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Relationships between landcover proportion and indices of landscape spatial pattern

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Abstract

Recent studies have related percolation theory and critical phenomena to the spatial pattern of landscapes. We generated simulated landscapes of forest and non-forest landcover to investigate the relationship between the proportion of forest (P_i) and indices of patch spatial pattern. One set of landscapes was generated by randomly assigning each pixel independently of other pixels, and a second set was generated by randomly assigning rectilinear clumps of pixels. Indices of spatial pattern were calculated and plotted against P_i. The random-clump landscapes were also compared with real agricultural landscapes.

The results support the use of percolation models as neutral models in landscape ecology, and the performance of the indices studied.with these neutral models can be used to help interpret those indices calculated for real landscapes.

Introduction

Spatial pattern of landscapes is a primary focus of landscape ecology (Harris 1984; Forman and Godron 1986; Krummel *et al.* 1987; Urban *et al.* 1987; Ambrose and Bratton 1990), due to the relationship between spatial configuration and ecological processes (Senft *et al.* 1987; Turner 1989; Cale *et al.* 1989; Graham *et al.* 1991). Development of quantitative indices of spatial pattern (Bowen and Burgess 1981; O'Neill *et al.* 1988a) can be used to enhance our understanding of relationships between spatial pattern and ecological processes.

Recent studies have begun to relate percolation theory and critical phenomena to the spatial pattern of landscapes (O'Neill *et al.* 1988b; Gardner *et al.* 1987; Turner *et al.* 1989). Percolation theory is applied to a large array of points or pixels on which pixels are occupied independently of each other (Stauffer 1985; Orbach 1986). A cluster forms when a group of occupied neighbor pixels are connected by common vertical or horizontal edges, and a percolating cluster is a cluster which extends between opposite sides of the array.

Applications of percolation theory to ecological questions model a landscape as a large grid (or a raster landcover map) with pixels occupied by landcover type i at a given proportion, P_i. This model considers only one landcover at a time (type i and all others, j), and is generally used as a neutral model (see Gardner *et al.* 1987). As the proportion of landcover i (P_i) approaches a critical proportion (P_c), the probability that a percolating cluster will form changes from near 0.0 to 1 .O, approximating a step-function. This critical phenomenon for percolation arrays has been well studied by physicists, and for infinitely large arrays, P_c = 0.5928 (Stauffer 1985).

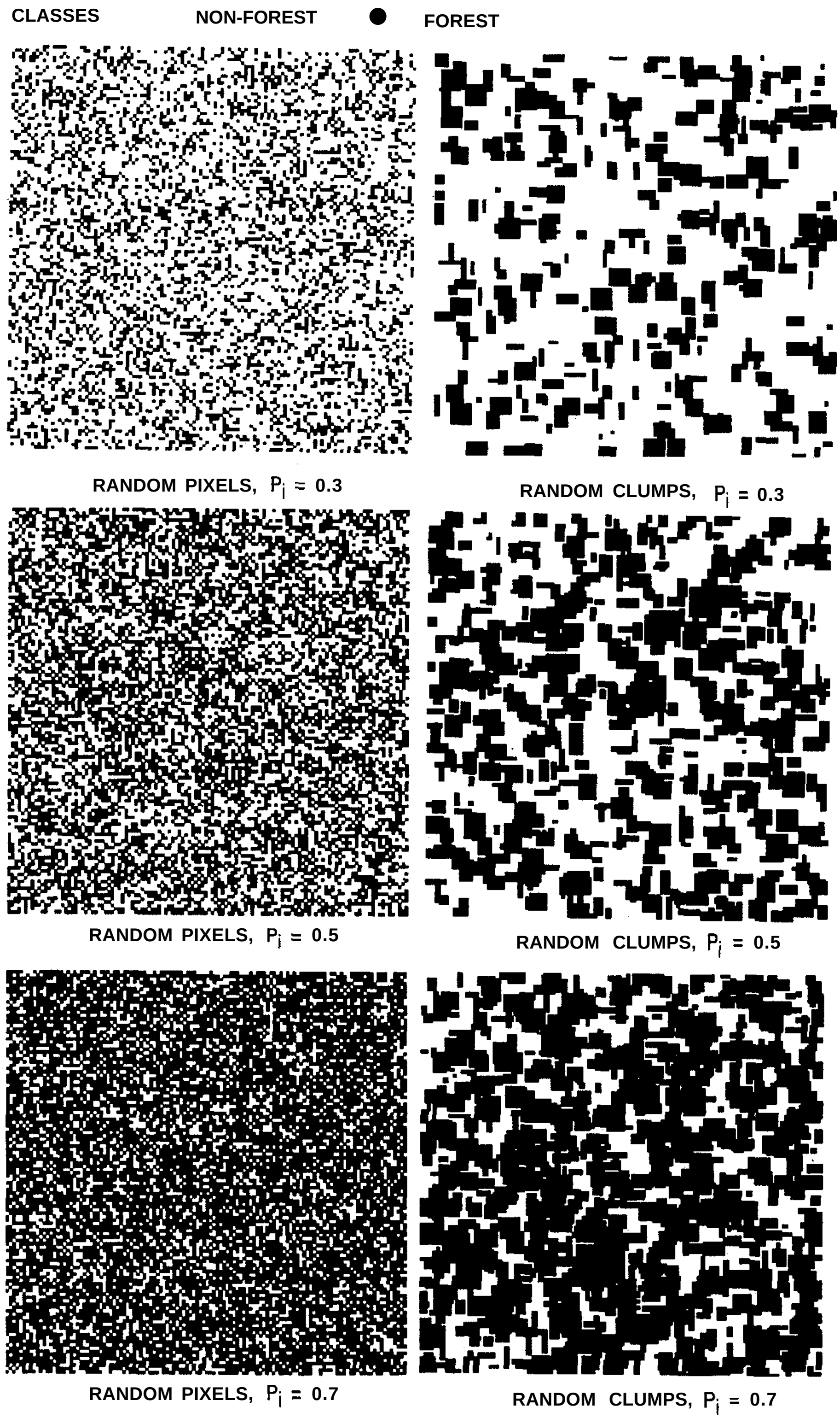

Fig. 1. Examples of simulated landscapes generated by assigning independent random pixels or randomly placed rectilinear clumps. See text for explanation.

Percolation theory deals specifically with the number and properties of clusters on a large array, questions not unlike those of landscape ecologists considering patches on a landscape. However, the connection between percolation theory and spatial properties of patches at landscape scales has not been made.

The purpose of this study was to investigate the relationships between landcover proportion (P_i) and indices of patch spatial pattern on a landscape, using computer-generated landscape arrays. Simulated landscapes were also compared with Thematic Mapper (TM) classifications of real landscapes.

Methods

Simulated landscapes consisting of 2 landcover types (landcover i, and all other landcovers, j) were generated at various proportions of i (P_i). Each landscape consisted of a grid of 120 by 120 pixels. One set of landscapes was generated on a pixel by pixel basis, with each pixel occupied independently with probability P_i as required for percolation arrays. A second set of landscapes was generated such that randomly placed rectilinear clumps of random length and width were added until P_i ($\pm$ 0.006) was reached. The maximum patch length was chosen to approximate the maximum woodlot length commonly found in Thematic Mapper (TM) images of agricultural landscapes in Indiana. The algorithm allowed clumps to overlap so that irregular patches often resulted. Ninety landscapes of each type were generated over a range of P_i ($0.05 < P_i < 0.95$). Examples are given in Fig. 1.

The spatial pattern of each simulated landscape was analyzed using HISA (Habitat Island Spatial Analysis), a FORTRAN routine we developed by modifying Turner's (1990) program called SPAN. HISA was designed primarily to quantify the spatial pattern of a single- landcover type from TM satellite images, and it calculates a number of measures of spatial pattern. Measures of area and distance are calculated according to the pixel size associated with the input data. The following attributes are measured by HISA:

1. Patch size (S), patch perimeter (l), and distance to the nearest neighbor (n) of the patch.

2. Fractal dimension (d) is used as a measure of patch shape complexity (Mandelbrot 1983), and the overall fractal dimension is estimated by regressing log S against log 1, where d is twice the slope of the regression line (Burrough 1986).

3. Contagion (C) quantifies the adjacency of landcover types, and the value can range from 0 to 1, approaching 1 when a clumped pattern is present (O'Neill *et al.* 1988a; Turner 1990), and is given by

$$C = [K_{max} + \Sigma\Sigma q_{i,j} \log(q_{i,j})]/K_{max}$$

where $q_{i\,j}$ is the proportion of pixels of landcover i adjacent'to pixels of landcover j, and $K_{max} = 2.77$, the theoretical maximum for 2 landcover types.

4. A proximity index (PX) was developed which distinguishes isolated patches from those which are part of a complex of patches. The index is calculated for each patch using area (S) and nearest neighbor distance (n) of that patch and each k neighboring patches whose edges are within 10 pixels of the patch being indexed, where

$$PX = \Sigma(S_k/n_k),$$

and S_k is the area of patch k, and n_k is the nearest neighbor distance of patch k. Thisindex is absolute, and allows comparison among landscapes of any size, as long as the search buffer used around each patch is the same. The 10 pixel buffer used corresponds to 300 m on TM images, and can be adjusted to accommodate different pixel sizes.

PX can be scaled as a proportion of the maximum possible value of PX (when the number of patches > 1) for the landscape being analyzed, so that

$$PX_s = PX/PX_{max}$$

where PX_{max} equals the value of PX for 2 patches each approximately half the total area of the landscape (E) separated by the minimum possible n. Due to the nature of percolation arrays, patches which touch other patches on pixel diagonals are considered discontinuous neighbors, and n in this case is estimated as the difference between the distance across the diagonal of a pixel and the distance between 2 sides, or 12.5 m.

$$PX_{max} = E/12.5$$

The value of PX, ranges from 0 to 1, but does not allow comparison between landscapes of different extents (areas), since PX_{max} varies with landscape extent (see Milne (1991) for a discussion of landscape extent). PX, is more readily interpreted than PX, and might be useful in comparative studies of landscapes of similar extent, or where deviations from maximum possible proximity is of interest.

5. Patch elongation index (G) (Carrere 1990) is given by

$$G = 1/\sqrt{S}$$

6. A linearity index (LN) was developed which is based on the medial axis transformation (MAT) skeleton of each patch. The MAT skeleton is derived from a depth map of the patch, where each pixel value represents the distance (in pixels) to the nearest edge. The MAT skeleton is then produced by removing all pixels from the depth map except local maxima (pixels with no neighbors having greater values) (James 1988). The linearity index is based on the fact that elongated patches of a given area will have MAT skeletons closer to their edges than square patches of the same area. The index is calculated using the average (b) of all the values in the MAT skeleton such that

$$LN = 1/S[S/(2b - r)^2) - 11$$

where S is the area of the patch (in pixels), r = 0 if the MAT skeleton contains side-by-side rows, r = 1 if not. Dividing by S normalizes the index since the maximum possible value of the numerator for a patch equals S (when b = 1). LN = 0 for square patches, and LN approaches 1 for large patches which are all edge.

This linearity index reflects linear features of the patch which may not necessarily be the overall elongation of the patch. Dendritic patterns result in higher values of LN due to the elongated appendages of the patch. Inflated values may also result from patches with even small interior openings since these represent edge, and the MAT skeleton will surround the opening, resulting in lower MAT values than if the opening were not present.

7. Average depth and maximum depth to the patch MAT skeleton can be used to evaluate edge and interior conditions found in a landscape. HISA can also output area in edge and interior conditions, as defined by the user.

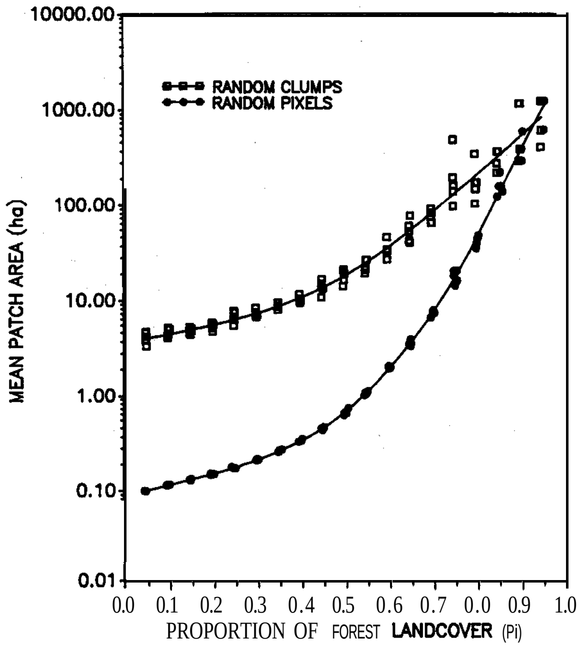

Fig. 2. Relationship between proportion of forest landcover (Pi) and mean patch area in simulated random landscapes.

The indices were plotted against P_i to determine the possibility of critical phenomena associated with these indices, and to elucidate the behavior of these indices in the absence of confounding factors such as topographical effects and human land-use activity. To illustrate trends, smooth curves were fit to the data by cubic spline interpolation.

To understand how the simulated landscapes compare with real landscapes, TM classifications of north-central Indiana landscapes which delineated forest landcover from all other landcovers were submitted to HISA. Four landscapes with predominantly blocky patterns associated with intensive agriculture, and 5 landscapes dominated by river drainages showing dendritic patterns were selected. Simulated 200 by 200 pixel landscapes were generated using the 'random clump' algorithm, matching the proportion of forest cover (Pi) found in the real landscapes. T-tests were conducted between the indices from the simulated landscapes and the real landscapes of similar P_i.

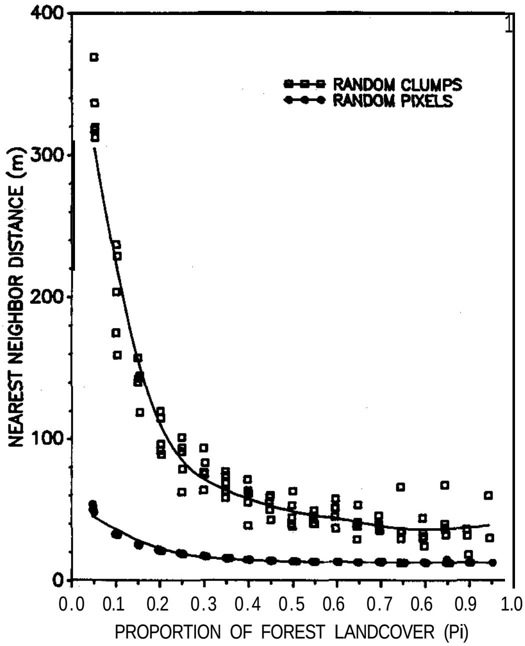

Fig. 3. Relationship between proportion of forest landcover (P_i) and mean distance to nearest patch in simulated random landscapes.

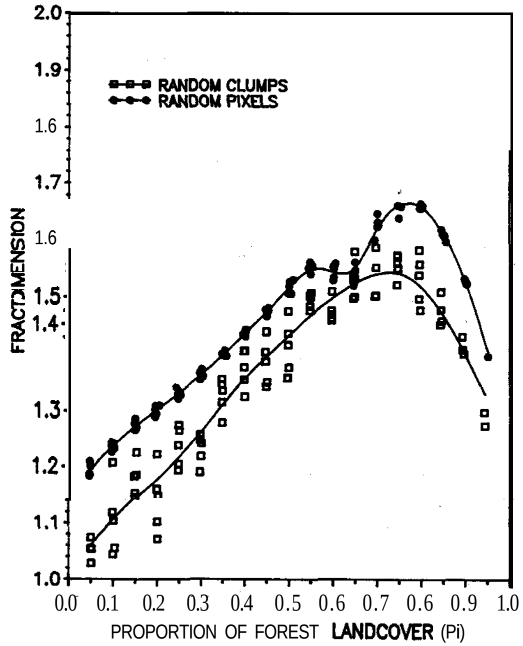

Fig. 4. Relationship between proportion of forest landcover (P_i) and overall landscape fractal dimension in simulated random landscapes.

Results

Mean patch area (S) for Random Pixel Landscapes (RPLs) and Random Clumped Landscapes (RCLs) shows a smooth increase as P_i increases (Fig. 2). The mean patch area of RPLs is low at low P_i, since most patches consist of l-3 pixels, while RCLs are made of patches which are generally > 20 pixels. At high P_i, a single patch dominates the entire landscape in both RPLs and RCLs, causing patch area curves to converge.

Nearest neighbor distance (n) values are less than 60 m (2 pixels) for RPLs at low P_i (Fig. 3), since many small patches are scattered across the landscape. For RCLs, fewer, larger patches are found at low P_i, resulting in generally larger nearest neighbor distances. Nearest neighbor distance declines rapidly as P_i increases, and begins to level off at about P_i = 0.4 for both types of landscapes.

Fractal dimension (d) shows a steady increase as P_i increases for both landscape types, with a slight decline between P_i = 0.55-0.65 (Fig. 4). This decline is likely due to changes in patch area/perimeter relationships associated with the formation of a percolating cluster. Evidently, the coalescence of several smaller patches and the formation of the large percolating cluster reduces average patch complexity slightly and causes a reduction in overall fractal dimension. The decline in fractal dimension when P_i > 0.85 is probably increasingly due to edge effects as the patches have significant portions of their edges determined by the straight edges of the lattice, and partly due to a reduction in patch irregularity as holes are filled in and the patches approach homogeneity.

The contagion index (C) for RCLs showed a slight decline as P_i increased (Fig. 5). Although the algorithm assigned clumps with the same size distribution at all P_i, at high P_i, many of the added clumps had significant portions overlapping existing clumps, resulting in more protrusions from existing patches, causing a relative increase in edge, and a decline in contagion values. On RPLs, landscapes are dominated by large, contiguous clumps of non-forest landcover at low P_i, and large clumps of forest at high P_i. At P_i = 0.5 the landscape is

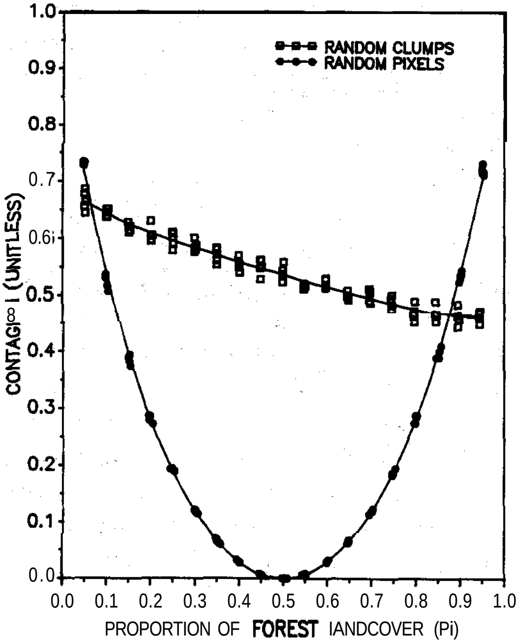

Fig. 5. Relationship between proportion of forest landcover (P_i) and landcover contagion in simulated random landscapes.

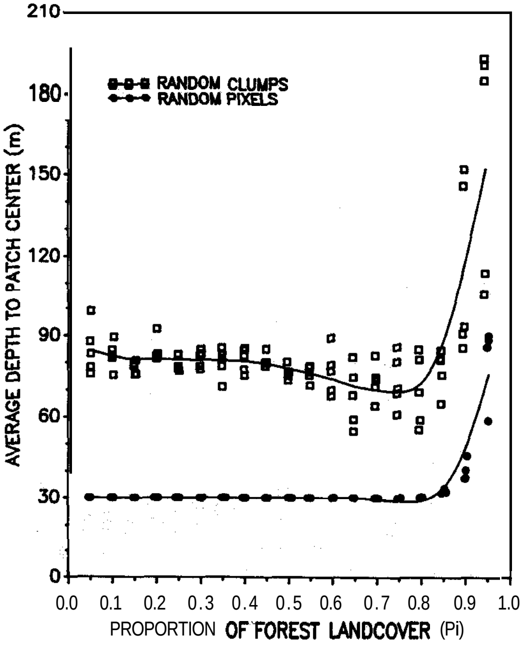

Fig. 7. Relationship between proportion of forest landcover (P_i) and mean average depth to patch center in simulated random landscapes.

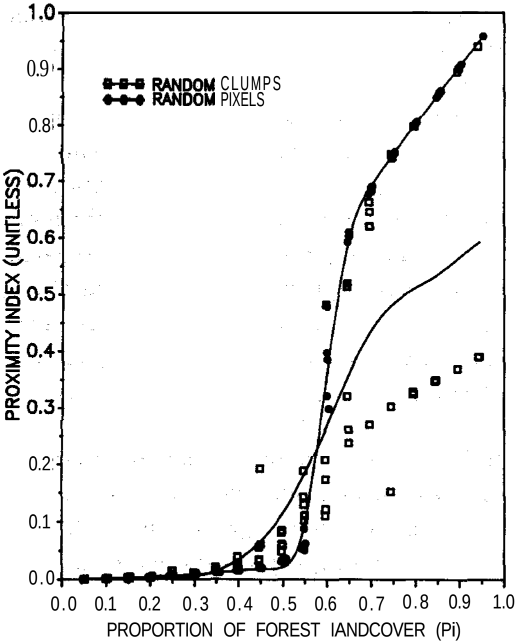

Fig. 6. Relationship between proportion of forest landcover (P_i) and mean patch proximity index in simulated random landscapes.

composed of many small patches, and a pixel is as likely to be adjacent to a forest pixel as a non-forest pixel.

The proximity index (PX_s) clearly shows the development of a percolating cluster at P_c for both landscape types, with a significant jump in the index values at P_c (Fig. 6). The percolating cluster itself has increased area, and it is in close proximity to many of the other patches in the landscape, resulting in increased PX_s values for the percolating cluster and its many neighbors. There is a distinct fork in the trend for RCLs when $P_i > P_c$, which is caused by differences in the nearest neighbor distance of the largest patch. If the nearest neighbor is a diagonal element then the PX, value falls on the upper fork, and if the nearest neighbor is a full pixel away, the PX, value is located on the lower fork. Presumably there is a third fork for nearest neighbors which are 2 pixels away, although such a configuration would be fairly rare when P_i is high. The lowest proximity value in Fig. 6 at P_i = 0.75 may represent such a case. The sensitivity of the proximity index to small differences in nearest

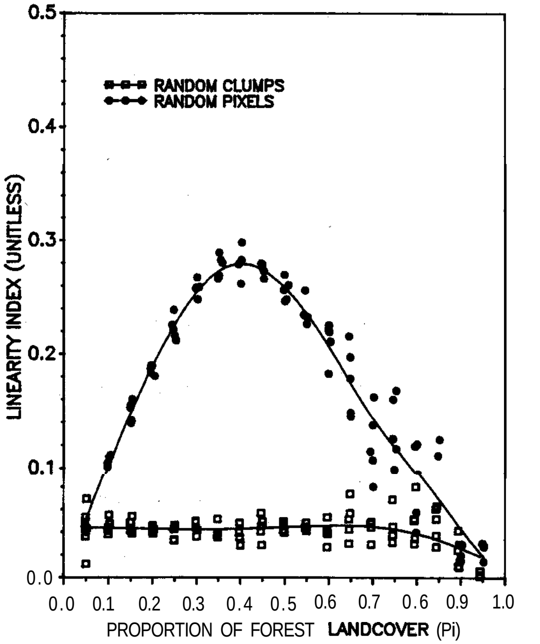

Fig. 8. Relationship between proportion of forest landcover (P_i) and mean patch linearity index in simulated random landscapes.

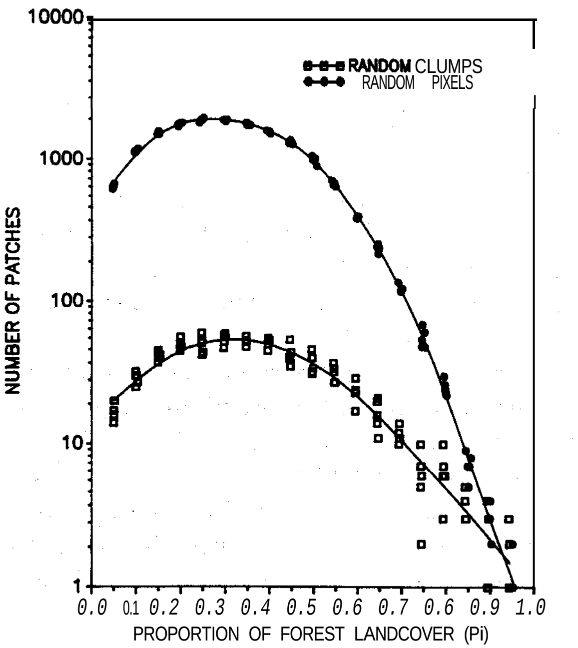

Fig. 9. Relationship between proportion of forest landcover (P_i) and mean number of patches in simulated random landscapes.

neighbor distance at high P_i should be recognized when studying landscapes with high P_i values. Several landscapes at $P_i \geq 0.95$ consisted of a single patch, in which case PX_i is undefined.

Average depth (b) remains at low levels when P_i < 0.85 (Fig. 7) due to the existence of many holes within patches as they coalesce.

The linearity index shows very different trends for RPLs and RCLs (Fig. 8). The RCLs were formed by addition of rectilinear clumps, and although irregular patches result from overlap, markedly linear features did not develop. RPLs showed a steady increase to a peak at P_i = 0.4. The linearity index is very sensitive to average depth (b) when patch area is small, and the decline when P_i > 0.4 is due to very small increases in b.

Patch number shows a smooth increase and decrease, with the peak for both landscape types at approximately P_i = 0.3 (Fig. 9). There is no appearance of a marked decline in patch number associated with the formation of a percolating cluster at P_i = 0.59.

The comparison of RCLs with real Indiana landscapes is summarized in Tables 1 and 2. The RCL algorithm was designed to produce patches that approximate the size of patches found in agricultural landscapes in Indiana, yet all the calculated indices are significantly different with the exception of patch perimeter. Note that in these agricultural landscapes the patches are smaller and closer together than those in the simulated landscapes, with a higher mean proximity index value. This reflects an uneven spatial and size distribution in real landscapes, probably related to decisions by farmers about woodlot size and location based on soil productivity and topography. Note also that this analysis uses the unscaled PX values since the subset extents vary. Contagion is higher in the simulated landscapes since there are fewer, larger patches.

The river dominated landscapes have larger patches that are on average farther apart than in simulated landscapes. The proximity index for these landscapes indicates a higher value for the dendritic pattern than might intuitively be expected from the mean area and nearest neighbor values. In most of the dendritic landscapes there were forests associated with the steeper slopes near river bottoms, resulting in a number of large patches in close proximity to other large patches, producing proxi-

Table 1. Comparison of indices of spatial pattern of forest landcover between simulated landscapes (RCL, N = 6) and landscapes dominated by agriculture (N = 4).

	Simulated		Agricultural			
Index	Mean	(std. dev.)	Mean	(std. dev.)	T	Prob > T
Proportion forest	.070	(.022)	.068	(.013)	-0.12	.91
Patch area (ha)	4.51	(0.42)	3.28	(1.00)	2.74	.02
Patch perimeter (m)	858.0	(42.0)	805.5	(153.1)	- 0.67	.55
Nearest neigh. (m)	273.1	(76.6)	169.6	(38.8)	-2.46	.04
Fractal dimension	1.05	(0.02)	1.25	(0.03)	13.34	.0001
Contagion	.665	(.016)	.602	(.032)	-4.21	.003
Proximity (PX) index	0.168	(0.178)	0.478	(0.182)	2.68	.03
Linearity index	.033	(0.014)	.160	(0.010)	16.74	.0001
Average depth (m)	90.9	(8.5)	41.3	(1.9)	- 13.79	.0001

Table 2. Comparison of indices of spatial pattern of forest landcover between simulated landscapes (RCL, N = 6) and landscapes dominated by river drainages (N = 5).

	Simulated		Riparian			
Index	Mean	(std. dev.)	Mean	(std. dev.)	T	Prob > T
Proportion forest	.244	(.006)	,242	(.008)	-0.52	.61
Patch area (ha)	6.8	(1.0)	14.0	(5.3)	2.98	.04
Patch perimeter (m)	1163.6	(110.4)	2144.3	(636.8)	3.40	.02
Nearest neigh. (m)	81.4	(12.3)	111.3	(27.8)	2.38	.04
Fractal dimension	1.24	(0.04)	1.34	(0.02)	5.41	.0004
Contagion	.606	(.015)	.628	(.022)	1.93	.09
Proximity (PX) index	1.00	(0.28)	20.87	(16.53)	2.69	.05
Linearity index	.042	(0.008)	.186	(0.019)	16.57	.0001
Average depth (m)	81.4	(7.0)	42.4	(3.6)	- 11.16	.0001

mity values (PX) > 100 for these patches. The majority of the remaining patches were much smaller and more isolated, located on the agricultural uplands. The proximity index provides information on the dispersion of patch size classes that cannot be derived from mean patch area and nearest neighbor distance information alone.

Discussion

Our results document the behavior of various spatial pattern indices as a function of P_i in neutral landscapes that are free of the effects of topography and human activity. This will allow better interpretation of those indices when calculated for real landscapes, and will help separate the effects of topography and human activity from the expected behavior of the indices.

Percolation theory has been proposed as a potential neutral model for studies of landscape spatial pattern (Gardner *et al.* 1987), including the fact that percolation clusters form on infinite random lattices at a critical proportion (P_c) of occupied cells, with potential application to models of the spread of disturbance and animal movement (O'Neill *et al.* 1988b, Turner *et al.* 1989).

Our results show that most of the indices studied behave in a similar way in both random lattices and those occupied with contagion, although usually at different magnitudes. The indices which do not behave similarly are contagion and linearity. Our results also suggest that most indices do not exhibit critical behavior as might be inferred from percolation theory. Properties of the largest cluster change dramatically at P_c, but the average properties of all clusters on the lattice are not expected to exhibit critical behavior. We did not observe a marked change in patch area and patch number. The indices which appear to exhibit critical behavior near P_c (P_i = 0.59) are fractal dimension and the proximity index. The proximity index probably reflects the existence of a percolating cluster better than any other index since a percolating cluster is quite large and is a neighbor to most other patches on the lattice. Fractal dimension would be expected to drop at P_c when many smaller, irregular patches coalesce into a much larger patch, with much of its border formed by the edge of the lattice. It is interesting to note that critical behavior was not as pronounced for RCLs, where the assumption of independently occupied cells was violated, although a percolating cluster does appear to form at approximately P_i = 0.59.

A potential application of this approach is in the formulation of neutral models for the analysis of change over time in real landscapes. As landcover proportion changes over time, it may not be readily apparent if the changes in spatial pattern can be attributed to specific causal agents, or if differences are what might be expected by random changes in landcover proportion. The neutral models reported here may be specifically applicable only to agricultural landscapes, but the finding that a percolation model exhibits behavior similar to another neutral model should encourage the increased use of neutral models in landscape studies, and that percolation -models themselves may be adequate neutral models for many landscape analysis purposes.

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