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Scale problems in reporting landscape pattern at the regional scale*

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Abstract

Remotely sensed data for Southeastern United States (Standard Federal Region 4) are used to examine the scale problems involved in reporting landscape pattern for a large, heterogeneous region. Frequency distributions of landscape indices illustrate problems associated with the grain or resolution of the data. Grain should be 2 to 5 times smaller than the spatial features of interest. The analyses also reveal that the indices are sensitive to the calculation scale, *i.e.,* the unit area or extent over which the index is computed. This "sample area" must be 2 to 5 times larger than landscape patches to avoid bias in calculating the indices.

Introduction

A strong motivation for developing Landscape Ecology has been the need to deal with ecological impacts at large spatial scales (Hett 1971; Krummel *et al.* 1980, 1983, 1984; Mankin *et al.* 1981). An expanding human population, combined with continuing development, are causing unprecedented land use changes (Krummel *et al.* 1986; Franklin and Forman 1987). Vast areas of natural vegetation are being changed into agriculture or urban areas (Klopatek *et al.* 1983). Infrastructure, such as roads and power lines, are impacting the remaining natural areas (Krummel *et al.* 1987).

These land use changes, in turn, have serious impact on large-scale ecological systems. Deforestation increases carbon dioxide in the atmosphere (Chan *et al.* 1980; Emanuel *et al.* 1984). Fragmentation often reduces biodiversity (Kareiva 1986; Pacala 1987) and, consequently, decreases genetic diversity.

Major environmental changes may involve alterations in spatial pattern at the regional scale. Some general circulation models of the atmosphere predict hotter and drier conditions in the mid-latitudes as a result of increased Carbon Dioxide. Studies based on that scenario predict that the American Cornbelt will move far to the north and east (Blasing and Solomon 1984). Forests would change species or transform into shrubs or grassland (Sedjo and Solomon 1989). If rates of climate change exceed rates of forest migration, the ecosystem will be at risk for increased disease and fires (Batie and Shugart 1989).

Even without global changes, spatial pattern is important in structuring ecological communities (Levin 1976). Pattern is particularly important in maintaining the coexistence of competitors (Levins and Culver 1971; Slatkin 1974; Comins and Noble 1985). Pattern may be determined by disturbance (Paine and Levin 1981) and may, in turn, determine how disturbances propagate through the system (Turner *et al.* 1989).

Dealing with landscape change will require increased sophistication in our ability to monitor spatial pattern. The question then arises: at what

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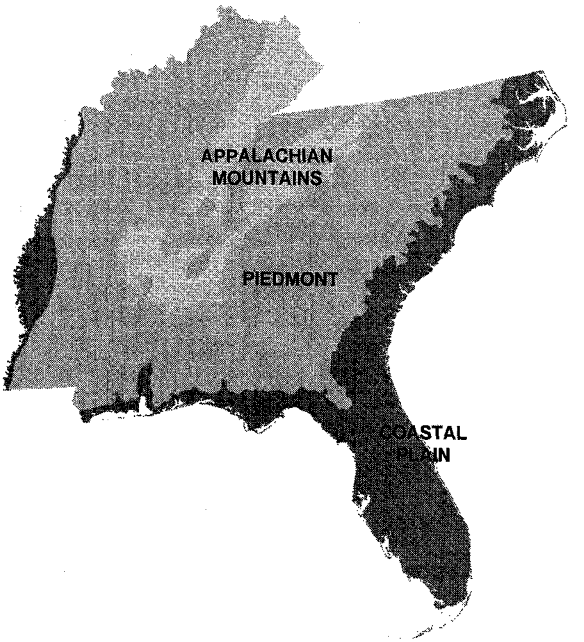

Fig. 1. Standard Federal Regions adopted by the **U.S.** Environmental Protection Agency (Office of Management and Budget 1974). Region 4 contains portions of 3 of the Omemik (1987, Omemik and Gallant 1989) ecoregions.

spatial scale **is** it relevant to monitor, report and assess landscape patterns? For the individual investigator, developing the principles of landscape ecology, relatively small spatial scales may suffice. However, for purposes of monitoring status and assessing changes across the continent, there is a need to consider the regional scale.

The regional scale

A region is an area of similar vegetation, geology, and historic landuse such that principles of landscape ecology established anywhere within the region can be reasonably expected to extrapolate across the region (Omernik 1987). A region can be loosely defined as an area containing 10^3 to 10^6 landscape units. The landscape unit will depend on the question being asked. For questions of forest biodiversity, the logical unit might be a forest patch. For questions of water quality assessment, the unit might be a watershed.

However, in many cases, a region is less a logical unit of ecological interaction and more a convenient socio-political unit for assessment and regulatory purposes. One example is the Standard Federal Regions (OMB 1974) that have been adopted by the Environmental Protection Agency. No one, of course, is suggesting that a Federal Region is ecologically uniform. Nevertheless, environmental status and trends must be reported by the Federal Region as a unit (OMB 1974). The scale question then becomes what problems will arise in reporting landscape pattern over the heterogeneous administrative region? For the purposes of the present paper, we will focus on Region 4 in Southeastern U.S.A. Figure 1 shows that Region **4** contains portions of three of the aggregated ecoregions suggested by Omernik and Gallant (1989).

The differences between landscapes and reporting regions raise a series of questions. What happens as one aggregates landscape metrics to the regional scale? A common sense approach would subdivide the region into more homogeneous subregions. However, even this approach is, at present unguided by any quantitative study of the issue. Explicit examination of the question will bring to light a number of unexpected scale phenomena that were previously unknown and must be considered in future regional studies.

The spatial data base

Landcover was taken from the prototype database developed by Loveland *et al.* (1991). The database contains classified land cover for the conterminous United States. The database uses Advanced Very High Resolution Radiometer (AVHRR) imagery (1 km^2 grain size) collected from March through October, 1990. For present purposes, cover classes were aggregated into Anderson Level **I** (Anderson *et al.* 1976) categories. This results in 9 potential cover types, of which 7 occur in Region **4** (Hunsaker *et al.*, in press). The AVHRR database captures major landscape features but loses fine details, such as small scale fragmentation and road cuts. Thus, the resolution is too coarse for relating spatial changes to many ecological processes. However, it should be sufficient for investigating how measures of pattern aggregate to regional scales.

Region 4 contains portions of **3** ecoregions (Fig. 1). The first is the southern tip of the Appalachian mountains, largely covered with forest (Omernik region 11). The second contains the plains to the east and south of the mountains (Omernik region III). The third subregion is the coastal areas and wetlands (Omernik region VIIF).

To calculate landscape indices, the region was subdivided into 1505 hexagons, each containing 640 km^2. This subdivision corresponds to the sampling design being utilized in the U.S. Environmental Protection Agency's Environmental Monitoring and Assessment Program (EMAP). This approach provides a sufficiently large sample to examine the statistical properties of the pattern indices.

On each hexagon, we calculated Dominance, D (O'Neill *et al.* 1988),

$$D = 1 - \mathrm{SUM}_k \, [(-P_k \ln P_k)/\ln n]$$

where P_k is the proportion of land cover k, Contagion, C (Li and Reynolds 1993),

$$C = 1 - \mathrm{SUM}_i \, \mathrm{SUM}_j \, [(-P_{ij} \ln P_{ij})/n \ln n]$$

where P_{ij} is the proportion of the total adjacencies involving land covers i and j, and Shape Complexity, **S** (O'Neill *et al.* 1988). We also calculated three additional indices, Pmax, Enat, and C_5. Pmax is the proportion of the hexagon covered by the most common landuse type. Enat compares natural edges to total edges. An edge is an adjacency of 2 pixels with different land uses. A forest-grassland edge would be considered natural, while a forest-urban edge would not. Enat is the ratio of types of natural edges (*i.e.*, $N_{i,j}$) to all possible types of edges (*i.e.*, $N_{k,l}$).

The index C_5 is another measure of contagion. It compares the number of pixels that are in patches of 5 pixels or greater (*e.g.*, N_5) to the total number of pixels (*e.g.*, N_{all}). The ratio N_5/N_{all} is averaged over all land use types. The index was calculated for C_3 through C_7 and a value of 5 pixels was chosen to define a patch because C_5 had the most reasonable statistical distribution.

Statistical properties of landscape indices

The first set of analyses deals with the statistical properties of the indices. For a large region, an ideal index would show values spanning the potential range of the index and have the mean and standard deviation reasonably centered in the potential range.

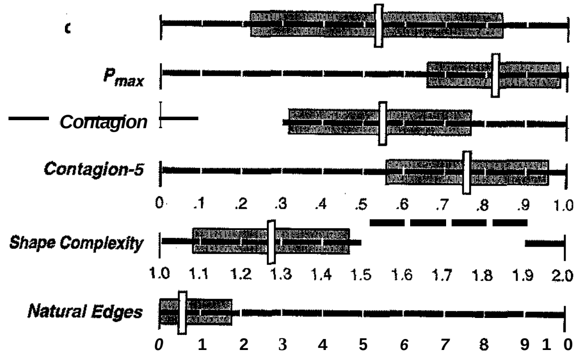

Fig. 2. Bar graphs illustrating the mean, standard deviation, and range of landscape indices calculated for Region 4.

Table 1. Pearson correlation coefficients for landscape indices calculated for Region 4.

	Pmax	Contagion	Contagion 5	Shape Complexity
Dominance	0.86	0.72	−0.42	−0.44
Pmax		0.40	−0.20	−0.48
Contagion			−0.48	−0.25
Contagion 5				−0.24

Figure 2 shows that D, C, C_5 and **S**, calculated for the entire region, have reasonable behavior by this criterion. The mean for **S** is relatively low. We will show in later analyses that the coarse resolution of the AVHRR data biases the calculation of shape complexity.

In contrast to these four indices, Pmax and Enat appear to be compressed at the high and low ends of their respective ranges. Because of this restricted range, these indices are unlikely to be able to distinguish between patterns in this region.

A second criterion for a useful set of landscape indicators is statistical independence. If some of the indicators are highly correlated, they may not be measuring different aspects of pattern. Table 1 shows that the indices have an intermediate level of correlation, except for D with C and D with Pmax. With n = 1505, all of the coefficients are significant at alpha = 0.05. Therefore, this set of pattern indices is far from an ideal set. However, except for the high correlations with Dominance, it is clear that each index adds additional information about pattern.

Figure 3 shows the scatter plot of Dominance and Contagion for Region **4.** The dominant feature

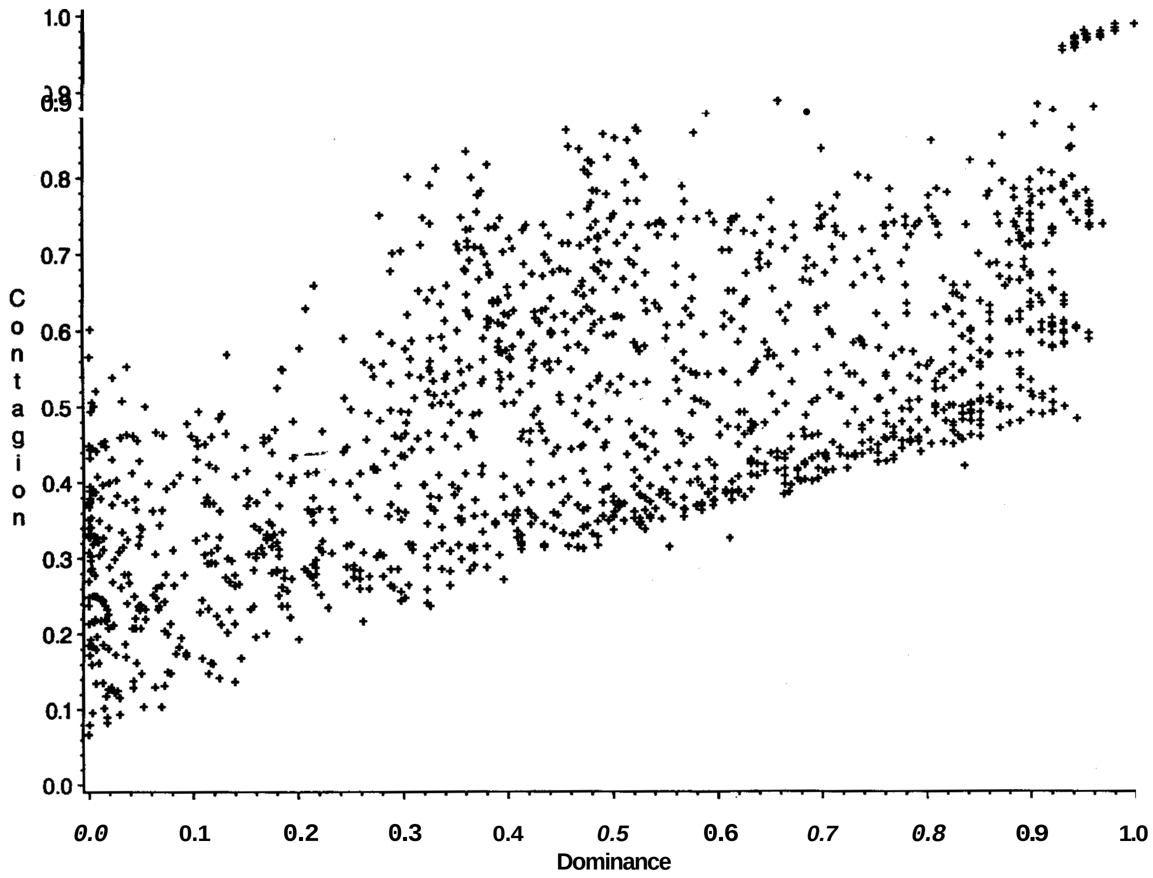

Fig. 3. Graph of Dominance and Contagion for all hexagons in Region 4.

of the graph is the lack of points in the upper left and lower right portions of the figure. Simply stated, as dominance increases, the landscape must have fewer, larger clusters and contagion must increase. It is not possible to have significant fragmentation (low contagion) on a landscape dominated by a single land use (high dominance). On the other hand, when dominance is low, the landscape is covered by many land uses, and it is impossible to have a single, contiguous cluster. Therefore as dominance approaches 0, the values of contagion are restricted.

The relationship between D and Pmax (Fig. 4) is even more dramatic. When there are only two land cover types, the value of dominance is a simple function of Pmax:

$$D = 0.6931 + \text{Pmax} \ln \text{Pmax} + (1-\text{Pmax}) \ln (1-\text{Pmax}) \quad (1)$$

The hexagons with only 2 land uses in Figure 4 all lie on the curve described by **Eq.** 1. Although a greater range of D values are possible for more than 2 land types, the restrictions are severe.

Grain and extent

Grain and extent define the range of spatial scales under consideration. Grain is the spatial resolution of the data. The grain is defined by the pixel size, the smallest spatial unit for which a single land use type is specified. That is, the pixel cannot be subdivided into several land uses. In the present study, the grain is 1 km^2. Extent is the total area of the map being considered. In the present study, the extent is Region 4 (Fig. 1).

Often, in addition to grain and extent, it is neces-

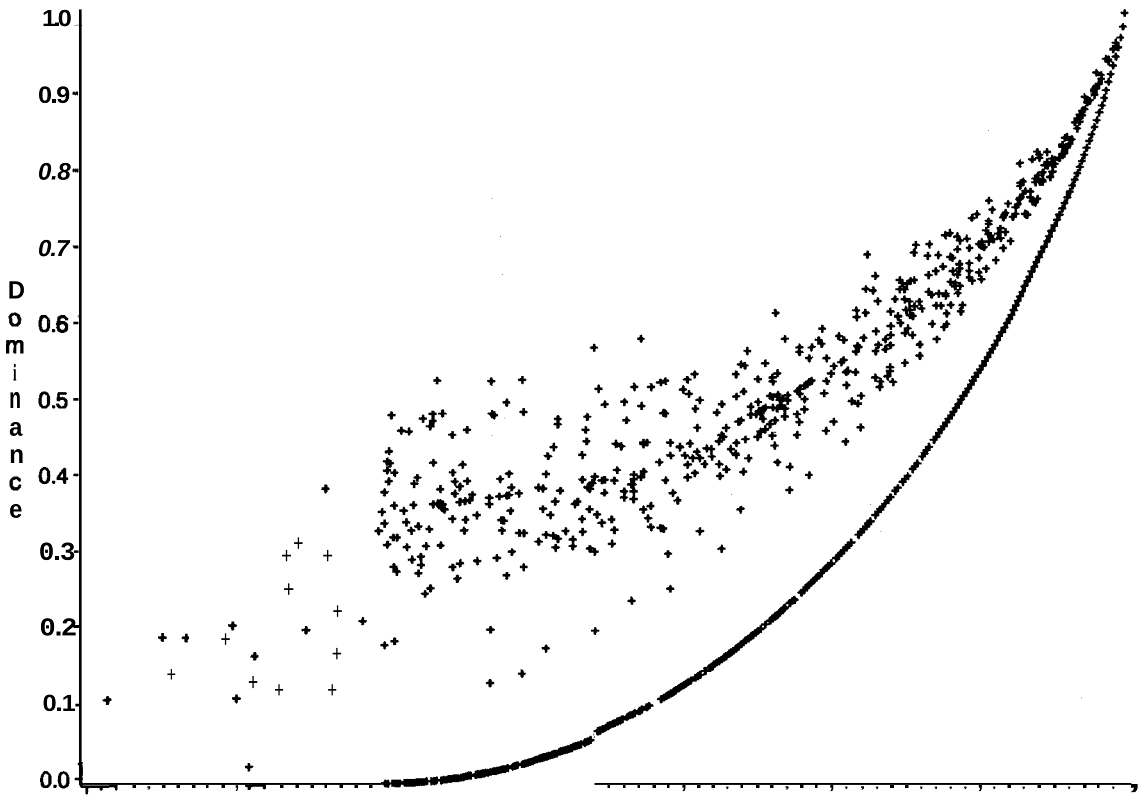

Fig. 4. Graph of Dominance and Pmax for all hexagons in Region 4.

sary to define an intermediate scale for sampling or calculation. When sampling is done, the dimensions of the sample unit become an important scale. But even with complete coverage, it is necessary to characterize heterogeneity and necessary to monitor for changes in heterogeneity across space and through time. It would be possible, for example, to calculate a single value of Dominance for all of region 4. This single value, however, contains no information on how D varies across the region. The region must be divided into intermediate scale units and D must be calculated for each unit in order to obtain information on variance. In the present study, the intermediate scale is the calculation unit, the 640 km^2 hexagon.

Problems with grain arise when elements of the landscape pattern (*e.g.,* patches) are scattered and are as small or smaller than a pixel. Consider a small forest patch (<< 0.5 km^2) surrounded by agriculture. With a grain size of 1 km^2, the forest patch will be lost. The pixel is classified as agriculture.

Now consider the frequency distribution of forest patch sizes on a landscape. Consider **a** bell-shaped distribution with patches ranging from 0.01 km^2 to 100 km^2. With a grain size of 1.0 km^2, the smallest patches (0.0 to 0.5 km^2) are lost. Values between 0.5 and 1.0 km^2 are lumped as 1.0's. The first class (1.0 km^2) has too many members.

The problem will be most acute when the mode of the landscape distribution lies to the left of center, *i.e.,* the patches tend to be small. If the mode of the distribution lies far to the right, forest tends to occur in large patches and should be adequately sampled. The small number of uncharacteristically small patches will probably not seriously affect cal-

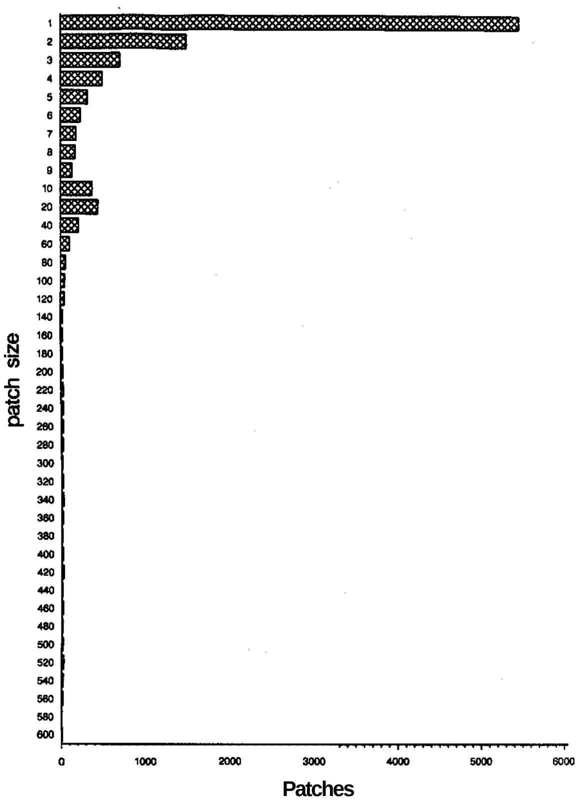

Fig. 5. Frequency distribution of patch sizes for subregion ***C***, the coastal plains. Values are the total area occupied by patches of a given size, summed over all landcover types and over all hexagons.

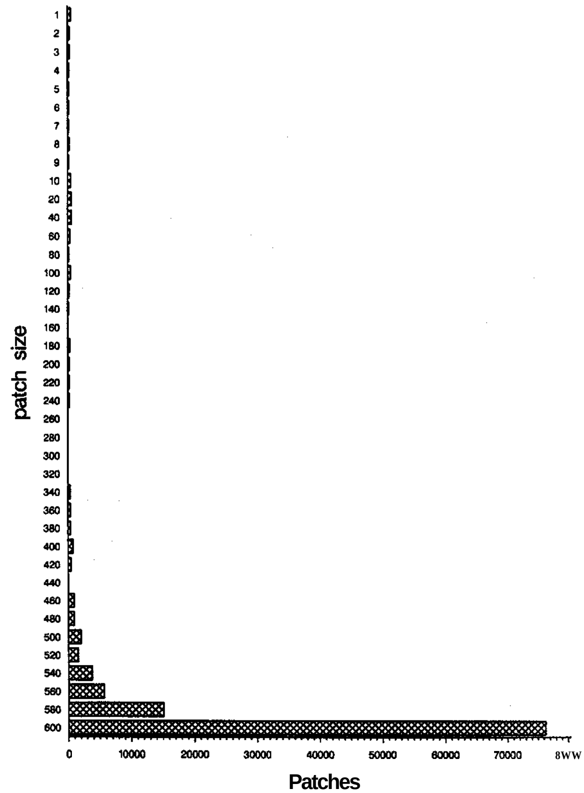

Fig. 6. Frequency distribution of patch sizes, summed over all land cover types and all hexagons for subregion **A,** the forested mountain area. Values are the total pixels in patches of a given size.

culation of landscape indices that are based on patch size.

Figure ***5*** shows the sample distribution of patch sizes. The graph shows the total area, summed over all land uses and over all hexagons, contained in patches of a given size. The figure is for the coastal plain ecoregion. This coastal area is fragmented and the mode of the distribution lies far to the left of center. The figure suggests that the 1 km^2 grain of the AVHRR database biases the estimates of small patch sizes.

A similar problem arises if the calculation unit is small relative to the patch sizes being measured. Consider a landscape that is almost completely covered with forest. Patch sizes will be large and the landscape frequency distribution will show a mode that lies far to the right of center. **A** significant amount of forest is distributed in patches as large or larger than 640 km^2. In this case, the hexagonal sampling unit acts like a "cookie cutter", artificially creating many forest "patches" of exactly 640 km^2. The result wil be a distortion of the true distribution and the sample distribution will overestimate patches at 640 km^2. Even if the patches aren't much larger than 640, still the boundaries of the hexagon will begin to slice the patches, being recorded as several small patches, rather than one large patch.

Figure 6 shows the sample distribution of patch sizes, summed over all land uses, for the forested mountain ecoregion. The distribution of patch sizes lies far to the right and the sample distribution in Figure 6 shows the characteristic peak at the largest patch size.

Implications of scale for landscape indices

Using a coarse-grained database biases the estimation of small patch sizes. An arbitrary, but practical, rule of thumb can be derived from our experience: for indices that are sensitive to small landscape features, the grain of the data should be 2 to 5 times smaller than the feature of interest. Therefore, in estimating corridors between forest patches, forest gaps, width of riparian zones, or small, dissected wetlands, the bias introduced by coarse-grained data would produce unacceptable distortion.

At the same time, it is important to remember that the total area involved in small patches is a relatively minor percentage of the total region. Even with the extreme case shown in Figure 5, only 2% of the total area is involved in small patches. Landscape indices such as D and C are based on the relative proportions of area occupied by different land covers. Missing the 1 or 2% of a landcover that is contained in small patches does not significantly change the overall proportions and, therefore, these indices are insensitive to the bias introduced by coarse-grained data.

This observation has two important implications. First, indices based on the relative proportions of land covers may not provide reliable information on fine-scaled features of the landscape. Second, because these indices are insensitive to this bias, they may provide reliable estimates of meso- and macro-scaled features in spite of the bias in the coarse-grained data.

The situation is rather different from the bias introduced by the 640 km^2 calculation unit. The total area now involved is considerable (Fig. 6). Too many hexagons have a value of D and C near 1.0 because the total hexagon is almost filled with a single land cover. As discussed in an earlier section, this means that D and C will show unusually high correlations. Too many hexagons have a simple shape complexity equal to 1.0, because the calculated value is based on a simple hexagonal patch with straight sides. The 640 km^2 hexagon is simply too small for accurate estimation of these indicators. Figure 7 shows the frequency distribution of values for shape complexity, summed across all of Region 4. The bimodal distribution indicates a clear bias. Too many hexagons show a value of 1.0, indicating that the patch filled the hexagon. The calculation unit should be 2 to 5 times greater than the largest patch on the landscape or significant error can result.

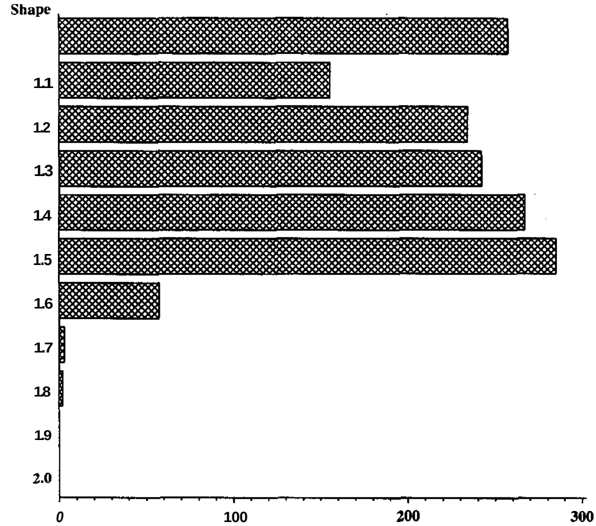

Fig. 7. Frequency distribution of values for contagion summed over all hexagons of Region 4. The figures illustrate the bias introduced by a small calculation unit.

An additional problem is introduced in the calculation of shape complexity. Following O'Neill *et al.* (1988), this index is found by regressing the logarithm of the perimeter against the logarithm of the area of all patches in the hexagon. Shape complexity is twice the slope of this regression. When there are very few "patches" because of the "cookie cutter" bias of using 640 km^2 hexagons, the regression does not provide an accurate estimate. At the very least, the investigator should be alert to this problem and disregard calculated values of shape complexity that are below 1.0 or above 2.0. Inclusion of these infeasible values could seriously distort regional mean estimates.

A further complication arises in deciding how to assign a value of shape complexity if the entire hexagon is filled with a single landcover. A brief discussion will clarify the problem. Consider 2 perfect squares with areas, A_i, and sides, s_i, and therefore, $A_i = s_i^2$.

A	s	p = 4s
25	5	20
36	6	24

The definition of shape complexity is twice the slope of the ln-ln regression, *i.e.*, *Table* **2.** Landscape indices calculated for Region 4, and for 3 subregions: A – southern Appalachian mountains, B – Eastern plains, C – Coastal areas. Values are means with standard deviations in parentheses. The # Edges index measures the number of different kinds of adjacencies, summed across hexagons.

	Subregions A	B	C	Region 4
# Hexagons	188	947	370	1505
Pmax	0.96	0.82	0.70	0.81
	(0.07)	(0.15)	(0.15)	(0.16)
Dominance	0.85	0.51	0.40	0.52
	(0.16)	(0.31)	(0.22)	(0.31)
Contagion	0.72	0.50	0.54	0.54
	(0.22)	(0.21)	(0.18)	(0.22)
Contagion 5	0.73	0.79	0.70	0.76
	(0.22)	(0.17)	(0.20)	(0.19)
Shape Complexity	1.17	1.27	1.33	1.27
	(0.23)	(0.19)	(0.15)	(0.19)
# Edges	1.5	1.6	4.1	2.2
	(1.5)	(1.3)	(3.1)	(2.2)

$$2 * (\ln P_1 - \ln P_2)/(\ln A_1 - \ln A_2) =$$
$$2 * (\ln 24 - \ln 20)/(\ln 36 - \ln 25) =$$
$$2 * 0.1824/.3646 = 1.0$$

The interpretation is that simple shapes like squares have values of 1.0. More complex shapes have more tortuous perimeters and therefore have larger values for shape complexity.

The hexagon is also a simple shape, such that $A = 6/4\, s^2\, 3^{0.5}$. Consider 2 hexagons:

A	s	P = 6s
640	15.6949	94.1693
610	15.3226	91.9357

The calculation of shape complexity proceeds as before:

$$2 * (\ln 94.1693 - \ln 91.9357)/(\ln 640 - \ln 610) =$$
$$2 * (0.24/0.48) = 1.0.$$

To estimate the shape complexity for a single object filling the entire space, the usual approach uses 2*(lns/lnA). For example, with the first square above:

$$2 * (\ln 5/\ln 25) = 1.0.$$

However, the simple side/area ratio only works for squares. The equations for the area of both squares and hexagons can be put in the form $A = k\, s^2$. In the case of a square, k = 1.0 and causes no problems. In the case of the hexagon, $k = 6/4\ (3^{0.5}) = 2.5980762$. In this case, the constant must be considered. The equation now becomes

$$2 * \ln s/\ln (A/k) = 1.0$$

We recommend simply setting shape complexity equal to one if a hexagon contains only one cover type. It remains, however, that the "cookie cutter" effect of the 640 km^2 hexagon adds smooth sides and biases the shape complexity toward lower values.

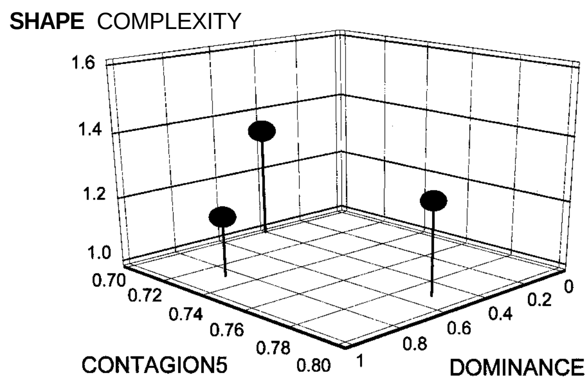

Fig. 8. Three dimensional "pattern space" showing the three subregions **as** points characterized by landscape indices.

Reporting at the regional scale

The next issue concerns the appropriate scale for reporting landscape pattern indicators for a heterogeneous area such as Region IV. Table 2 gives means and standard deviations for the three subregions. These values can be compared to the indicators calculated for the entire region. The first observation is that subregion B is much larger than the other two. Therefore, indicator values for subregion B dominate the grand mean. Second, in spite of the biases introduced by the hexagonal calculation unit, the indicators do a reasonable job of separating the landscape patterns among the subregions. Subregion A is dominated by forest and shows the

Table 3. Calculated distances **(Eq. *2)*** for the three subregions from an ideal (D = 0.9, C_5 = 0.9, S = 1.9) and a degraded state (D = 0.1, C_5 = 0.1, S = 1.1).

	Subregion		
	A	B	C
Ideal State	0.75	0.75	0.78
Degraded State	0.98	0.82	0.71

highest values for Pmax, D, and ***C*.** Forest patches tend to be larger than 640 km^2 so the shape complexity shows a low value. At the other extreme, the highly dissected coastal area (Subregion ***C)*** shows much lower values for Pmax, D, and ***C*,.** Notice that, on average, Subregion C has many more different kinds of edges or adjacencies, indicating a landscape with many landcover types interwoven into a complex pattern.

The final observation about Table 2 is that the grand mean for the entire region tends to lose the distinctions among subregions, providing an intermediate average value. One would expect that large, undesirable landscape changes could occur in subregions **A** or ***C*** without detecting any significant change in the grand mean.

Reporting landscape status in pattern space

Figure **8** shows the relative position of the three subregions in a three dimensional space formed by D, ***C*,,** and **S.** This approach suggests a simple metric, distance (Z), that defines the distance between landscapes in pattern space. The metric is simply the geometric distance:

$$Z = (\text{SUM}\,[(D_1 - D_2)^2 + (C_{5,1} - C_{5,2})^2 + (S_1 - S_2)^2])^{0.5} \qquad (2)$$

For three indicators, the metric has a potential range: $0 < Z < 1.73 = 3^{0.5}$.

To illustrate the metric, let us assume that we wish to evaluate the current status of the landscape patterns in the three subregions. We could ask how far the present landscapes deviate from an ideal landscape with nearly complete forest cover (D = 0.9), in large **(C,** = 0.9) and complex **(S** = 1.9) patches. We might also ask how far the landscape deviate from a totally degraded state with many landcover types (D = 0.1), in dissected (C_5 = 0.1) and simple patches **(S** = 1.1).

Table ***3*** shows the distance values. The values are not well distributed over the potential range of Z, but follow expectations in indicating that subregions A and B are closer to the ideal than the heavily impacted coastal area (subregion ***C).*** Likewise, the metric indicates that the forested mountains (subregion A) are furthest from a degraded state and the coastal areas (subregion ***C)*** are closest.

In addition to defining the current status of a landscape, the distance metric can also be used to define the direction and magnitude of change through time. In a long-term monitoring program, such as EMAP, the distance metrics could be calculated at each remeasurement period. The metric would indicate how much overall change had occurred in the region and whether the change could be interpreted as degradation or recovery in landscape pattern.

Notice that a distance metric can be defined on any arbitrary number of pattern metrics. Equation 2 easily generalizes to

$$Z = \{\text{SUM}_i\,[M_{i,t} - M_{i,t+1}]^2\}^{0.5} \qquad (3)$$

where $\mathbf{M}_i$ is any indicator of pattern.

There would be two major constraints on using this approach. First, ideally the axes of the pattern space, *i.e.*, the M_i, should be orthogonal. Falling short of this ideal, the axes should be as independent as possible, showing smaller correlation coefficients than are evident in Table 1. Second, the sensitivity of the individual indicators to landscape changes will need to be established. The critical question is whether the indicator can detect a small initial degradation, sufficient to warn society of the risk of further change. An insensitive indicator might only show significant change after irreparable damage had been done.

Sampling versus full coverage

Table 4 compares full coverage with a sample. The question is whether a 25% areal sample would suffice for calculation of landscape indices if full coverage information, such as AVHRR, were not available.

Table 4. Differences in pattern indicators between full coverage (640 km^2 hexagons) and a 25% sample (160 km^2 hexagons). Tabulated values are the differences in means (X_{160}–X_{640}), divided by the standard deviation (SD_{640}).

	Subregions		
	A	B	C
Pmax	0.00	**0.13**	0.33
Dominance	0.19	0.10	0.04
Contagion	0.68	0.38	0.50
Contagion 5	0.50	0.12	0.10
Shape	1.39	0.21	0.07
#Edges	–0.57	–0.41	–0.64
#Cover types	–0.72	–0.52	–0.62

Table 5. A test of the sensitivity of $D = \ln n + SUM_i P_i \ln P_i$.

Landcover	Case 1	Case 2	Case 3
A	0.5	0.5	0.6
B	0.1	0.14	0.1
C	0.1	0.14	0.1
D	0.1	0.05	0.1
E	0.1	0.05	0.09
F	0.1	0.1	0.01
Dominance	0.2937	0.3406	0.5316
% Change		16%	81%

To address this question, we sampled 160 km^2 hexagons. These smaller hexagons have the same central point as the 640 km^2 hexagons. To give an impression of how well the sample estimated the subregional mean, tabulated values are normalized by the standard deviations, *i.e.,* the values are calculated as ($X_{,,,}$ $- X_{640}$)/SD_{640}. Notice that the sign is positive if the sample is larger than the calculation based on the full 640 km^2 hexagon.

In general, drawing the hexagonal samples did not result in unreasonable sampling error. The largest error is less than 1.5 standard deviations. The errors appear to be greatest in subregion A and least in subregion C. This is probably because subregion C is a highly dissected area, something like a checkerboard. The smaller sampling unit seems adequate to capture the basic pattern under these circumstances.

Of greater concern than the magnitude of the error is the systematic bias. The sample always overestimates the first 5 indices and always underestimates the last two. Undoubtedly the bias occurs because the calculation unit problem seen at 640 km^2 are compounded at 160km^2.

Discussion

An important finding of this study concerns the sensitivity of landscape indices to grain and calculation scales. Some indices may show a bimodel distribution (Fig. 7) because they are unacceptably biased by the boundaries of the calculation units. In general, the grain should be 2 to 5 times smaller than the smallest feature of interest and the calculation unit should be 2 to 5 times larger than the largest feature of interest.

Because of the biases introduced by the scale of the calculation unit, we found that drawing a sample, even a 25% sample, could compound the problem. The sample unit would necessarily be smaller than the calculation unit and the systematic bias would increase. Our findings indicate that systematic scale bias tended to appear in frequency distributions of landscape properties such as patch sizes and calculated indices. The distributions showed unexpectedly high values for the smallest (Fig. 5) or largest (Fig. 6) classes. Particularly diagnostic were frequency distributions that were bimodal (Fig. 7).

The study also revealed some important characteristic of the basic pattern indices. The indices are not orthogonal (Table 1). The result is reasonable since Pmax, D, and C are functions of the P_i's, the proportions of the landscape in each landcover type. But there are also significant correlations with **S** and **C,.** In fact, the correlations may simply mean that the hexagonal samples tended to fall into a few categories of pattern. Nevertheless, the search for orthogonal landscape indices should continue. Certainly, C_5, or some measure of the frequency distribution of patch sizes, seems to provide more independent information than contagion.

The analyses show that the current set of landscape indices captures major features of pattern, but shows little sensitive to the fine-grained features of the landscape. Obviously, if the objective is to detect all changes, the most sensitive measure is the total number of pixels that have changed landcover.

The insensitivity of the indices to a small amount of fine-scaled bias should not be taken as an indication of general lack of sensitivity to pattern changes. Table 5 contains some simple calculations illustrating how sensitive an index like Dominance really is to changes in pattern. Case 1 is a landscape with 50% of the area in landcover A and 10% in the other *5* cover types. In Case 2, 10% of the landscape has changed from types D and E into types B and C. This effects a change in pattern but not a major change in dominance by type A. Nevertheless, the 10% change in the landscape causes a 16% change in the index. In case 3, the 10% change is from types F and E into the dominant type, and almost eliminating type F. In this case the change has made an important change in dominance and the 10% change in the landscape is amplified to an 81% change in the dominance index.

Another purpose of this study was to determine a reasonable approach for reporting landscape pattern in a heterogeneous region. A single mean value may be too insensitive to detect small changes and may be biased by the value of the largest subregion. In many cases, it would be useful to isolate a subregion, such as the Florida Everglades, that is particularly sensitive to landscape change. In any case, the better defined the subregion, in an ecological sense, the more sensitive and interpretable will be the landscape pattern indices.

The study also suggests that a useful way to report on landscape status is by means of a pattern state space (Fig. 8) and a distance metric (Eq. 3) that measures overall differences between landscapes or changes through time. The distance metric can accommodate a number of indices, but the greater the number of indices, the more the metric will tend to average across small changes. **A** reasonably small number of orthogonal measures of pattern will provide a more sensitive metric of change.

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