are not controlled by ecological factors, then non-ecological stratifications might be a better choice. County maps of composition and pattern, for example, might be more informative than ecoregion maps because land-use decisions are often made at the county level.

The questions we address pertain to the use of ecoregions for sampling and mapping land-cover patterns: (a) Are ecological stratifications superior to other similarly-scaled stratification schemes such as administrative units or watersheds?; (b) Considering forest pattern indices, are ecoregions effective for stratification after accounting for different amounts of forest?; and (c) Do estimates of between- and within-stratum variance components support the use of ecoregions for mapping land-cover patterns? Answers to these questions lead to insights about the spatial scales at which landscape patterns are created, which in turn can inform the discussion of sampling versus wall-to-wall mapping in remote sensing.

Methods

Land-cover Maps

We measured land-cover composition and pattern on the National Land Cover Data (NLCD) which is a wall-to-wall map of the conterminous 48 states and District of Columbia. The NLCD mapping project used Landsat Thematic Mapper (TM) data (circa 1992) to map 21 classes of land-cover (Table 1) at a spatial resolution of 0.09 ha pixel^{-1} (Vogelmann *et al*.,

TABLE 1. AGGREGATION OF NLCD LAND-COVER TYPES FOR ANALYSIS OF LAND-COVER PATTERNS

NLCD categories	Aggregated category
Open water, perennial ice/snow	Water
Low intensity residential, high intensity residential, commercial/industrial/transportation, urban/recreational grasses	Developed
Bare rock/sand/clay, quarries/mines, transitional	Barren or disturbed
Deciduous forest, evergreen forest, mixed forest, woody wetlands	Forest
Shrubland	Shrubland
Orchards/vineyards, pasture/hay, row crops, small grains, fallow	Agriculture
Grasslands/herbaceous	Grassland
Emergent herbaceous wetlands	Wetland

2001). The TM data were mapped into the land-cover classes using a combination of digital image processing techniques and logical modeling using associated ancillary data (Vogelmann *et al.*, 1998). Accuracy assessments of the NLCD (Stehman *et al.*, 2003b; Wickham *et al.*, 2004) suggested aggregating the 21 NLCD land-cover types into eight generalized categories (Table 1) for measurements of composition and pattern.

Stratification

We tested the "level 3" strata ($n = 84$) from Omernik (1987) and will refer to these strata as "ecoregions." For comparison, we chose Bailey's ecological regions, states and counties, and watersheds as hierarchically nested, geographically defined stratifications. For Bailey's (1995) stratification, we considered ecological "sections" ($n = 164$) within ecological "provinces" ($n = 35$). We used four levels of U.S. Geological Survey (1999) hydrological units (watersheds) defined by "2-digits" ($n = 18$), "4-digits" ($n = 204$), "6-digits" ($n = 332$), and "8-digits" ($n = 2099$). Our administrative units included 49 states (including the District of Columbia) and 3,089 counties (U.S. Geological Survey, 2002).

Composition and Pattern Measurements

For comparison with studies mentioned earlier, measurements were made within a grid of 56.25 km^2 (250 pixels $\times$ 250 pixels) analysis units superimposed on the NLCD map. The units are large enough to measure pattern indices on the NLCD map, and small enough to estimate within-stratum variance for the stratifications tested (O'Neill *et al.*, 1996). Within each analysis unit, we calculated 17 landscape-level and forest indices (Table 2) representing different aspects of land-cover composition and pattern. Some of the indices were also used by Griffith *et al.* (2003b) and others were selected based on statistical criteria (Riitters *et al.*, 1995; Cain *et al.*, 1997). Indices were obtained by tabulating the frequencies of different land-cover types or the frequencies of different types of adjacencies (e.g., a forest pixel adjacent to an agriculture pixel), or by identifying contiguous occurrences of each land-cover type ("patches") to determine patch areas and patch perimeter lengths. Adjacency and patch contiguity were evaluated in the four cardinal directions only, and individual patches were truncated at the boundaries of analysis units.

Nine landscape-level indices (Table 2) included measures of land-cover composition, diversity and aggregation, and descriptors of the number and shape of patches. With a few exceptions the correlations among these indices (Table 3) were small ($r < 0.50$). Eight forest indices (Table 2) included measures of aggregation, edge, and patch size and shape. We purposefully included several popular forest indices that exhibited a high correlation with percent forest (Table 4).

Each analysis unit was associated with an ecoregion, section, county, and 8-digit watershed according to the location of its center point. Analysis units were excluded if their center point was not in those strata, or if they contained missing pixels (e.g., units that crossed international borders), or if they contained only water pixels. Analysis units were also excluded from the forest pattern analysis if they did not contain any forest. A total of 137,345 analysis units met the criteria for the landscape-level analysis, of which 126,662 contained some forest. The sample sizes were reduced for some indices because of computational requirements such as a minimum number of patches (Table 2).

Variance Components Analysis

Variance components analysis (Searle *et al.*, 1992) is a statistical technique to analyze the sources of variation in a set of observations. It has been applied, for example, to study the variance structure of indicators of lake condition (Kincaid *et al.*, 2004) and to test hierarchical designs for analyzing spatial pattern in benthic macrofauna (Cole *et al.*, 2001). We used the technique to estimate the variances associated with different levels of each of the stratifications. Using the Bailey (1995) stratification as an example, the nested linear model for index Y is:

$$Y_{ijk} = \mu + P_i + S_{j(i)} + U_{k(ij)} \quad (1)$$

where Y_{ijk} is the index value for the k^{th} analysis unit in section j within province i, μ is the overall mean, P_i is the effect due to province i, $S_{j(i)}$ is the effect of section j within province i, and $U_{k(ij)}$ is the residual variation for analysis unit k within in section j and province i. The parentheses in the subscripts indicate the hierarchical nesting; the values in parentheses are the higher-level strata.

Assuming a random effects model, let Var $(P_i) = \sigma^2_{\text{province}}$, Var $(S_{j(i)}) = \sigma^2_{\text{section}}$, and Var $(U_{k(ij)}) = \sigma^2_{\text{unit}}$. The total variance ($\sigma^2_{\text{total}}$) is the sum of the three components:

$$\sigma^2_{\text{total}} = \sigma^2_{\text{province}} + \sigma^2_{\text{section}} + \sigma^2_{\text{unit}} \quad (2)$$

The proportions of total variance associated with provinces, sections, and units are respectively ($\sigma^2_{\text{province}}/\sigma^2_{\text{total}}$),

TABLE 2. LAND-COVER COMPOSITION AND PATTERN INDICES CALCULATED WITHIN 56.25 KM^2 ANALYSIS UNITS. EXCEPT AS NOTED, 137,345 ANALYSIS UNITS WERE USED FOR LANDSCAPE-LEVEL INDICES AND 126,662 FOR FOREST INDICES. "ln" INDICATES LOGARITHMIC TRANSFORMATION

	Landscape-level Indices
PctAgr	Percent agriculture land-cover
PctDev	Percent developed land-cover
PctFor	Percent forest land-cover
SiDiv	Simpson (1949) diversity index applied to land-cover proportions
ShCont	Contagion index (Li and Reynolds, 1993) measures overall aggregation of land-cover types
NumPat (ln)	Number of patches of all land-cover types
PARatAdj	Average patch standardized perimeter-to-area ratio (Baker and Cai, 1992) for patches larger than four pixels that do not touch the boundary of the analysis unit (includes both internal and external perimeters)
TopoD	Average patch topological dimension (Riitters *et al.*, 1995), for patches larger than four pixels that do not touch the boundary of the analysis unit
PAFract	Fractal dimension corresponding to patch perimeter complexity from perimeter-area scaling (Krummel *et al.*,1987), for a minimum of 20 patches larger than four pixels that do not touch the boundary of the analysis unit ($n = 135{,}317$)
	Forest Indices
F_Conn	Forest connectivity (Riitters *et al.*, 2000) measures forest aggregation
F_AWPatSiz (ln)	Area-weighted average forest patch size
F_EARat (ln)	Number of forest – nonforest pixel edges per forest pixel
F_PatSiz (ln)	Average forest patch size
F_NumPat (ln)	Number of forest patches
F_PARatAdj	Same as PARatAdj except forest patches only ($n = 118{,}226$)
F_TopoD	Same as TopoD except forest patches only ($n = 118{,}226$)
F_PAFract	Same as PAFract except forest patches only ($n = 88{,}352$)

TABLE 3. CORRELATIONS AMONG LANDSCAPE-LEVEL INDICES

	PctAgr	PctDev	PctFor	SiDiv	ShCont	NumPat	PARatAdj	TopoD
PctDev	−0.01	—						
PctFor	−0.33	−0.03	—					
SiDiv	−0.01	0.17	−0.08	—				
ShCont	0.09	−0.18	0.08	−0.92	—			
NumPat	−0.10	0.18	0.00	0.68	−0.78	—		
PARatAdj	0.09	0.03	0.03	0.50	−0.46	0.36	—	
TopoD	−0.37	−0.05	0.26	0.07	−0.04	−0.15	−0.10	—
PAFract	−0.25	0.06	−0.09	0.18	−0.32	0.54	0.33	−0.21

TABLE 4. CORRELATIONS AMONG FOREST INDICES

	PctFor	F_AW PatSiz	F_Conn	F_EARat	F_PatSiz	F_NumPat	F_PARat Adj	F_TopoD
F_AWPatSiz	0.92	—						
F_Conn	0.91	0.98	—					
F_EARat	−0.90	−0.98	−1.00	—				
F_PatSiz	0.81	0.91	0.94	−0.95	—			
F_NumPat	0.66	0.39	0.33	−0.30	0.08	—		
F_PARatAdj	0.53	0.55	0.55	−0.55	0.61	−0.06	—	
F_TopoD	0.33	0.38	0.42	−0.42	0.44	−0.12	0.25	—
F_PAFract	−0.06	−0.12	−0.25	0.25	−0.25	0.38	0.16	−0.32

($\sigma^2_{section}/\sigma^2_{total}$), and ($\sigma^2_{unit}/\sigma^2_{total}$). Unbiased estimates of variance components can be computed from the analysis of variance (Proc Nested, SAS Institute, Inc., 2003). The observed mean squares at each level are equated to their expected values (which are linear combinations of the true variances) to solve for the estimated variance components. We followed the same general procedures to estimate the percentage of total variance attributable to each level for ecoregions, administrative units, and watersheds.

Regression Analysis of Forest Pattern Indices

The objective of the regression analysis was to determine whether Omernik (1987) ecoregions explained a large proportion of total variance in forest pattern indices after taking into account the amount of forest present. The dependent variables were the forest indices, and the independent variables were different combinations of ecoregions and percent forest. Separate regressions were fitted within each ecoregion because the specific relationship varies among ecoregions. For example, the number of forest patches usually increases with percent forest in ecoregions with little forest overall, but decreases with percent forest in mostly forested ecoregions, and the relationship is curvilinear in ecoregions exhibiting a wide range of percent forest. A second-order polynomial accounts for many of the possibilities.

We fitted three regression models in a general linear modeling framework (Proc GLM, SAS Institute, Inc., 2003). Model I includes only ecoregions as a classification variable:

$$\text{Model I:} \quad Y_{ij} = \mu + E_i + U_{j(i)} \tag{3}$$

where E_i is the mean effect of ecoregion i and $U_{j(i)}$ is the residual variance among analysis units within ecoregion i. Model I is the same as the nested model used in the variance components analysis for ecoregions. Model II adds regression terms for percent forest (*PctFor*) and fits a second-order regression within each ecoregion:

$$\text{Model II:} \; Y_{ij} = \mu + E_i + A^*PctFor_{j(i)} + B^*Pctfor^2_{j(i)} + U_{j(i)} \tag{4}$$

where A and B are regression coefficients estimated within ecoregions, and E_i can now be interpreted as the intercept for ecoregion i. Model III drops the ecoregion intercept term:

$$\text{Model III:} \quad Y_{ij} = \mu + A^*PctFor^2_{j(i)} + B^*Pctfor^2_{j(i)} + \mathrm{U}_{j(i)}. \tag{5}$$

For comparison among the three models, we examined the R^2 values as an overall measure of goodness-of-fit. The R^2 value represents the percentage of total variance among analysis units that is explained by the model, and it naturally increases when more terms are included in the model.

Results

The stacked bar charts in Figure 1 show the results of the variance components analyses for landscape-level indices. Omernik (1987) ecoregions accounted for 75 percent of the total variance for percent forest and 66 percent of the total for percent agriculture. In contrast, only 20 to 34 percent of the total variance of land-cover pattern indices, and 13 percent of the total for percent developed, was attributable to ecoregions. Similar results were obtained for the Bailey (1995) stratification and furthermore, provinces accounted for more variance than sections for percent forest and percent agriculture whereas the opposite was typical for the other indices.

Strata defined by watersheds and administrative units also accounted for more variance of percent forest and percent agriculture in comparison to the other indices. For the watershed stratification, 2-digit and 4-digit watersheds together accounted for more of the total variance than 6-digit and 8-digit watersheds for percent forest and percent agriculture. For the administrative stratification, states and counties accounted for about the same percentage of total variance of percent forest and percent agriculture. For the other indices, counties typically accounted for more of the total variance than states.

Comparison among stratifications must recognize that the proportion of total variance explained by any stratification is partly due to the number of strata (or roughly, the average size of strata). Other things equal, smaller and

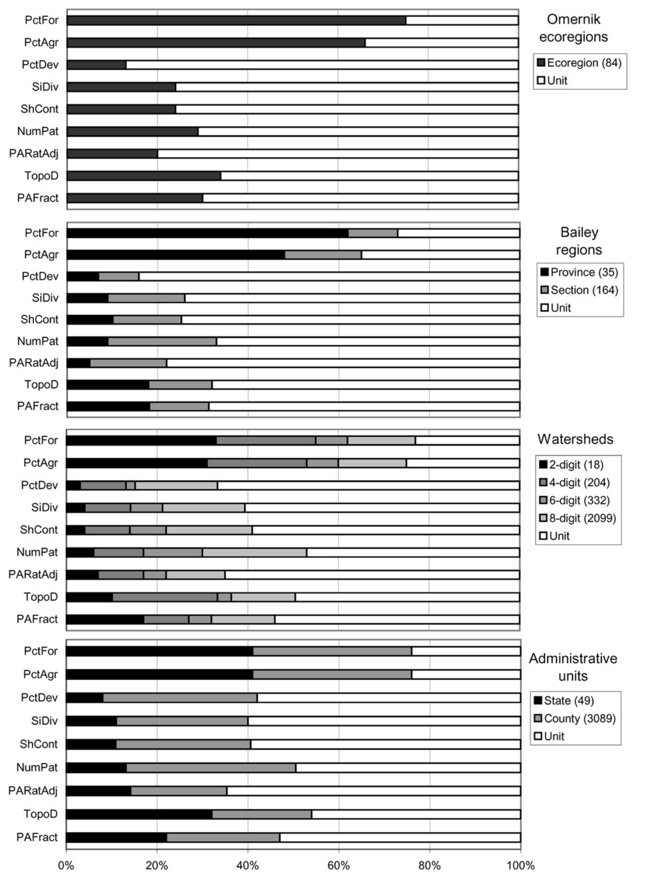


Figure 1. Percentage of total variance of landscape-level composition and pattern indices attributable to levels in four geographic stratification schemes. The number of strata at each level is indicated in the legends.

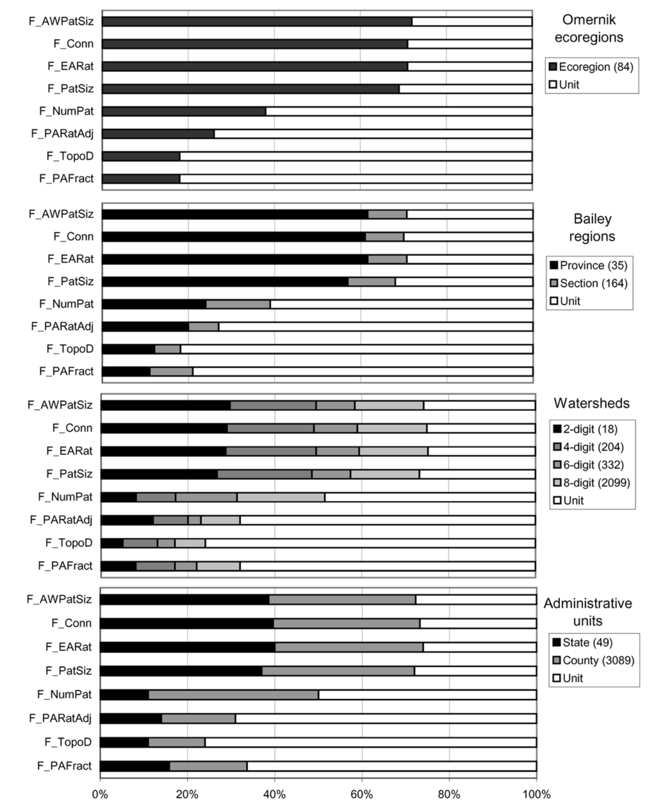


Figure 2. Percentage of total variance of forest pattern indices attributable to levels in four geographic stratification schemes. The number of strata at each level is indicated in the legends.

therefore more numerous strata should explain a higher proportion of the total variance of any index. In that sense, Omernik (1987) ecoregions are slightly better than Bailey (1995) provinces and sections in accounting for variance of percent forest or agriculture, because more of the total variance was attributable to 84 ecoregions than to 164 sections within 35 provinces. By the same logic, provinces might be better because only 35 provinces accounted for two-thirds as much of the variance as was accounted for by 84 ecoregions.

When considering the geographic scale of variance for a given index, note that if a small number of large strata account for less variance than a large number of small strata, then more of the variance is exhibited at finer geographic scales. For example, Bailey (1995) sections account for three times more variance of number of patches than provinces. The implication is that in comparison to the regional scale variance of percent forest and percent agriculture, the variance in number of patches is expressed at a more local geographic scale. Furthermore, since the within-section variance is twice as large as the sum of variance components for provinces and sections, the most informative geographic scale for this index is smaller than sections.

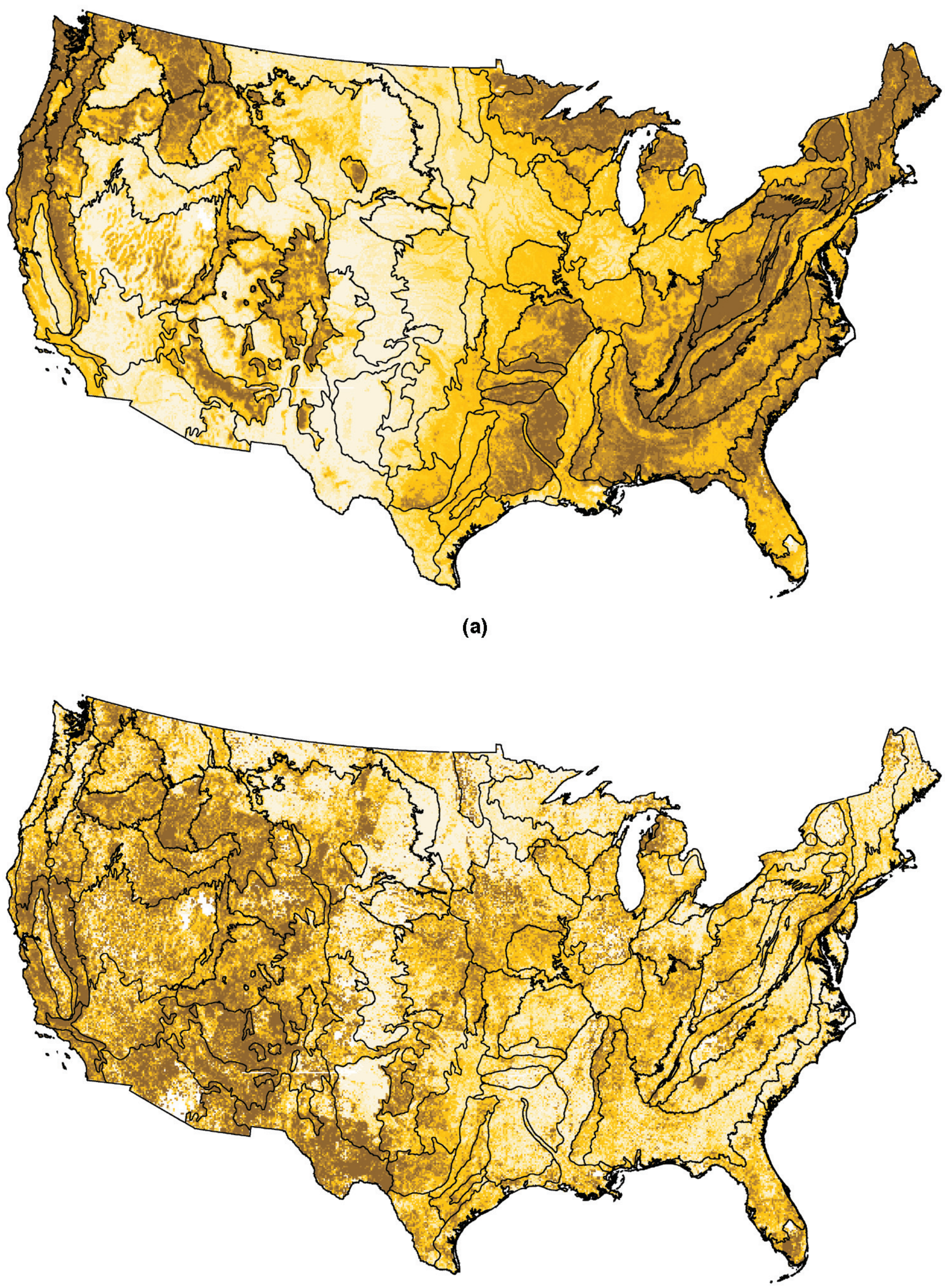
The overall impressions gained from Figure 1 can be summarized as follows. For percent forest and percent agriculture, all of the stratifications accounted for a substantial portion of total variance, and for a given stratification the higher-level strata accounted for more variance than lower-level strata. This suggests that the most informative geographic scale for percent forest and percent agriculture is regional. For all of the other indices, none of the stratifications accounted for a large portion of total variance, and a comparatively large number of units were typically required to account for as little as one-third of total variance. This suggests that most aspects of land-cover spatial pattern are expressed at local geographic scales.

Figure 2 illustrates the results of the variance components analysis of forest pattern indices. As expected, for the four indices that are highly correlated with percent forest (area-weighted average patch size, connectivity, edge-area ratio, and average patch size), the results are roughly the same as the results obtained for percent forest in the landscape-level analysis (Figure 1). Considering the other four indices, the Omernik (1987) and Bailey (1995) stratifications accounted for less than 40 percent of the total variance, and even a much larger number of watersheds or counties typically accounted for less than 40 percent of the total variance. The within-stratum variance of these forest pattern indices was typically two to three times larger than the between-stratum variance. These results mirror the landscape-level results and suggest that most aspects of forest spatial pattern are also expressed at local geographic scales.

Table 5 shows the R^2 values for the three regression models relating forest pattern indices to Omernik (1987) ecoregions and percent forest. For comparisons, the R^2 values for Model I are roughly equivalent to the variance

Table 5. Percent of Total Variance Explained by Three Models Relating Forest Pattern Indices to Ecoregions and Percent Forest. Models are Defined in Equations 3 through 5 in the Text

	F_AW PatSiz	F_Conn	F_EARat	F_PatSiz	F_NumPat	F_PARatAdj	F_TopoD	F_PAFract
Model								
I	71	70	71	68	38	26	17	18
II	96	93	93	92	86	38	22	22
III	96	92	92	90	84	37	17	19



(a)

(b)

Plate 1. National maps of the percent of forest (a) and fractal dimension from perimeter-area scaling (all land-cover types, (b)) within 56.25 km^2 analysis units. The color ramp is from the smallest values (light) to the largest values (dark). Boundaries of Omernik (1987) ecoregions are shown for comparison.

components for ecoregions in Figure 2. The increase in R^2 for Model II was largest for the number of patches which exhibited only a moderate correlation ($r = 0.66$) with percent forest, and we attribute this to the underlying curvilinear relationship between number of patches and percent forest. For all indices, percent forest alone (Model III) explained more variance than ecoregions alone (Model I). The difference in R^2 between Model II and Model III represents the percentage of variance explained by ecoregions after adjusting for differences in percentage forest among ecoregions. This difference is very small for all forest indices, indicating that the proportion of total pattern variance that is accounted for by ecoregions results from an accounting for differences in percent forest among ecoregions, not from an accounting of differences in forest pattern among ecoregions. Although not shown, similar results were obtained for a parallel analysis using Bailey's (1995) provinces and sections in the regression models.

The difference between regional and local scales of variance is illustrated by national maps (Plate 1) of percent forest (Plate 1a) and fractal dimension from perimeter-area scaling (all land-cover types, Plate 1b). Forest area distribution exhibits a smooth appearance that is clearly associated with Omernik (1987) ecoregion boundaries. The coarser appearance of the map of patch shapes indicates a more local scale of variance, and this index is less clearly associated with ecoregion boundaries. These visually apparent differences explain why several different types of large strata can account for a substantial proportion of the variance of percent forest, and why no large strata can account for a high proportion of variance for indices of forest pattern that are not correlated with percent forest.

Discussion

From a sampling perspective, our results show that any geographical stratification will improve statistical precision, at least somewhat, when estimating any of the landscape-level or forest indices. Furthermore, when estimating land-cover composition, there should be substantial gains in precision for indices of forest, agriculture, and similarly distributed land-cover types (e.g., shrublands and grasslands) but not for land-cover types that are not concentrated in particular ecoregions (e.g., urban and water). When estimating the proportions of dominant land-cover types, gains should also be larger for stratifications that are either based at least partly on dominant land cover (Omernik, 1987) or on biophysical factors that determine dominant land cover (Bailey, 1995). For all of the stratifications tested, we would not expect large gains in precision for any index of land-cover pattern except for those that are highly correlated with the percent of the dominant land-cover type within strata, but these arguably are measures of dominant composition rather than pattern.

From a mapping perspective, ecoregion-level estimates of dominant land-cover percentages are reasonable first approximations. However, it is not clear that ecoregion-level statistics developed from sampling are sufficient for mapping. Omernik (1987) and Bailey (1995) ecoregions left unexplained 25 to 35 percent of the total variance in percent forest and agriculture, suggesting that percent of dominant land-cover types varies considerably within individual ecoregions (see Plate 1). Ecoregions are probably not useful for mapping non-dominant land-cover types, or land-cover pattern, because the within-ecoregion variance is typically two to four times larger than between-ecoregion variance. Thus, it is unlikely that any regional, geographically defined stratification will be an adequate substitute for wall-to-wall mapping when assessing or managing land-cover pattern.

Although our analysis used only one land-cover map, the results can be applied to the analysis of changes in land-cover composition and pattern. Many analyses of change have focused on finding significant differences among ecoregions in a sampling framework. Attempts to extend those results to ecoregional mapping would benefit from additional analysis of the within- and between-ecoregion variances of change. In the United States, significant ecoregional differences in the rate of urban development are likely to be obtained as people migrate to southern and coastal ecoregions. However, people do not migrate to ecoregions, they migrate to particular places within ecoregions, and new urban development is concentrated near existing urban areas. We can speculate that analyses of change from either a sampling or a mapping perspective will be more accurate with local stratifications than with regional stratifications.

In the United States, we expect that most changes in forest spatial patterns will be related to urban development (e.g., Wear *et al*., 2004). Roads accompany urban development and have profound impacts on some aspects of pattern such as patch size (Riitters *et al*., 2004b). Parcelization (i.e., the legal subdivision of ownership) is likely to continue, making it more likely that different owners will make different land-use decisions for increasingly smaller tracts of land (Birch, 1996; Sampson and DeCoster, 2000; Gobster and Rickenbach, 2004). These factors translate to increased variance of forest spatial pattern at increasingly local geographic scales. As a result, we expect a reduction of variance associated with ecoregions and an increase in variance associated with local geographic scales. For sampling and mapping forest patterns, ecoregional stratification will continue to be effective where humans have relatively little influence on forest pattern generation, but we think this will represent a smaller percentage of total area over time.

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