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Indices of landscape pattern

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Abstract

Landscape ecology deals with the patterning of ecosystems in space. Methods are needed to quantify aspects of spatial pattern that can be correlated with ecological processes. The present paper develops three indices of pattern derived from information theory and fractal geometry. Using digitized maps, the indices are calculated for 94 quadrangles covering most of the eastern United States. The indices are shown to be reasonably independent of each other and to capture major features of landscape pattern. One of the indices, the fractal dimension, is shown to be correlated with the degree of human manipulation of the landscape.

Introduction

During the past two decades, environmental analyses have been conducted at increasingly larger spatial scales. From the impact of site-specific activities (*e.g.*, power facilities), analyses have moved to synergistic and cumulative effects on landscapes (Krummel *et al.* 1984), to continental impacts of acid precipitation and to global effects of CO_2 and other trace gases.

As analyses move to larger scales, it becomes necessary to deal with new phenomena that arise at these levels (O'Neill *et al.* 1986, Allen *et al.* 1987). The spatial patterning of ecosystem types is a unique new phenomenon that arises at the landscape level (Klopatek *et al.* 1983). The problem, therefore, is to detect and quantify pattern in the spatial heterogeneity of landscapes. Our approach is to develop and test a set of indices that capture important aspects of landscape pattern in a few numbers. The indices are tested on a data set that covers most of the eastern United States. By correlating the indices with ecological phenomena such as the propagation of disturbances or the movement of organisms, it should be possible to link small-scale ecological information with pattern at the landscape level.

Materials and methods

The analyses are based on digitized maps of land cover available from the U.S. Geological Survey (Fegeas *et al.* 1983). The maps are derived from high altitude aerial photography at a 1:250,000 scale with each scene (Fig. 1) covering one degree of latitude and two degrees of longitude. Seven land use categories (Table 1) are provided on the tapes. The data describe the shape and extent of each land use patch in both grid and polygonal format. The polygonal format provides a series of vectors describing the boundaries enclosing a single land use category. Minimal polygon size is 16 ha for most categories with individual grid units of 200 meters.

Table 1. Land use categories used in the calculation of pattern indices (Fegeas *et al.* 1983)

1. Urban or built-up land: residual, industrial, etc.
2. Agricultural land: cropland, orchards, etc.
3. Rangeland: herbaceous and shrub-brushland.
4. Forest: deciduous, evergreen, and mixed.
5. Water: stream, lakes, estuaries, etc.
6. Wetlands: forested and nonforested.
7. Barren land: beaches, exposed rock, strip mines, etc.

Four-hectare resolution is used for categories 1 and 5 and for miscellaneous subcategories such as strip mines, confined cattle feeding operations, etc. Figure 1 shows the landscape scenes included in the analyses. Grid tapes were available for all 94 scenes. For the shaded scenes, polygon tapes were also available.

We developed three indices of pattern, two based on information theoretic measures (Shannon and Weaver 1962) and one on fractal geometry (Mandelbrot 1983). The first index, D_1, is a measure of dominance:

$$D_1 = \ln n + \sum_{i=1}^{m} P_i \ln P_i \qquad (1)$$

where P_i is the proportion of the grid cells on the landscape in land use i and n is the total number of land use categories in a particular scene. The term, ln n, represents a maximum with all land use types present in equal proportions. Since P_i is less than 1.0, ln P_i is negative and the summation in Eq. (1) yields a negative value. Therefore, D_1 represents the deviation of the calculated value from the maximum. As the summation term in Eq. (1) increases to the maximum, the value of D_1 approaches 0.0. The use of the maximum term in the equation tends to normalize the index across landscapes with different numbers of land cover types.

The dominance index, D_1, measures the extent to which one or a few land uses dominate the landscape. At large values of D_1, the summation term in Eq. (1) deviates from the equiprobable maximum and the landscape is dominated by one or a few land uses. At small values of D_1, many land use types are found in approximately equal proportions.

The second index, D_2, is a measure of contagion:

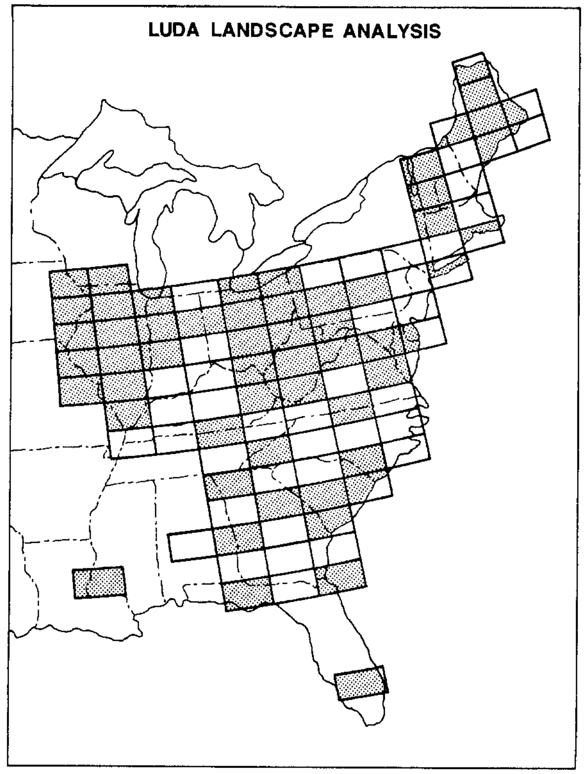

Fig. 1. Map of the eastern United States showing the quadrangles included in the present analysis. Shaded rectangles indicate scenes with data available in both grid and polygon (*i.e.*, vector) formats.

$$D_2 = 2n \ln n + \sum_{i=1}^{n} \sum_{j=1}^{n} P_{ij} \ln P_{ij} \qquad (2)$$

where P_{ij} is the probability of a grid point of land use i being found adjacent to a grid point of land use j. The term, 2n ln n, represents a maximum in which all adjacency probabilities are equal, *i.e.*, for a randomly chosen spot on the landscape, there is an equal probability of any land cover being adjacent to the chosen spot. As in Eq. (1), the summation in Eq. (2) yields a negative value and D_2 represents the deviation of the calculated value from the maximum .

The contagion index, D_2, measures the extent to which land uses are aggregated or clumped. At high values of D_2, the summation term deviates from the equiprobable maximum and large, contiguous patches are found on the landscape. At low values, the landscape is dissected into many small patches.

Table 2. Landscape indices and summary information for 94 landscapes in Eastern United States. The percentage of the landscape in urban, agriculture and forest is given by P_1, P_2, and P_4, respectively. The indices D_1, D_2, and D_4 relate to the dominance, contagion, and complexity of patterns, respectively. The value of U is calculated from the ratio of intensely managed land uses to undisturbed areas

Site	P1	P2	P4	D1	D2	D3*	U
Albany NY	11.6	19.0	64.2	0.74	12.0	1.41	0.46
Athens GA	2.8	17.6	76.7	1.06	14.6	1.32	0.26
Atlanta GA	9.3	20.8	68.1	1.05	16.0		0.44
Augusta GA	3.2	31.2	48.2	0.69	18.4	1.36	0.56
Aurora IL	6.0	87.2	4.2	1.40	17.4	1.28	20.70
Baltimore MD	9.6	58.0	24.3	0.67	13.6		2.74
Bangor ME	3.8	7.7	64.9	0.83	15.3		0.17
Beaufort NC	6.8	12.0	41.3	0.47	18.1		0.28
Belleville IL	2.3	80.1	15.6	1.29	19.8	1.29	5.22
Bluefield WV	2.9	16.1	78.8	0.93	9.5	1.34	0.24
Boston MA	23.6	6.4	60.2	0.80	16.3		0.48
Brunswick GA	4.0	4.2	53.2	0.75	17.8		0.10
Burlington IL	1.5	80.0	14.6	1.25	19.5	1.28	5.19
Cantoan OH	13.0	46.9	37.0	0.67	12.0	1.45	1.61
Charleston WV	1.8	9.6	87.4	1.31	12.2	1.38	0.13
Charlottesville VA	4.3	28.5	66.6	1.15	16.6	1.42	0.49
Charlotte NC	9.7	37.6	49.9	0.88	17.2		0.94
Chattanooga TN	6.2	26.8	61.7	0.77	12.4		0.53
Chicago, IL	13.6	61.8	7.3	0.65	14.6	1.29	8.82
Cincinatti, OH	11.0	75.9	11.9	1.03	12.3		7.30
Clarksburg WV	2.1	31.7	63.7	1.10	16.0	1.41	0.53
Cleveland OH	12.9	50.4	13.6	0.48	15.2	1.25	3.98
Columbus OH	5.8	67.6	24.7	0.93	13.3	1.39	2.97
Corbin KY	5.0	25.9	64.7	0.84	12.7	1.35	0.48
Cumberland WV	1.7	24.9	71.4	1.19	17.2	1.35	0.37
Danville IL	2.3	93.5	3.7	1.49	13.2	1.25	25.91
Davenport IW	3.3	86.0	7.5	1.21	13.7	1.27	10.03
Decatur IL	2.4	89.3	7.4	1.36	13.2	1.27	12.26
Dothan AL	1.9	46.1	46.2	0.95	16.7		0.95
Dubuque IW	1.4	87.1	9.1	1.28	14.3	1.24	8.82
Dyersburg KY	1.7	73.9	16.4	1.08	19.1		3.72
Eastport ME	1.1	5.8	65.2	0.85	16.0	1.33	0.09
Edmunston ME	0.5	10.5	81.9	1.12	14.4	1.45	0.13
Evansville KY	4.9	53.3	31.6	0.61	12.8		1.59
Florence SC	1.9	30.4	43.1	0.74	17.3	1.34	0.49
Fredrickton ME	0.4	3.4	74.8	0.95	14.1	1.41	0.04
Ft Wayne IN	4.0	88.1	5.8	1.29	12.7		14.43
Georgetown GA	2.9	20.0	47.6	0.69	17.1	1.42	0.31
Greenville SC	6.3	29.4	61.5	0.84	12.9		0.58
Glens Falls NY	2.3	19.0	75.5	1.05	14.5	1.32	0.28
Greensboro NC	5.8	38.0	54.0	0.82	13.1	1.38	0.80
Hartford CN	17.6	13.7	48.4	0.63	15.8		0.64
Harrisburg PA	4.6	48.7	43.9	0.98	18.9	1.33	1.00
Huntington KY	2.0	29.3	66.9	1.15	16.8	1.28	0.47
Indianapolis IN	6.0	67.5	25.0	0.93	14.3	1.30	2.93
Jacksonville FL	11.6	3.7	56.4	0.68	16.3	1.38	0.20
Jenkins KY	0.8	6.3	90.7	1.22	10.3	1.34	0.08
Johnson City TN	4.1	32.8	59.4	0.98	17.6		0.62
Knoxville TN	5.4	16.5	75.9	1.18	17.0	1.37	0.29
Lake Champlain NY	2.7	26.5	62.2	0.94	18.3	1.36	0.46
Lewiston ME	1.4	5.7	87.5	1.53	22.8		0.08

Table 2. Cont.

Site	P1	P2	P4	D1	D2	D3*	U
Louisville KY	9.9	61.7	27.0	1.00	16.8		2.64
Macon GA	2.0	36.7	54.5	0.96	18.0		0.64
Marion OH	5.5	85.2	8.5	1.40	18.1	1.29	10.69
Millinocket ME	0.5	2.8	78.0	1.18	18.0	1.39	0.04
Montgomery AL	1.7	33.3	61.8	1.06	17.0		0.56
Muncie IN	3.3	93.9	2.1	1.50	14.4	1.27	47.04
Nashville TN	8.1	50.1	38.2	0.73	13.0		1.51
Natchez MI	1.0	34.5	55.4	0.91	17.9	1.39	0.58
Newark NJ	32.3	29.0	28.0	0.37	13.4		1.96
New York NY	52.1	5.3	11.2	0.53	13.4	1.35	4.28
Norfolk VA	6.6	29.2	43.2	0.56	16.6		0.63
Paducah KY	2.3	69.0	23.4	1.05	17.4	1.29	2.86
Peoria IL	3.3	91.4	3.7	1.40	13.9	1.27	25.15
Phenix City AL	3.0	21.8	71.3	1.10	17.4	1.29	0.34
Pittsburgh PA	6.7	30.1	59.5	0.95	16.9	1.33	0.62
Portland NH	7.6	6.1	76.6	1.21	20.7		0.17
Presque Isle ME	0.3	3.3	86.6	1.23	14.0	1.37	0.04
Providence RI	12.1	5.7	44.8	0.55	17.3	1.30	0.38
Quincy IL	1.1	79.8	17.4	1.33	17.1	1.31	4.56
Raleigh NC	7.8	26.5	64.1	1.03	16.6	1.28	0.53
Richmond VA	5.7	17.6	51.1	0.52	12.8	1.41	0.43
Roanoke VA	5.0	26.2	67.4	1.11	17.1		0.46
Rockford IL	7.0	82.9	5.8	1.10	12.3	1.26	12.20
Rocky Mount NC	3.0	28.8	33.3	0.48	18.6		0.63
Rome GA	3.0	21.0	73.5	1.17	18.6	1.27	0.33
Savannah GA	3.2	27.8	33.4	0.55	16.2	1.33	0.49
Scranton PA	9.8	22.6	64.2	0.96	16.6		0.50
Salisbury VA	4.5	37.9	31.9	0.37	13.0	1.44	1.03
Sherbrooke ME	0.2	0.5	91.2	1.41	15.5	1.37	0.01
Spartanburg SC	4.7	28.3	63.1	0.99	18.6		0.51
St. Louis MO	7.3	42.7	46.8	0.90	17.1	1.28	1.05
Tallahassee FL	2.6	19.6	61.1	0.82	16.1	1.39	0.30
Toledo OH	5.8	65.7	3.4	1.00	18.7	1.29	18.21
Valdosta GA	1.9	18.2	58.7	0.87	16.2		0.26
Vincennes IN	4.0	64.0	28.6	0.87	12.9		2.29
Waycross GA	1.1	37.3	49.5	0.75	13.7		0.63
Warren PA	2.0	15.8	79.6	1.28	18.0		0.22
Washington DC	13.1	24.0	37.7	0.34	13.0	1.40	0.91
West Palm FL	5.3	25.9	8.2	0.24	19.7	1.33	0.80
Williamsport NY	1.3	30.2	67.2	1.19	16.3		0.47
Wilmington DL	14.4	29.1	27.6	0.19	12.3		1.06
Winchester KY	4.6	60.4	33.9	0.92	12.5		1.91
Winston Salem NC	4.0	34.8	60.3	1.09	17.1		0.64

*Calculated only for scenes for which the data were available polygonal format.

Information theoretic indices, such as D_1 and D_2, have been criticized (*e.g.*, Pielou 1975, Phipps 1981) because of their sensitivity to varying values of n. The 94 landscape scenes analyzed here have $n = 6$ or 7. Therefore, potential problems with widely varying values of n did not arise in this study.

The third index, D_3, is a measure of the fractal geometry of the landscape (Mandelbrot 1983). It is estimated by regressing polygon area against perimeter for each patch on a digitized map. The fractal dimension is related to the slope of the regression, S, by the relationship (Lovejoy 1982):

$$D3 = 2\,S. \tag{3}$$

Because D_3 requires perimeter-area information, this index could only be calculated for the 58 quadrangles for which vector data sets were available (Fig. 1).

The fractal dimension, D_3, is an index of the complexity of shapes on the landscape. If the landscape is composed of simple geometric shapes like squares and rectangles, the fractal dimension will be small, approaching 1.0. If the landscape contains many patches with complex and convoluted shapes, the fractal dimension will be large (Krummel *et al.* 1987).

Results

Table 2 gives the values of the indices calculated for the 94 landscape scenes. The table also contains the percentage of the scenes in urban (P_1), agriculture (P_2, forest (P_4), and a measure of disturbance (U). This measure is a ratio consisting of intensely managed land uses, P_1 (urban) + P_2 (agriculture), divided by relatively undisturbed land uses, P_4 (forest) + P_6 (wetlands). The ratio, U, is included to test whether any of the pattern indices are correlated with human activities and disturbance.

Values of the indices cover a sufficient range to discriminate among different landscape types (Table 2). D_1 ranges from a low of 0.19 for Wilmington, DL to a high of 1.53 for Lewiston, ME. The possible range of this index for seven land cover types is from 0.0–1.94 so the measured values encompass 69% of the potential range of the index. This spread is important because discrimination between landscape data sets would be difficult if the measured values fall within a narrow range. Low values of D_1 are associated with landscapes in which many land use types (*e.g.*, urban, agricultural, and natural vegetation) occur in approximately equal proportions within the quadrangle. High values, indicating dominance of the landscape by one or a few land uses, are associated with intensive crop production or undisturbed forests.

The contagion index, D_2, has a potential range of 0.0 to 6.8 for seven land cover types. The values for the eastern landscapes range from 1.29 for Albany, NY to 6.19 for Lewiston, ME. The fact that Lewiston, ME has the maximum value for both D_1 and D_2 indicates some redundancy of information in these two indices, at least at the extremes. This is reasonable because Lewiston is dominated by forests (87% coverage) that form essentially one large cluster, giving a high index for contagion as well as for dominance. Low values of D_2, indicating highly dissected landscapes, tend to occur where human development (*e.g.*, Albany, NY) or topography (*e.g.*, Bluefield, WV) dissect the landscape into many small patches. Perusal of the table, however, will reveal many exceptions. High values of D_2 may be associated with landscapes having many land use types (*e.g.*, Dyersburg, KY) and low values may occur where neither development nor topography dominate (*e.g.*, Corbin, KY) as a result, there is no significant correlation between the indices (Table 4) even though they show some relationship at the extremes.

The fractal dimension D_3, has a potential range of 1.0 to about 1.5. The upper value of 1.5 corresponds to shapes drawn by random Brownian movement with zero autocorrelation (Burrough 1983). The sampled landscapes cover 42% of the range. The smallest values of D_3 (*e.g.*, 1.23 for Dubuque, IA) are associated with agricultural landscapes where simple rectangular shapes dominate. The high values (*e.g.*, 1.44 for Edmundston, ME) are associated with areas where topography or the coastline force land use patches into complex shapes.

Geographic patterns in indices

The ability of the indices to discriminate among landscape types can be judged by examining their geographic distribution. We would expect the indices, for example, to discriminate between the agricultural landscapes of the central states and the mountainous landscapes of the Appalachian region.

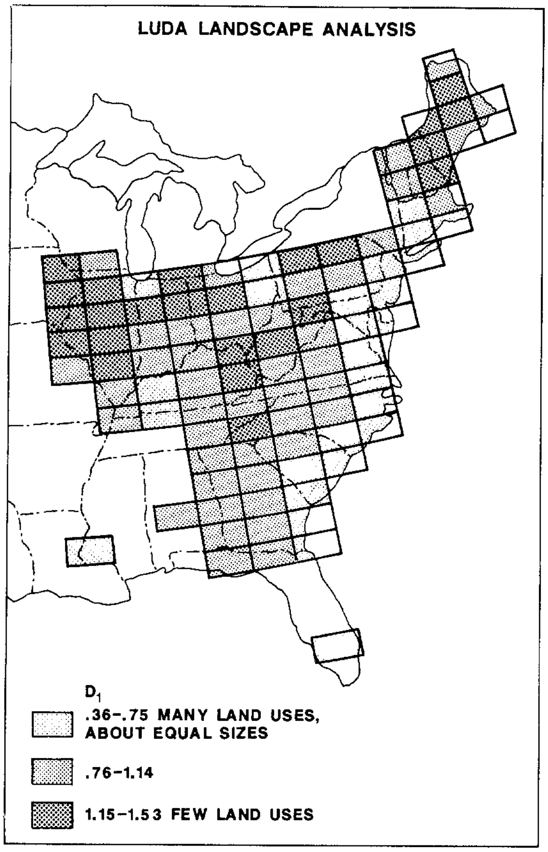

Fig. 2. Geographic distribution of the dominance index, D_1 (Equation 1).

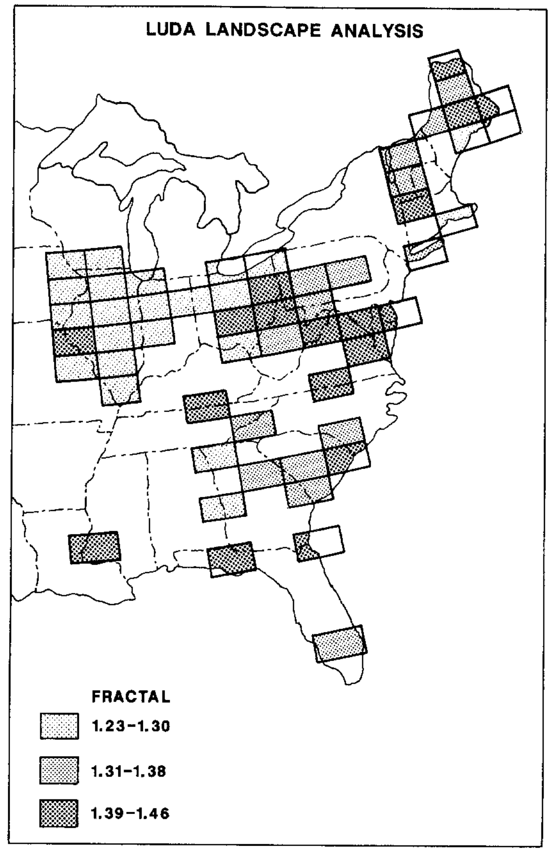

Fig. 3. Geographic distribution of the fractal dimension, D_3 (Equation 3).

Figure 2 shows the distribution of D_1. High values of D_1, indicating few land cover types, are found in the agricultural regions of the upper Midwest and in the forests of New England. Low values of D_1, indicating many cover types of about equal area, are found in the coastal regions where urban, agricultural, forest, and wetland cover tends to be mixed in complex patterns.

Figure 3 shows the geographic distribution for the fractal dimension, D_3. Low values, indicative of simple patch shapes, occur in agricultural regions. Higher values, associated with complex patch shapes, are found in coastal/estuarine areas and regions of complex topography. Both D_1 and the fractal dimension, therefore, seem to capture broad-scale features of the landscape taken as a unit.

There is no apparent overall pattern in the geographic distribution of D_2 (Fig. 4). Highly dissected landscapes are found throughout the eastern United States and do not seem to be simply associated with gross features such as topography. Thus, in contrast to D_1 and D_3, D_2 seems to capture the fine-grained arrangement of individual patches on the landscape.

Statistical properties of indices

Measured values of an ideal index should be distributed over the full range of potential values. If most values fall in the middle of the range, then many landscapes will have similar values and the index will have little power to discriminate. The ideal situation is unlikely to be realized because extreme values are infrequent and some central tendency

Table 3. Frequency distributions of pattern indices. Values given are the percentage of the total landscape scenes with index values that fall within each decade, from the lowest to the highest value for each index. D_1 is the dominance index, D_2 is contagion, and D_3 is fractal dimension

Decade	D_1	D_2	D_3
1	2	11	7
2	3	11	9
3	8	18	19
4	11	13	7
5	15	16	15
6	18	11	10
7	17	9	10
8	12	5	9
9	9	2	9
10	5	4	5

can always be expected. Table 3 shows the frequency distributions of the indices with the range divided into 10 equal intervals or decades. The distribution are quite broad with the highest frequencies spread across a number of the central decades. The distributions appear to be sufficiently broad to permit adequate discrimination among landscapes.

Useful indices should also be relatively independent of each other. At the very least, it is important that they do not duplicate the same pattern information. A simple test of the relationship among the indices is given by calculating correlation coefficients between indices (Table 4). Because calculation of the fractal dimension, D_3, requires polygonal data, it was only possible to compare indices for 58 scenes.

The high negative correlation between P_2 (agriculture) and P_4 (forest) expresses a general property of eastern landscapes: they tend to be dominated by either forest or agriculture. This is not surprising since most of the agricultural land in the eastern United States is in areas that were originally forest. The correlation between P_2 and D_1 indicates that landscapes that are dominated by a single land use tend to be agricultural. The low correlation of D_1 with P_4 indicates that forested landscapes are not simply dominated by forests but tend to have other land uses as well.

D_2 is not correlated with either P_2 or P_4, which seems to confirm the conclusion reached from Figs

Table 4. Pearson correlation coefficients expressing the relationships between landscape indices. P_2 is the proportion of the landscape in agriculture, P_4 is the proportion in forest. D_1 is an index of dominance, D_2 of contagion, and D_3 is the fractal dimension of patches

	P_4	D_1	D_2	D_3
P_2	−0.84	0.42	0.06	−0.60
P_4		0.02	−0.10	0.52
D_1			0.05	−0.38
D_2				−0.18
U		0.15	0.05	−0.50

2–4: D_2 captures the fine-grain texture of the landscape rather than overall properties. This conclusion is further reinforced by the lack of a significant ($p < 0.05$) correlation between D_2 and either D_1 or D_3. D_2 appears to be related to small-scale patterns that are not captured by the other indices.

The relationship between D_1 and D_3 is significant ($p < 0.005$). Landscapes dominated by agriculture (high D_1) tend to be divided into simple squares and rectangles, giving small fractal dimensions. However, over most of the range of D_1, there is no relationship between D_1 and D_3. The significant correlation results from the relationship that exists over the high range of the dominance index.

The fractal dimension shows highly significant correlations ($p < 0.0001$, Table 4) with P_2, P_4 and U. This reflects the fact that landscapes dominated by agriculture tend to have simple polygons and low fractal dimensions (negative correlation), and landscapes dominated by forest tend to have complex shapes and high fractal dimensions (positive correlation). The correlation with U indicates a relationship between fractal dimension and the degree to which the landscape has been manipulated by man. Human activities related to crop production and urban development tend to simplify shapes, smooth and flatten contours, and result in simpler polygonal shapes (Krummel *et al.* 1987).

In summary, the three indices are not completely independent of each other and at extreme values may duplicate information. However, the correlations are not large enough to indicate that any of the three should be dropped from further use as a pattern index.

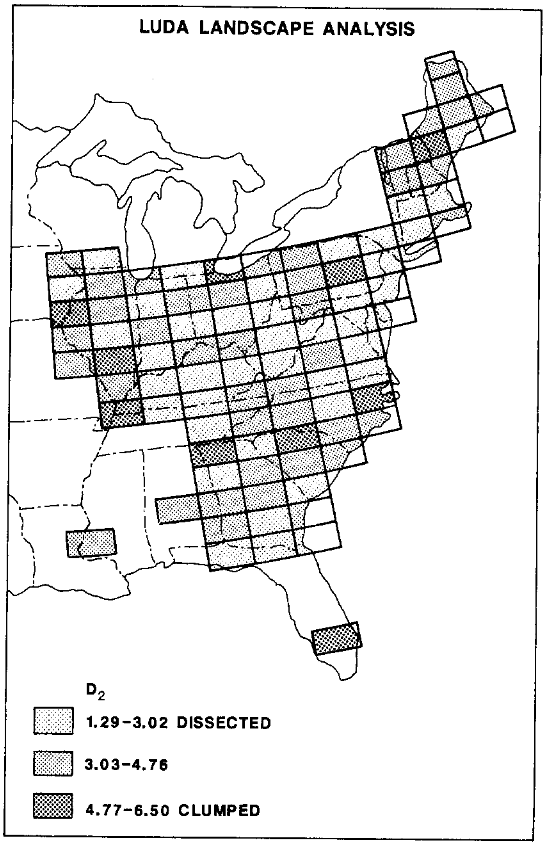

Fig. 4. Geographic distribution of the contagion index, D_2 (Equation 2).

Indices and landscape classes

Another way to test for the need to retain all three indicators is to construct a type of dichotomous key (Table 5). By emphasizing the high and low instances of each index (see Figs 2–4) it is possible to determine whether all three indices are needed to divide the landscapes into meaningful subgroups that would be useful for ecological assessment.

First, let us consider scenes that have high values for both D_1 and D_2 (landscapes dominated by a few land uses that are highly clumped). Does the additional specification of the fractal dimension help discriminate among this group in a meaningful way? The answer is yes. Forested landscapes have a high D_3, *e.g.*, Sherbrooke, ME (91% forest). Agricultural landscapes have low fractal dimensions, *e.g.*, Belleville and Burlington, IL, both with about 80% agriculture. The interesting exception would seem to be Rome, GA (Table 5, 73% forest). However, the forests in the Rome quadrangle are primarily pine plantations, subject to the same shape simplification as row crops.

Table 5. Landscape scenes with high (upper 33%) or low (lower 33%) values for the landscape indices (see legends for Figs 2–4)

D_1	D_2	D_3	Landscape scenes
High	Clumped	Complex	Sherbrooke
High	Clumped	Simple	Belleville, Burlington, Rome
High	Dissected	Complex	Charleston, Charlottesville, Clarksburg
High	Dissected	Simple	Danville, Davenport, Decatur, Rockford
Low	Clumped	Complex	None
Low	Clumped	Simple	None
Low	Dissected	Complex	Richmond. Salisbury, Washington
Low	Dissected	Simple	None

As a second test, we can consider scenes with high D_1 (few land uses) and low D_2 (dissected into small patches). In this case, a large fractal dimension is associated with rugged topography, *e.g.*, West Virginia and Virginia. By including D_3, it is possible to differentiate these forested landscapes from areas in Illinois and Iowa (Danville, Davenport, Decatur, Rockford) where flatter topography permits simple linear shapes to be imposed on the landscape.

The combination of low D_1 (many equal land uses) and low D_2 (dissected) occurs in combination with a high fractal dimension (complex shapes). This combination characterizes coastal areas where a mixture of urban, agricultural, and natural land uses are further constrained by the dissected coastline (Richmond, VA, Salisbury, VA, Washington, DC).

The eastern landscapes contained no examples with low D_1 (many equal land uses) and high D_2 (clumped) since this is almost a contradiction in terms. This is also partially the reason that there is a small positive correlation between D_1 and D_2 in Table 3. Also, there are no examples of low D_1, low D_2 and low D_3 in the eastern United States, which helps explain the small negative correlation between D_2 and D_3 in Table 2.

Discussion

Our analyses support the argument that a small set of indices can capture significant aspects of landscape pattern. The indices discriminate among major landscape types such as urban coastal landscapes, mountain forests, and agricultural areas. There is excellent sensitivity to some determinants of pattern, *e.g.*, the ability to recognize the agricultural pattern in the Rome GA tree plantations (Table 5).

Useful indices have a number of desirable features which seem reasonably satisfied by the set proposed and tested here. First, the measured values (Table 3) are reasonably distributed across the potential range of the index, providing maximum discrimination. Second, the indices performed well in discriminating the geographic distribution of landscape pattern types (Figs 2–4). Third, Table 4 indicates that the information contained in each of the indices is relatively independent. Fourth, it appears that all three indices, taken together, are helpful in discriminating among landscape types (Table 5).

An interesting result, emerging from the analysis of geographic distributions, was that D_1 and D_3 seem to capture gross features of landscape pattern. On the other hand, D_2, measuring how individual pixels are arranged relative to each other, seems to relate to a fine-grained texture on the landscape. The fact that one of the indices captures a different scale of pattern could be valuable in further investigations.

An interesting feature of the correlation analysis is the relationship between D_3 and landscape disturbance, U. Based on the Krummel *et al.* (1987) analysis, one would expect that increased agricultural or urban disturbance would lower fractal dimension and that is exactly what the correlation shows (Table 4). This result seems to lay a firm foundation to the claim that fractal dimension is a reasonable index of human activities on the landscape.

Perhaps the most exciting prospect raised by the study is the possibility of remotely sensing ecological change at the landscape level. The indices were deliberately designed to minimize the need for groundtruth information. It now seems possible to take raw satellite or aircraft data in the form of reflectances and divide the reflectances into discrete classes. In the simplest case, the total range of reflectance could be divided into seven equal intervals. Even without knowing what each discrete class represents in terms of vegetation or land use, changes in the indices over time provide valuable information. Thus, an increase or decrease in the fractal dimension through time indicates the degree to which human activities are disturbing and simplifying the landscape patterns, regardless of the specific land uses.

Continued research will be critical in applying the indices to landscape ecology and large-scale environmental assessment. In particular, correlations must be established between index values and ecological processes occurring on the ground. The basic question is: 'Knowing only the values of the indices and how they change through time, how well can one specify the corresponding ecological changes?' Although this represents a difficult research question, there is good reason for optimism. For many processes, it is possible to intuit the significance of the indices. Small values of D_2 indicate a dissected landscape and a large ratio of forest edge to forest interior. Changes in D_2 indicate change in the forest edge ratio and should be predictive of changes in populations of edge species. It may also be possible to relate changes in D_2 with generalizations derived from island biogeography theory. For many large-scale problems, the prospect of remotely sensing environmental changes over large spatial units opens new possibilities for understanding continental and global processes.

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Literature cited

Allen, T.F.H., O'Neill, R.V. and Hoekstra, T.W. 1987. Interlevel relations in ecological research and management: some working principles from hierarchy theory. J. Appl. Syst. Anal. 14: 63–79.

Burrough, P.A. 1983. Multiscale sources of spatial variation in soil. The application of fractal concepts to nested levels of soil variation. J. Soil Sci. 34: 577–597.

Fegeas, R.G., Claire, R.W., Guptill, S.C., Anderson, K.E. and Hallam, C.A. 1983. Land Use and Land Cover Digital Data. Geological Survey Circular 895-E, U.S. Geological Survey, Washington, D.C. 21 pp.

Klopatek, J.M., Krummel, J.R., Mankin, J.B. and O'Neill, R.V. 1983. A theoretical approach to regional energy conflicts. J. Env. Managem. 16: 1–15.

Krummel, J.R., Gardner, R.H., Sugihara, G., O'Neill, R.V. and Coleman, P.R. 1987. Landscape pattern in a disturbed environment. Oikos 48: 321–324.

Krummel, J.R., Gilmore, C.C. and O'Neill, R.V. 1984. Locating vegetation at-risk to air pollution: an exploration of a regional approach. J. Env. Managem. 18: 279–290.

Lovejoy, S. 1982. Area-perimeter relation for rain and cloud areas. Science 216: 185–187.

Mandelbrot, B. 1983. The Fractal Geometry of Nature. W.H. Freeman and Co., New York, NY. 460 pp.

O'Neill, R.V., DeAngelis, D.L., Waide, J.B. and Allen, T.F.H. 1986. A Hierarchical Concept of Ecosystems. Princeton University Press, Princeton, NJ 253 pp.

Phipps, M. 1981. Entropy and community pattern analysis. J. Theor. Biol. 93: 253–273.

Pielou, E.C. 1975. Ecological Diversity. Wiley-Intersciences, New York, NY. 165 pp.

Shannon, C.E. and Weaver, W. 1962. The Mathematical Theory of Communication. University of Illinois Press, Urbana, IL. 125 pp.