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Percolation in neutral landscapes: landscape metric sensitivity to critical thresholds and a new class division index

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Key Words: landscape indices, neutral landscapes, cellular automata, percolation, landscape models, fragmentation.

Abstract

When fragmentation occurs, function and spatial structure in the landscape are affected. existing critical points were those changes are irreversible. Percolation thresholds in the landscape are critical points were the spatial connectivity is lost. In this paper, we created, under different occupation densities, five types of neutral landscapes ("random", "ortho", "anneal", "block" and "patches") using cellular automata. We then used these neutral landscapes, to find the percolation thresholds of patterned landscapes. We then measured landscape structure of these landscapes using measures like number of patches, total edge, mean patch size, weighted mean patch size, contagion, adjacency, mean fractal dimension, lacunarity, spatial block entropy, mass entropy and landscape division to establish the ability of these measures to characterize patterns in the landscape and their sensitivity to percolation thresholds. We also developed a new index called "class division" based on landscape division. Our results show that percolation thresholds of patterned landscape differ form those of random maps, and that many measures do not show a geometric phase transition or relation with critical percolation values. We argue that critical spatial percolation values are always going to be less than or equal to functional percolation threshold, therefore they are a good parameter to establish conservation strategies. We conclude that identifying critical values in such quantities is important in order to establish conceptual models for forest management and conservation policies.

Introduction

Landscapes can be considered complex dynamic systems, whose internal dynamics create non-random spatial and temporal patterns. Space-time changes in landscape structure result from ecological and socio-economic pressures on the landscape. Forman (1995) explains and conceptualizes land transformation as a dynamic process consisting of five phases: a) perforation: making holes in the landscape, b) dissection: subdivision of landscape with lines of equal width, c) fragmentation: breaking into small areas, d) shrinkage: decrease in size and e) attrition or disappearance of objects. Landscape fragmentation is not seen as an independent phenomenon, but as the result of the interaction of two forces, perforation and dissection. Jaeger (2000) states that fragmentation is the main land transformation process, and all the phases are part of them. Therefore, what Forman defines a fragmentation phase, is just a dissipation phase for Jaeger. The notion proposed by Jaeger is that landscape fragmentation occurs only when one or more subunits of habitat, ecosystems or land-use in the landscape suffer from spatial breaking, leaving areas without physical connection.

Understanding landscape fragmentation is affected by our ability to quantify and to relate pattern to forces driving the spatial transformation. Many quantitative measures have been developed to measure landscape structure and dynamics, but they all seem to fail to establish links between pattern and process, and many configurations can produce the same value (Gustafson 1998). As shown by Riitters (1995), many of the current landscape fragmentation and structure measures are related, resulting in a few metrics that can accurately measure different aspects of landscape structure.

In general, spatial fragmentation of landscapes is measured as the change in landscape heterogeneity over time. Metrics considering patch structure (number, types, shapes, edges and arrangement), functional structure (class proportions) and local structure (neighboring, proximity of classes, connectivity) are the most broadly used (Li & Reynolds 1994, Riiters et al 1995, McGarigal & McComb 1995, Gustafson 1998). In addition to using these three types of metrics, gaining a clear understanding of the spatial configuration of the landscape is crucial to determining the effects of landscape restoration or aggregation (reversal of fragmentation). In this approach, certain landscape configurations, with a critical density of classes, would facilitate the natural reversal of the fragmentation process. Percolation theory helps to explain this reversal process when considering that geometric connectivity of a system changes (e.g. from no-connectivity to high connectivity) at a certain critical threshold (Stanley et al. 1999). A critical threshold is defined as a sudden change in the general behavior of the system (Turner & Gardner 1991, Stanley et al 1999). In terms of landscape dynamics, complex spatial patterns change with an increase in density, allowing small-scale interactions to propagate over long distances (Milne et al 1996), therefore understanding the critical percolation value is crucial to understanding landscape dynamics.

We think that a good set of landscape measures should not only be sensitive to changes in landscape structure, but also to changes in the percolation threshold. We consider that landscape fragmentation metrics must be sensitive to sub-critical and supercritical behaviors, as they are apparent when percolation is analyzed as a function of occupation density. The strongest case of this approach is when a sharp geometric phase transition appears. We consider the percolation threshold to be a good point of reference, since percolation is a phenomenon related to the pattern of the landscape and the underlying dynamics of land cover change (With & Crist 1995, With & King 1997, Plotnick & Gardner 1993). We also think that the determination of percolation thresholds for different landscape patterns would help us to establish minimum density requirements to prevent habitat degradation or irreversible changes in the landscape. The most frequently reported percolation threshold value is 0.59, and it is generally restricted to random spatial distributions, the type of lattice, and the definition of neighborhood (With 1997). Evidently, real landscapes are not random, and their spatial organization is the result of internal dynamics and pressures from a combination of socioeconomic and biophysical forces.

The development of artificial landscapes using neutral models has been widely used for testing landscape metric behavior (Gardner & O'neil 1991, Milne 1992, Li & Reynolds 1994, Li & Archer 1997, Hargis et al 1998, He et al 2000, Jaeger 2000, Saura & Martinez 2000). The widespread use of neutral models is the result of their ability to control the structural complexity necessary to explain metrics behavior (With & King 1997). However, none of these studies relate spatial structure to process (Schumaker 1996, With & King 1997). Identifying the link between spatial structure and process is fundamental in order to develop sound theories in landscape ecology (Krummel 1987). Artificial landscapes (neutral landscapes) are used to define a set of possible non-random landscape structures, ranging form over-dispersed (regular) to clumped landscapes, and using random maps as a null model for significance testing. Several methods have been developed to create neutral landscapes (With & King 1997). These methods use random maps and random clumps, including binary, non-binary and hierarchical structures.

Cellular automata (CA) provide a general system to develop neutral landscapes, and to establish a link between dynamics and patterns. CA can model complex behaviors analogous to those found in systems of differential equations or iterated mappings (Wolfram 1984, 1988; Toffoli 1984). In this paper, we use landscapes derived from CA to analyze the sensitivity of landscape metrics to characterize landscape structure under different densities. We extend the use of neutral landscape to incorporate "neutral" dynamics to explain the changes in pattern due to local dynamics. We measure the sensitivity to changes in structure due to internal dynamics, and to percolation thresholds, of some of the common measures of landscape structure, such as contagion (Li & Reynolds 1993), mean fractal dimension (McGarigal & Mark 1995), number of patches and total edge. We also explore the use of landscape division (Jaeger 2000), weighted mean patch size (Stauffer 1985, Li & Archer 1997), spatial entropy (Wolfram 1983, 1984, and mass entropy (Tsang 1999) to account for changes in landscape structure.

Methods

A cellular automata (CA) matrix approach was selected as the main tool to simulate landscape patterns. The dynamics of the landscape were modeled using a transition function. The transition function provides specific rules for all of the state transitions (class changes). Since we are interested in testing landscape metrics, we limited our simulation to occupied/empty classes (e.g. Forest/Non-Forest). We consider the state 0 to be empty, and the state 1 to be occupied. Four CA rules were used in the construction of the 350x350 pixels landscape patterns: “anneal”, “ortho”, “block” and “patches”. Sequences of 50 landscapes were created for each type of landscape (totaling 250 landscapes) ranging form 0.05 to 0.95 occupation density. An additional set of 50 random landscapes was created using percolation maps, with occupation densities ranging from 0.05-0.95. Each landscape was created starting with an initial configuration of pixels randomly distributed with a given occupation density (percolation maps). The CA rule was then applied interactively for a fixed number of time steps. Every landscape in the set is independent, so the final occupation density and pattern, after applying the CA rule, is related to the initial random configuration and is independent of other landscapes of the same type.

Cellular Automata

A CA consists of a matrix of sites and a transition function that defines the changes of state at each site. The transition function takes into consideration the configuration of the surrounding neighborhood. Let $\mathbb{Z}^2$ be a 2-dimensional matrix. For $a \in \mathbb{Z}^2$, $a_{i,j}^t$ is the state of a site at position *i,j* in the time step *t*. We have defined the change of state of a site as:

$$a_{i,j}^{t+1} = \mathrm{F}[a_{i-r,j-r}^t, \ldots, a_{i,j}^t, \ldots, a_{i+r,j+r}^t]$$

Where **F** is an arbitrary function called *transition function*. **F** defines the CA deterministic rule and *r* is the range of **F,** and defines the neighborhood (Packard & Wolfram 1985). The neighborhood *N* is the set of surrounding sites. There are two *N* configurations, which are commonly used (Figure 1). The von Neumann Neighborhood considers only the 4 orthogonal contiguous sites plus the middle site, and the Moore neighborhood which considers the 4 diagonal sites in addition to the 4 orthogonal sites (Langton 1990, Packard &Wolfram 1985).

Random Maps and Cellular Automata generated landscapes

A. Random Maps

Let $\mathbb{Z}^2$ stand for a two dimesional artificial landscape, and $a = \{0,1\}$ a specific site (0 being non-forest and 1 being forest). Let $\Gamma \rightarrow [0,1]$ be a random number generator and d a random number. Let p be the probability that a site a is in state 1. In a percolation map construction, for each $a \in \mathbb{Z}^2$, the state of a, is going to be 1, if $d \leq p$, and 0 otherwise.

A set of 50 percolation maps was created with $0 < p < 1$. We called this landscape a random pixel-landscape, since it contains a random distribution of pixels with density of $p \cdot \mathbb{Z}^2$. Percolation maps were also used as the initial landscape before running the CA rules. Figure 2a shows a percolation map with $p = 0.5$.

B. Annealing Rule

This is a voting and totalistic rule in which the number of sites in the neighborhood that have a value of 0 or 1 determines the state of each site. In this rule, we use a Moore Neighborhood. Let ρ_0 be the number of sites with the value 0 in *N*, and ρ_1 the number of ones. If $\rho_0 < \rho_1$ then *a* will change to 1, otherwise if $\rho_0 > \rho_1$ then the value of *a* changes to 0. The landscape with initial *p*=0.5 is shown in figure 2c.

C. Ortho Rule

This rule is based on a simple CA created to simulate a digital computer (Toffoli & Margolus 1986). It uses the von Neumann Neighborhood. Let ρ_1 be the sum of cells with value 1 in *N*. Then, if $\rho_1 > 1$ then *a* stays the same, if ρ_1 ò 3 then *a* changes to 1. In the case of $\rho_1 = 2$, only if the upper and lower neighbor are different, the value of *a* changes to 0. In this rule, the corner sites always change to 0. We called this rule ortho, because the pattern generated looks like agricultural landscapes in boreal/mid-temperate regions with linear and orthogonal structures (figure 2g).

D. Block Rule

The block rule is a probabilistic non-uniform rule that uses a Moore neighborhood. A non-uniform probabilistic rule means that the rule applied in a site can be different than the one applied in another site. In this rule, the transition function is a set of functions F = $\{f_1, f_2, \ldots, f_m\}$ with fixed probabilities q_i of being applied in a site. Note that:

$$\sum_{i=1}^{m} q_i = 1 \ , \ m \in \mathrm{N}$$

The rule uses two functions: a) If *a* =1 or 0, and there is any site with a value of 1 in the diagonal or orthogonal neighborhood, then the site a stays or changes to 1. Otherwise, it changes to 0; and b) If *a* =1 or 0, and there is any site with a value of 1 in the orthogonal neighborhood, then the site *a* stays or changes to 1. Otherwise, it changes to 0. The probabilities of the rule occurring are 0.9 and 0.1 respectively. Note that the only difference is that the neighborhood is considered for the change of state. The result of this rule is a pattern with square shaped blocks with irregular edges (Figure 2e)

E. Patches Rule

This is a non-uniform probabilistic rule, as defined in the block rule. If the site *a* is 1, then it does not change. If the site *a* = 0, then it will choose a neighbor from a von Neumann neighborhood randomly with a probability of *q* = 0.2 each. If the site chosen has a value of 1, then *a* changes to 1. This creates irregular random clusters around the landscape. (Figure 2i)

Landscape statistics

The following landscape metrics were calculated for each artificial landscape: Mean patch area, number of patches, total edge, mean fractal dimension, Lacunarity, landscape division, class division, weighted mean patch size, spatial block entropy, mass entropy, contagion and adjacency.

The perimeter area fractal dimension (perimeter–area relation) is estimated using the following equation:

$$D = \frac{2\ln\left(\frac{P_i}{4}\right)}{\ln(A_i)}$$

We used this equation to calculate the perimeter area ratio of every patch. Mean fractal dimension $\overline{D}$ was calculated the same way as FRAGSTAS (McGarigal & Marks 1995) using the function:

$$\overline{D} = \frac{1}{n}\sum_{i=1}^{n} \frac{2\ln\left(\frac{P_i}{4}\right)}{\ln(A_i)}$$

where A_i and P_i are the area and perimeter of patch *i*. We have also divided the perimeter by 4 to correct for the effect of square shapes. The value of $\overline{D}$ is 1, as the shapes of patches tend to be round or square, and approaches 2 for highly convoluted surfaces.

Lacunarity was developed to describe fractal properties (Mandelbrot, 1983), but as shown by Plotnick (1996) and Dale (2000), it can be extended to the description of scale-dependent spatial heterogeneity. We used the “Gliding Box” algorithm proposed by Allain and Cloitre (1991). Let a_i be a site in the landscape $\mathbb{Z}^2$. Then for each $a \in \mathbb{Z}^2$, the mass *s* is determined (mass is the number of pixels of forest class) by counting the sites with forest cover inside of a box of size *b*. The probability of mass distribution would be $Q(s,b)$. Then the lacunarity $\Lambda(b)$ is calculated as:

$$\Lambda(b) = \frac{M_2}{(M_1)^2}$$

where the first moment $M_1 = \sum sQ(s,b)$, and the second moment is $M_2 = \sum s^2 Q(s,b)$. Given a class density and b, higher $\Lambda(b)$ indicates greater clumping. The algorithm was used varying *b* from 5 to 145 in steps of 10.

The spatial block entropy H^b , a metric useful in determining the organization or randomness of a landscape, is calculated as:

$$H^b = \frac{1}{b}\sum_i p_i \log p_i$$

where p_i is the probability of configuration *i* in 3x3 window in the landscape, and b is the block size. Higher values of H^b mean a higher degree of randomness in the landscape (all the possible configurations of blocks *b* on the landscape have the same occurring probability). This type of metric is widely used in the description of CA configurations

(Wolfram, 1983; 1984). Mass entropy *H* (Tsang, 1999) is a function of the probability *w* that an occupied site is part of a cluster size *s*. It is calculated as:

$$H = -\sum_s w_s \log w_s$$

Contagion is a measure of the adjacency of cover types. Using the modification of Li and Reynolds (1993):

$$C = 2\ln(q) + \sum\sum p_{ij}\ln(p_{ij})$$

Where p_{ij} is the probability of a class *i* being adjacent to a class *j*, and *q* is the number of classes. Lower values of *C* mean that there are many small patches, and as *C* approaches 1, there are large continuous patches in the landscape (Frohn 1998).

Movement in the Landscape

One simple way to define the possibility of movement in the landscape is estimating the probability that two sites taken randomly from the landscape belong to the same patch. Jaeger (2000) used this concept to define a degree of landscape division (*D*). We modified *D* to measure division within a class (class division D_L) segmented into *n* patches. Let *L* be a set of *n* patches of a certain class, so that $L = \{A_1, A_2, \ldots, A_n\}$ and $|L| = \sum_{i=1}^{n} A_i$ is the total class area. The total landscape area is $A_t = |L| + |L'|$, where L' is the set of patches in the landscape or region that do not belong to *L* (note that the whole landscape or region $R = L \cup L'$). Now, the probability p_i that a random site $a \in L \cup L'$ taken from the entire region belongs to a patch $A_i \in L$ is:

$$p_i = \frac{A_i}{A_t}$$

Coherence (*C*) (as called by Jaeger) is the probability that two sites taken randomly from the region belong to the same patch, so $C = \sum (p_i)^2$, and Landscape division $\mathrm{D} = 1 - \sum (p_i)^2$ is defined as the probability that two random places do not belong to the same patch. As D approaches 1, the landscape is highly divided (the probability of two patches being unconnected is high). Class division is calculated the same way as D, but p_i is the probability that a random site, $a \in L$, belongs to a path, $A_i \in L$, and is calculated as:

$$p_i = \frac{A_i}{|L|}$$

As class division approaches 1, the class is highly divided. That is, the total mass of the class is segmented into a large number of patches. As class division approaches 0, the class is distributed in a single large patch.

Weighted mean patch size (S), is calculated as:

$$S = \sum \frac{n_s s^2}{\sum n_s s}$$

where n_s is the number of patches of size s. This measure is not static as is the mean patch size, and it varies as the frequency distribution of patch sizes changes (Stauffer 1985, Li & Archer 1997).

Percolation Simulation

To estimate the percolation threshold with higher precision, an additional set of 50 sequences (0.3-0.8) was created for each type of landscape, totaling 100 landscapes for each type of CA rule and percolation map. Percolation was measured simulating flow throughout each landscape using the following CA rule: Let Z^2 be the landscape. In the percolation rule, a site a can be in any of 3 states: 0 (empty), 1 (occupied) or 2 (percolated). If $a = 1$, and there is at least one site in the neighborhood in state 2, then a changes to 2. In any other case, the site stays the same. The percolation simulation was applied to each of the artificial landscapes, starting with all sites at the top of the landscape in state 2, and it was iterated until an equilibrium condition was reached, where the density of sites in state 2, stayed the same from one generation to the other. We applied the percolation simulation using the 4N and 8N neighborhood (figure 1) to estimate the p_c (p_c^4 and p_c^8 respectively) under both neighboring rules. The probability of percolating cluster p_s is then calculated:

$$p_s \approx \frac{r_2}{r_1}$$

where r_2 and r_1 are the density of sites in state 2 and 1, respectively. To obtain an approximation of the percolation threshold (p_c) for each type of landscape, p_s as a function of occupation density (p) was adjusted to a Gaussian distribution to estimate the probability of a percolation cluster (Hori 1989).

Results

Landscape Spatial Organization

As seen in Figure 4a-b, the number of patches and total edge in non-random landscape is less than that seen in the random maps, as a consequence of spatial organization and aggregated structures. The “ortho” landscape is initially similar to a random landscape (for p less than 0.2). These differences indicate that the CA rule starts to have an effect on the landscape when a certain initial density is reached. Figure 3f-j shows the standardized number of patches and the fitted curve. There are clear differences in the maximum value and in the shape of the curve. Starting from low densities, the number of patches increases quickly with density until the space is filled. At this stage, patches start to aggregate, slowly decreasing the number of patches. Results indicate that dynamic processes modeled using the “anneal” and “ortho” rules, tend to aggregate pixels and drift the peak of the curve to the left as a consequence of fast aggregation of patches. The patches and block rule however, tend to reach a maximum number of patches at higher densities than a random map.

Results regarding entropy (Figure 5a) indicate that this measure increases with density until a maximum is reached, and then it decreases again. This change is a consequence of the change in the dominant class, from an empty landscape to a completely occupied one. Results indicate that the random landscape reaches a higher value of spatial entropy, meaning a higher degree of disorder in spatial organization, which is consistent with its own nature (random generation). The other 4 types of landscapes (anneal, block, ortho and patches) are the result of dynamic processes. The spatial organization from low to high disorder is as follows: block (0.28), anneal (0.3), patches (0.50), ortho (0.62), random (0.69). The lowest entropy is obtained in the block landscape, suggesting that this type of landscape has the highest level of order (see figure 2e).

In random maps, it is expected that the highest mass diversity and mass entropy will be reached just before the percolation threshold (Tsang & Tsang 1999). When high mass entropy is reached (i.e. high diversity of cluster sizes), and occupation density increases, patches start to connect quickly, therefore rapidly decreasing the mass entropy (figure 5b). Because the CA rule changes the way different patches are aggregated as a function of local configuration, it is expected that the maximum mass entropy will change under different landscape dynamics. Figure 5b indicates that random landscapes have their highest mass entropy just before p_c^4, and this is also true for the ortho, anneal and patches landscapes. The block landscape shows a different trend. At low densities, the landscape consists of block patches of equal size (see figure 2e). This results in low mass entropy. As occupation density increases, because the density of seeds (initial sites) increases and the block patches grow, they start to aggregate to form long patches of connected blocks, increasing the variety of patch sizes and mass entropy.

Landscape Shape and Connectivity (Fractal Dimension and Percolation)

When aggregation was measured with the contagion metric, our results indicated that the four CA landscapes were shown to be more aggregated than the random map (Figure 6a). The minimum degree of contagion is reached at p = 0.5. At this point, the lowest contagion, hence, the smaller patches, occurred in the random landscape followed by ortho, patches, anneal and block. These results were consistent with spatial entropy (Figure 5a) and adjacency probability (Figure 6b). An interesting trend is shown by the ortho landscape. Since the ortho CA rule starts with a random initial configuration of seeds, the CA rule does not have any effect at low densities, showing a “shift” in behavior when a critical density is reached and the CA rule starts to change the landscape structure. This behavior is more evident with Lacunarity (Figure 9b). When occupation density increases and this critical density (pì0.2) is reached, the quantity of holes suddenly starts to increase again, due to the aggregating dynamics of the ortho rule.

Lacunarity results indicate that the four CA rules have structures that are non-random (Figure 9a-e). It is also evident with Lacunarity, that block and patches landscapes have a clumped and more regular structure, and that anneal and ortho have clumps with a less regular distribution. Results of our Lacunarity analysis (at p = 0.5) for all the landscapes (Figure 9f) show how this measure can account for the density of holes in any given landscape. For example, at p=0.5 (Figure 2a-i), block and anneal have higher Lacunarity values than ortho and patches. The lowest Lacunarity at this occupation density is for random landscapes. The smallest holes are found in the random landscape, resulting in a small Lacunarity value, followed by ortho, patches, anneal and block (see figure 2). This trend is consistent with the spatial entropy results (Figure 5a). Lacunarity does not show any sensitivity to percolation thresholds.

Our results, from analyzing the mean fractal dimension ($\overline{D}$) under increasing occupation density, reveal the limitation of this measure to account for changes in landscape structure. Figure 7a shows $\overline{D}$ as a function of occupation density in all of the types of landscapes. Except for the block rule, $\overline{D}$ first increases as patches start to aggregate at low densities (in the sub-critical region). The maximum $\overline{D}_{\max}$ value is between p_c^8 and p_c^4 and then $\overline{D}$ decreases. $\overline{D}_{\max}$ is obtained in the transition between the sub-critical and super-critical regions, because as a large convoluted patch with high fractal dimension forms, a large number of small patches with low fractal dimension still exist on the landscape with high mass entropy (Figure 5b). The block landscape shows a different pattern in which $\overline{D}$ fluctuates with smaller amplitude as occupation density increases (Figure 7b). This indicates that changes in the general structure of the landscape ranging from more square-like shapes to long convoluted shapes, and the mean value is pulled down strongly by an increase in the number of small patches with less fractal dimension (see Figure 5b). However, $\overline{D}$ results must be interpreted with care, since its mean value and mass distribution are not equal as occupation density increases. For example, in figure 7a,the line marks the 0.5 occupation density. At this point, anneal, random and block landscapes have the same $\overline{D}$ value. However, as seen in figure 2 a-e, the general structure is significantly different (also see results in spatial and mass entropy above). It is also evident that $\overline{D}$ fluctuates as the percolation cluster becomes bigger with high occupation densities (see figure 7a for densities higher than 0.8). An additional problem is that the common method used to calculate fractal dimension has a weak relationship with the real estimation of fractal dimension (Schumaker 1996).

Plotting every patch's fractal dimension D as a function of occupation density (figure 8 a-e), reveals the relationship between percolation and the formation of percolation clusters. When $p \geq p_c$ (super-critical region), it is expected that a large convoluted patch will form (Stauffer, 1985). This fact is confirmed in our landscapes. For all of the types of landscapes, a discontinuity (gap) forms at p_c^4, showing that a structure with high D formed, which is the percolating cluster. For the block landscape, the gap forms, however, it is not very clear, since it seems to consist of different gap formations due to fluctuations in shape from regular to less regular.

Landscape Division, Class Division and Weighted Mean Patch Size

Our results reveal that D is sensitive to p_c (figure 3k-o). In all the types of landscapes created, when $p < p_c$ (sub-critical region), D is close to 1. As seen in the figure, when $p \geq p_c$ (super-critical region), D < 1since a big patch forms covering a high percentage of the landscape and the remaining areas are distributed in a low number of small patches. Class division (D_L) and weighted mean patch size (S) are also sensitive to p_c (Figure 4c-d). The formation of a large patch is clear in S, since the majority of the weight in the mass distribution of the landscape is located in the percolating cluster, resulting in a geometric phase transition. For D_L, a clear example of its sensitivity is shown in the figure. The small boxes show a 50x50 sample of the patches landscape. In the first box (read from left to right), only a small number of patches exist, so the D_L value is lower than that of the second box, where the density is higher, but it is distributed in more patches so its division is higher. The measures S and D do not show this sensitivity to class division. The percolation threshold estimated using the CA rule for 4N is confirmed using D_L and S.

Estimation of Percolation Thresholds

As seen in figure 3a-e, a geometric phase transition forms where the density equals the p_c for that particular landscape. As expected, patterned landscapes (non-random landscapes) have a higher or lower p_c than random maps (Table 1) due to patchiness or over-dispersion. Our p_c estimation for random maps is ≈0.589, which is a close approximation to the expected value of ≈0.592 (Stauffer 1985, Grimmett 1999). Patterns that resulted from CA rules that force sites to aggregate (segregate), like anneal and ortho, resulted in a lower p_c for the 4N neighborhood. However, patterns where the neighborhood local density are not considered in the transition function, tend to form structures whose aggregation depended only on the total initial occupation density, having higher percolation thresholds (block landscapes). When percolation was simulated using 8N, for each type of landscape, p_c was lower than using 4N. Because in an 8N neighborhood the possibility of connection is higher than in a 4N neighborhood, therefore, $p_c^8 \quad p_c^4$ for any landscape structure. The empirical relation $p_c^8 = 1 - p_c^4$ (Stauffer 1985), was shown to be valid only for random structures. The S metric shows a clear geometric phase transition when the percolation threshold is reached and a big cluster is formed, for all the types of landscapes analyzed (Figure 4b). These results are consistent with the estimation of p_c using the explicit flow simulation with CA.

Discussion

Our results confirmed that patterned landscapes have different p_c values and that their critical value is related to the general dynamics of the landscape. The four neutral landscapes generated (anneal, ortho, block and patches) have a different non-random geometry that is the result of the dynamic of the CA, and each landscape showed a distinctive percolation threshold. The reported percolation threshold value of 0.59 is restricted to random maps on a square lattice (Stauffer 1985, With 1997, Grimmett 1999). Our results are consistent with this, and the use of this percolation threshold does not apply to non-random maps. It is generally believed that p_c in non-random maps would have a lower value, due to the coalescence of space (With 1995). This was confirmed for the anneal, ortho and patches landscapes (Table 1), but not for the block landscape, which forms a random block aggregation of pixels (Figure 2). In fact, this landscape not only has a higher degree of aggregation (Figure 4b, 5a, 6a-b, 9f), but also a higher p_c value. The formation of denser block aggregations with large gaps that dissect the landscape is the main reason for this difference. These results are confirmed by figure 9f, where the block landscape shows a higher lacunarity value, meaning that the size of the holes is bigger than the holes in the rest of the landscapes. Furthermore, landscape and class division values show that for occupation densities higher than 0.59 (Figure 4d), all the landscapes except block have reached percolation. Therefore, class division and landscape division are low, but block landscapes have a high value. Hence, even though aggregation is high, the landscape is still divided. Consequently, the percolation threshold is going to be related to the landscape pattern of aggregation and division, in addition to the pattern and density of the gaps.

Our results differ from those of Gardner & O'Neill (1991). Their results show that if the adjacency (contagion) is higher than random maps, the p_c will be lower, and with lower adjacency, the p_c will be higher. We constructed the landscapes to have the same structure under different densities, so adjacency changed as a function of density (Figure 6b), in contrast to Grader & O'Neill who kept adjacency constant under different densities. For three of the CA landscapes (anneal, patch and ortho), adjacency was always higher than in random maps, but opposite to Gardner & O'Neill's (1991) results, the p_c value was lower. The only case where the p_c was higher with a higher adjacency was the block landscape. Given these results, we suggest that it is not possible to generalize the relationship between adjacency and percolation thresholds.

Our estimation of the percolation threshold for 8N confirms that the percolation threshold is smaller if more neighbor connectivity is allowed. However, the metrics that were sensitive to p_c show sensibility to p_c^4 and not to p_c^8, because to estimate patch indices a raster-vector method (Douglas-Peuker algorithm) was used in which diagonals are not considered a part of the same patch. The results indicate that there is a change in the geometrical behavior of a landscape, given a structuring dynamic, with an increase in occupation density. This change allows percolation to occur throughout the landscape. In a real landscape which experiences a decrease in forest cover over time, certain types of geometrical structures form as the result of internal non-random dynamics, such as deforestation. There is a critical point where the connectivity of the system is going to rapidly decrease and where movement across landscape is not possible. Near the percolation threshold, if a landscape is left for restoration, it would have a higher possibility of recovering because there will be a percolating cluster that has a very convoluted shape, making an aggregation process possible. For example, if we look at the anneal landscape (Figure 2c) at the p_c point (Figure 8a), it can be seen that there is a large percolating patch that has a high perimeter area fractal dimension. The rest of the patches are smaller and are surrounded by the big percolating patch (Figure 10). A good estimation of the percolation threshold in landscapes can be calculated using *S*. Our results show that this measure is useful in detecting structural changes in the landscape that cannot be detected by mean patch size, which is a commonly used measure. This measure can also be used to monitor functional changes in structure due to disturbances in the landscape (Li & Archer 1997).

Some authors have suggested that a single threshold value is not enough to describe the responses of all species in a community to changes in the landscape (With 1995). Others report that it is impossible for any landscape measure to account for scale-dependent variation, suggesting that landscape metrics do not have any ecological meaning (Vos et al 2001). We agree with this, but, based on our findings, we also believe that if we were able to measure a functional percolation threshold (f_c), the point where the system functionality is lost due to fragmentation, is going to be greater than or equal to spatial p_c. Therefore, this p_c threshold could be a useful caution principle. The reason for this is that habitat discontinuity is common in natural systems, and that species in an ecosystem have the ability to move in discontinuous aggregations of resources. For example, Keitt et al (1997) found using graph analysis and percolation applied to conifer forests, that species with low dispersion capabilities are affected by landscape configuration near percolation threshold, and that high dispersion capabilities increase connectivity in the landscape. This would support our theory that $f_c \geq p_c$.

Contagion and adjacency were not sensitive to percolation threshold since these metrics are not based on the geometrical properties of the landscapes. Although our results show that contagion can be useful for determining aggregation in binary maps, Frohn (1998) has shown empirically how this measure is sensitive to resolution, effects of raster orientation, and the number of classes. In addition, contagion does not distinguish class aggregation, but summarizes the configuration of all classes (Gustafson 1998). Our landscapes have the same resolution (350x350), number of classes and orientation, making contagion results relatively easy to interpret. However, in real landscapes the problems mentioned are critical, and since it is possible to obtain aggregation information with other indices, our suggestion is to use spatial entropy, mass entropy and lacunarity. Adjacency shows an interesting trend, related with the dynamic of the CA rule. For the block landscapes, adjacency changes linearly with occupation density, which is consistent with the block CA rule, which creates constant structures starting from random seeds. Landscapes like random maps, however, produce a quadratic variation of adjacency as a function of occupation density.

Although $\overline{D}$ seems to be sensitive to p_c, since the maximum $\overline{D}$ is reached close to the p_c value, its value seems to be meaningless in terms of landscape structure or space filling. These measures provide some insight into the general complexity of the landscape in terms of spatial pattern, but as explained by Li (2000), such fractal measure cannot be used to characterize the nature of space filling of ecological objects such as forest expansion. Another problem with $\overline{D}$ is that because it is a mean value, it is sensitive to the frequency of patches (Figure 7b), making it hard to interpret and use in comparative studies. It also has the same value even under different landscape structures (Figure 7a). By averaging fractal dimension, the information about individual patch shapes is lost (Hargis 1998). Therefore, instead of using mean fractal dimension, we suggest using every patch fractal dimension (perimeter / area relation) plotted against the occupation density, because it shows the formation of percolating patches. Our results also indicate that a patch with higher fractal dimension forms when the percolation threshold is reached (Figure 8a-e). This is useful in determining the possibilities of landscape restoration.

Lacunarity is a multi-scale method used to analyze a system's heterogeneity (Gustafson 1998). It has been shown (Dale 2000) that although lacunarity considers a range of different scales in one landscape, this measure does not detect patterns at different scales. Therefore, lacunarity is not a good measure of multi-scale patterns. Lacunarity is related to transnational invariance, which makes it possible to distinguish between geometries that may have the same fractal dimension, but are different (Allain & Cloitre 1991). If we look at the landscapes at approximately 0.5 occupation density (Figure 2a,c,e), the mean fractal dimension is the same for the random, anneal and block landscapes (Figure 7a), but the lacunarity value (Figure 9f) is different, making it possible to distinguish between these landscapes. Lacunarity could be a useful tool to determine the density of holes or coalescence of the landscape. However, we agree with Dale (2000) that degree of 'hole-iness' is not enough to quantify and describe the landscape. Therefore, we suggest that lacunarity should be used to complement fractal dimension measures.

For the indices that describe the general characteristics of the landscapes such as number of patches and total edge, our results are similar to results obtained for real maps (Gardner et al 1991) and clumped neutral maps (Saura & Martinez 2000), showing that non-random landscapes have less total edge and a smaller number of patches. These results are not surprising, because any process of aggregation will cause these two measures to decrease, and highly regular landscapes, such as a chessboard landscape, would cause these values to increase. This does not mean that these basic measures are not useful. They are good and simple measures that characterize a landscape and can be good indicators of change over time for a particular region, but they have a restricted role in comparing different regions or changes in structural pattern.

Total edge results have a strong relationship with spatial entropy. Spatial entropy and mass entropy were shown to be useful in the quantification of the spatial organization generated under the different CA dynamics. Although spatial entropy did not show a strong sensitivity to p_c, this measure can be useful to establish the degree of order in a landscape, and the change of organization over time. As the results show (Figure 5a), spatial entropy is very sensitive to pattern changes. For example, the ortho landscape at low densities, showed a structure equal to the random maps, but when occupation density reached a critical value, the CA rule started to "rule" the dynamics of the landscape. This caused change to occur by lowering the spatial entropy and organizing space. In real landscapes, land transformation and forest fragmentation processes change the landscape's spatial organization. These changes would reflect an increase of mass and spatial entropy, if the initial density of forest is high (the forest is the matrix). As soon as another land use class starts to dominate, mass and spatial entropy decrease again. It has been shown for random maps that the probability of maximum cluster size diversity and the percolation threshold, which is the point of geometric phase transition, are statistically the same (Tsang 1999). Our empirical study confirms these results for random landscapes, and shows that this relationship holds for anneal, ortho and patches landscape, but not for block landscapes, where there is an increase of the mass entropy after the percolating clusters have formed. We think that this finding is the result of the low number of patches that the block landscape has compared to the random landscape (Figure 4a). Mass entropy is a useful tool to understand system complexity (Tsang 1999) and the change of complexity over time.

The sensitivity of landscape division, class division and weighted mean patch size to percolation thresholds demonstrates how important it is to establish a landscape threshold point, since there is a major change in the geometry of the landscape, changing the possibility of movement at local scale. As described by Jaeger (2000), landscape division has some limitations, since it is only comparable within landscapes that have the same area. Therefore, it would be useful in comparing one region over time, but not in comparing two different regions. Class division corrects this problem. It measures the segmentation of a particular class, so that regions with different areas can be compared. For class division, if the class under analysis consists of only one patch, regardless of the total landscape area, the value for class division will be equal to 0. In real landscapes, this would mean that if a land cover class, such as forest, consists of only one patch in the total landscape, this class is not divided, even if the forest is a small proportion of the landscape. If we think of an animal moving in the landscape, from the perspective of class division, we assume that the best environment for movement would be the forest. Therefore, we are interested in how the animal would move across the forest, not the whole landscape, as we would be concerned with the landscape division index. Class division also shows a stronger sensitivity to p_{c}, compared to landscape division (Figure 3k-o, 4d).

The use of neutral models of landscape is important for the establishment of critical values of landscape structure. In neutral models, we can incorporate heterogeneity in a controlled way, allowing us to understand the links between index behavior and pattern (Gustafson 1998). We extended the use of neutral models to models were the structure of the pattern in the landscape was created with a dynamical process embedded in a CA rule. These “Dynamical Neutral Models” have neutral processes that are general abstractions of natural systems dynamics. They can be used to incorporate and test general landscape principles, and the behavior of landscape measures under different patterning dynamics. These types of models will help to study the behavior of indirect measures of structure, and perhaps to define a set of patterns that are common in real landscapes. Shumaker (1996) indicated that systems are too complex to reduce to a simple equation, suggesting that using metrics such as fractal dimension and contagion to quantify landscape properties is an impossible task. Although it might be true for contagion and fractal dimension, this generalization cannot be extended to other measures. Our study shows to give meaningful information about the structure, give different dynamics and landscape patterns. However, it is important to incorporate analysis of heterogeneity at different scales (Gustafson 1998), and to incorporate dynamics of mosaics of different habitat or classes (Wiegand et al. 1999). In addition, binary landscapes are considered “elementary landscapes” that can provide a sound base for the interpretation and quantification of landscape heterogeneity.

The heterogeneity of resources and disturbances results in patches of diverse size, shape, type and boundary conditions (Li 2000). There is a need not only to quantify change, but to relate change to dynamics. We think that given a certain dynamic, there will be a specific landscape pattern, and as a consequence of pattern, there will be a particular percolation threshold. The p_c value will be important in determining when fragmentation really occurs and in identifying the critical point at which the restoration process is difficult. Percolation threshold can be used as a critical point of fragmentation, and in conjunction with measure like landscape division, weighted mean patch size, lacunarity, mass and spatial entropy, some decisions can be made based on that information. Measures such as mean patch size, number of patches, total edge and others are descriptive measures of landscape structure, but they could also be the result of a large set of possible dynamic processes. Because their meaning is limited, interpretation and use of those measures must be restricted. As a result, they cannot be used to define fragmentation.

Landscape ecology depends completely on the development of measures of spatial and temporal heterogeneity at the landscape level. Such measures should embrace a whole meaning in order to create a meaningful theory. After a series of statistical and numerical analyses of landscape metrics, it can be seen clearly that correlation between metrics exists, since the same basic information is used, and that many measures can give the same value under different structures, or that certain measures are not sensitive to critical values. It has been suggested that the quantification of landscapes should be based on fundamental components of spatial structure, and that a set of such measures should be established. We extended this idea, and suggest that we should think of ecological quantities that have meaning in terms of landscape dynamic. Identifying critical values in such quantities is important in order to establish conceptual models for forest management and conservation policies.

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Figure 1. Neighborhood configurations commonly used in 2 dimensional lattices. a) the 4 nearest neighborhood (4N) or von Neumann neighborhood, b) the 8 nearest neighborhood (8N) or the Moore neighborhood. In both configurations the center site is considered as part of Neighborhood.

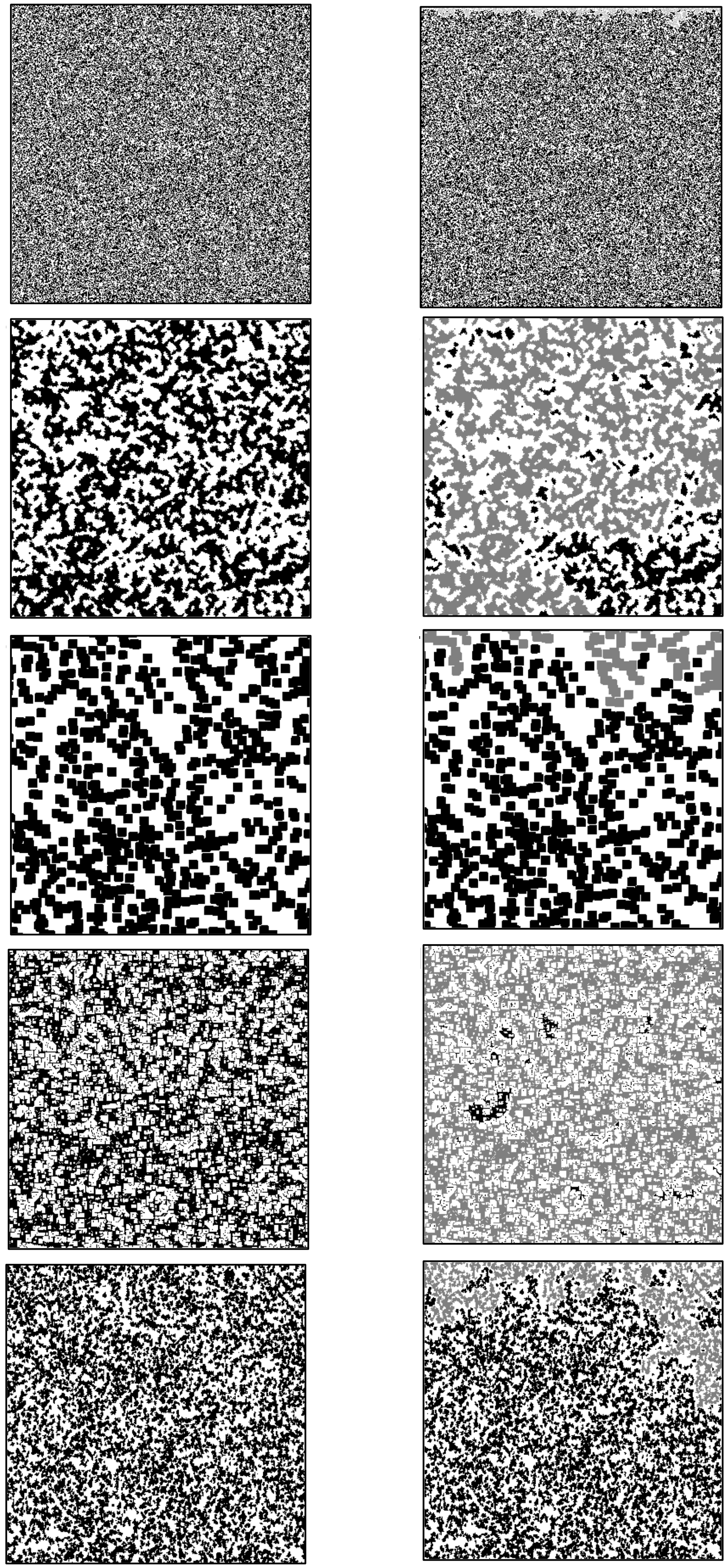


Figure 2. Artificial landscapes, with ≈ 0.5 occupation density, and percolation cluster (in Gray) in the same landscape. a,b) Random landscape, c,d) Anneal landscape, e,f) Block Landscape, g,h) Ortho landscape and i,j) Patches landscape.

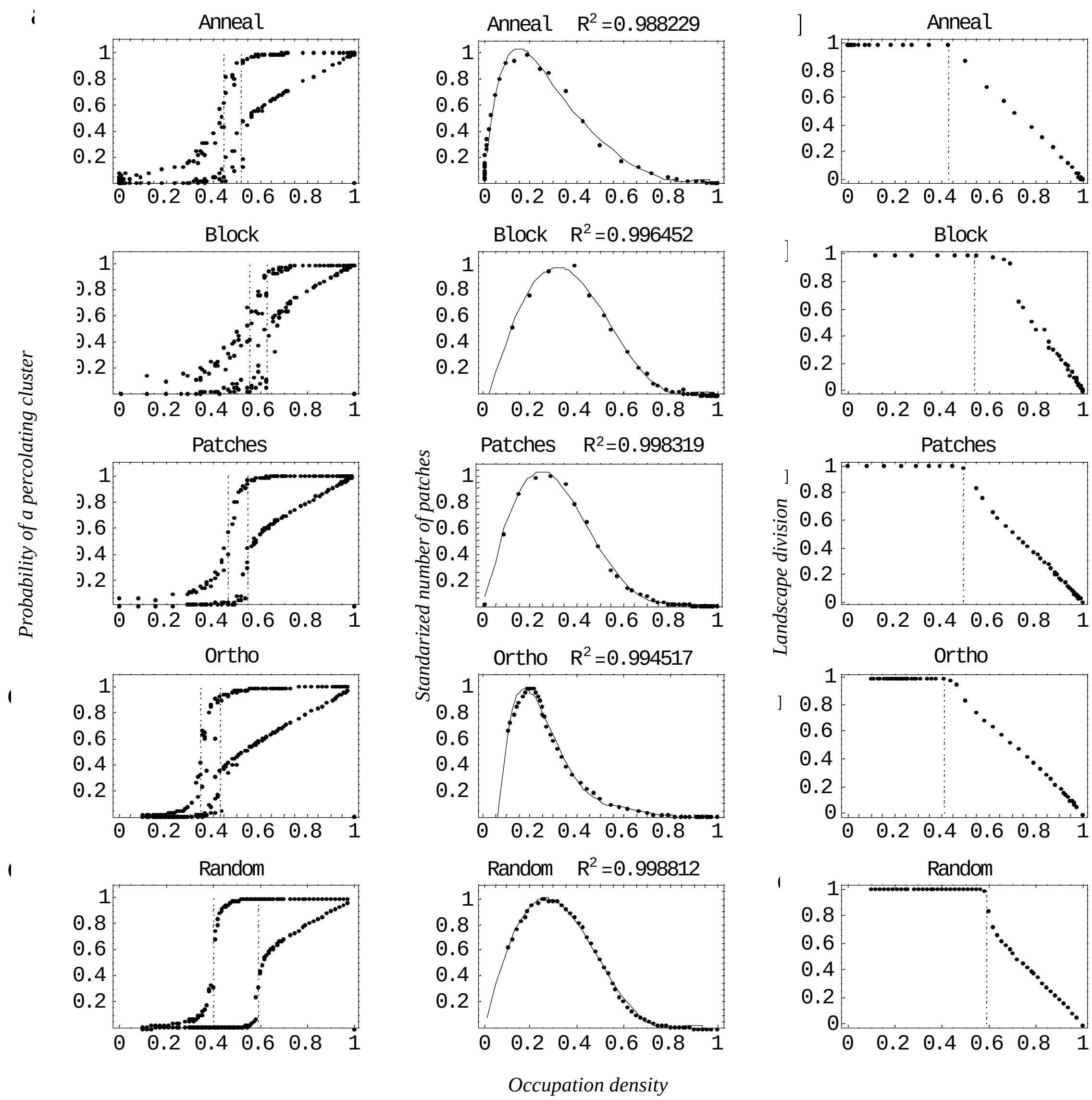


Figure 3. Percolation probability, number of patches and landscape division of under different occupation density for each artificial landscape. a-e) Percolation threshold estimation using the flow simulation. The continuous line represents the 4N and the dashed line the 8N percolation. f-j) Number of patches and adjusted curve. k-o) Landscape division showing (dashed line) the p_c value estimated for 4N.

Table 1. Landscape percolation thresholds for each artificial landscape. Results are shown with the von Neumann Neighborhood (4N) and the Moore neighborhood (8N).

Landscape Type	**4N**	**8N**
Ortho	0.426	0.350
Anneal	0.524	0.446
Patches	0.545	0.469
Random	0.589	0.398
Block	0.633	0.560

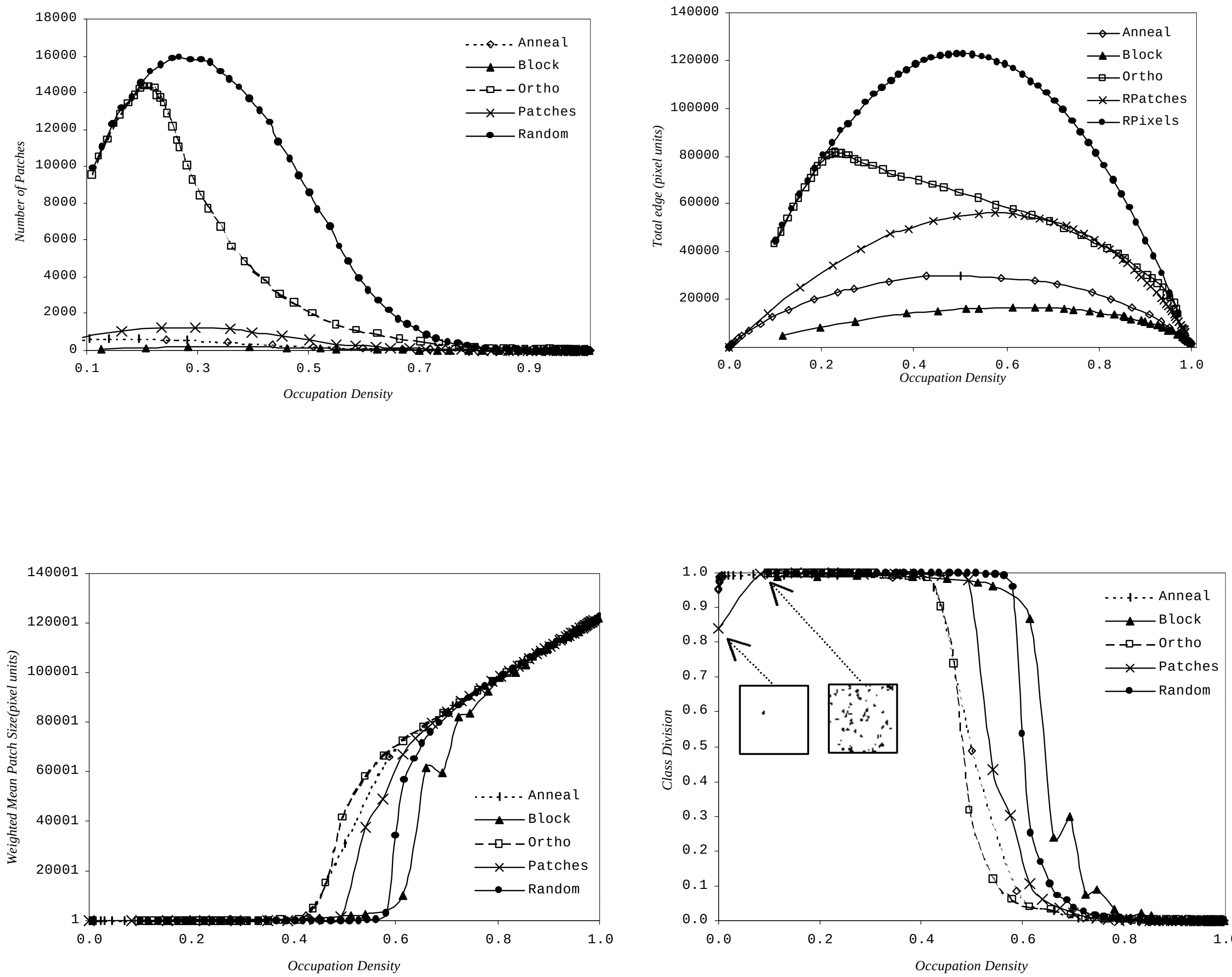
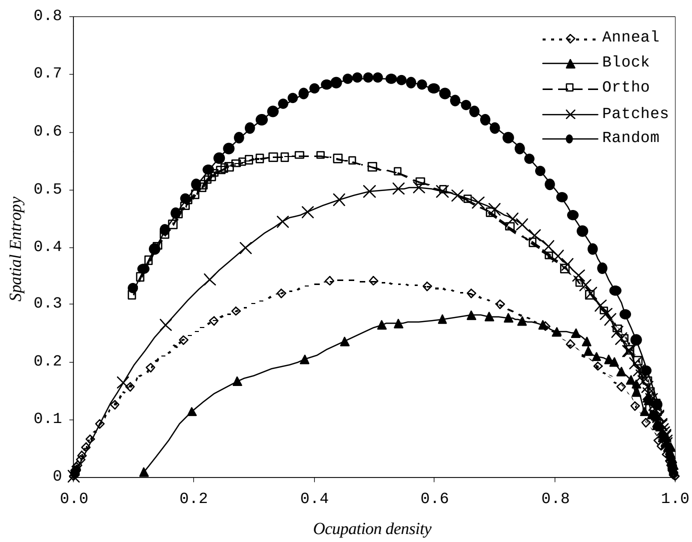
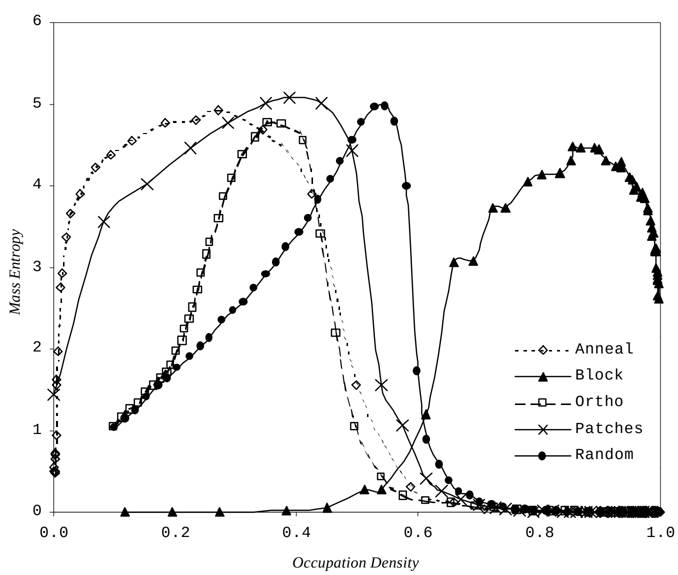


Figure 4. Results for the artificial landscapes, a) Number of patches b) Total edge. c) Weighted mean patch size (*S*) d) Class Division

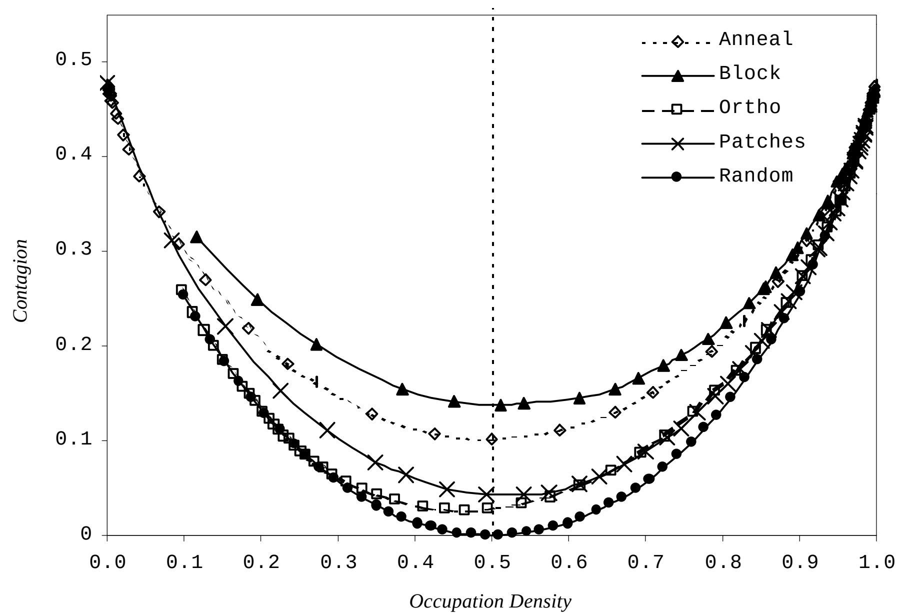
a


0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.0
0.2
0.4
0.6
0.8
1.0
Spatial Entropy
Ocupation density
Anneal
Block
Ortho
Patches
Random

b


6
5
4
3
2
1
0
0.0
0.2
0.4
0.6
0.8
1.0
Mass Entropy
Occupation Density
Anneal
Block
Ortho
Patches
Random

a



b

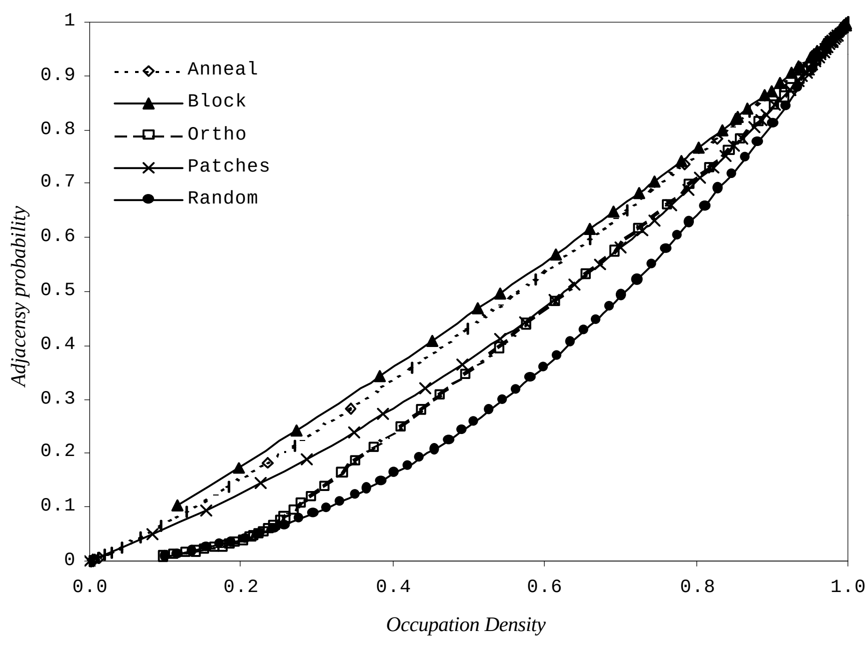


Figure 6. Results for: a) Contagion under different occupation densities for each of the artificial landscapes created. The dashed line indicates that p= 0.5; b) Occupied cells adjacency probability as a function of occupation density.

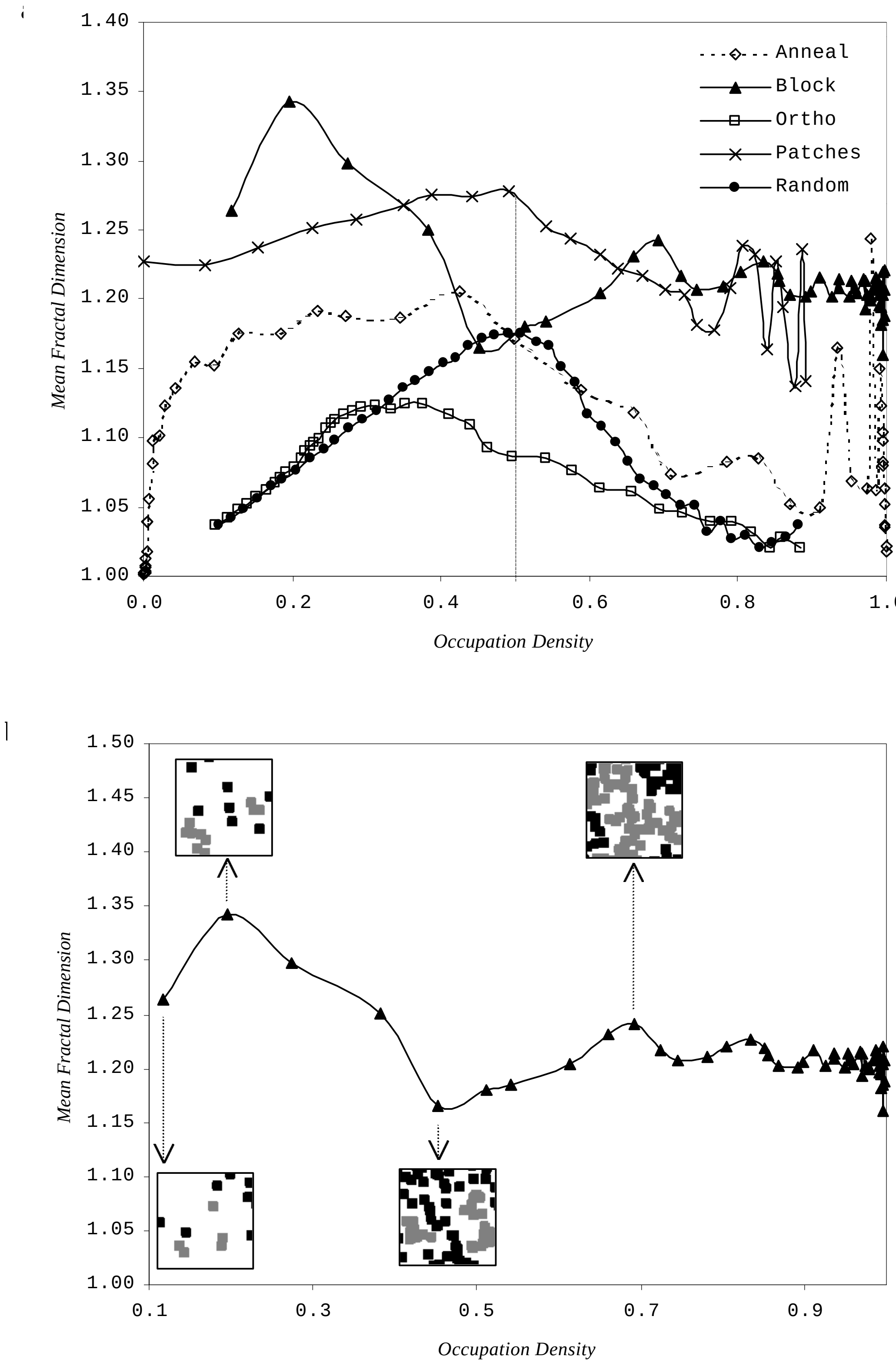


Figure 7. a) Mean fractal dimension. The dashed line, located at 0.5 occupation density, corresponds to the landscapes shown in figure 2. b) Block landscape mean fractal dimension $\overline{D}$ as a function of occupation density. The embedded boxes show a 100x100 window of 350x350 landscape, showing the structure of the landscape at different densities and its respective $\overline{D}$ value. The patches that define $\overline{D}$ are shown in gray.

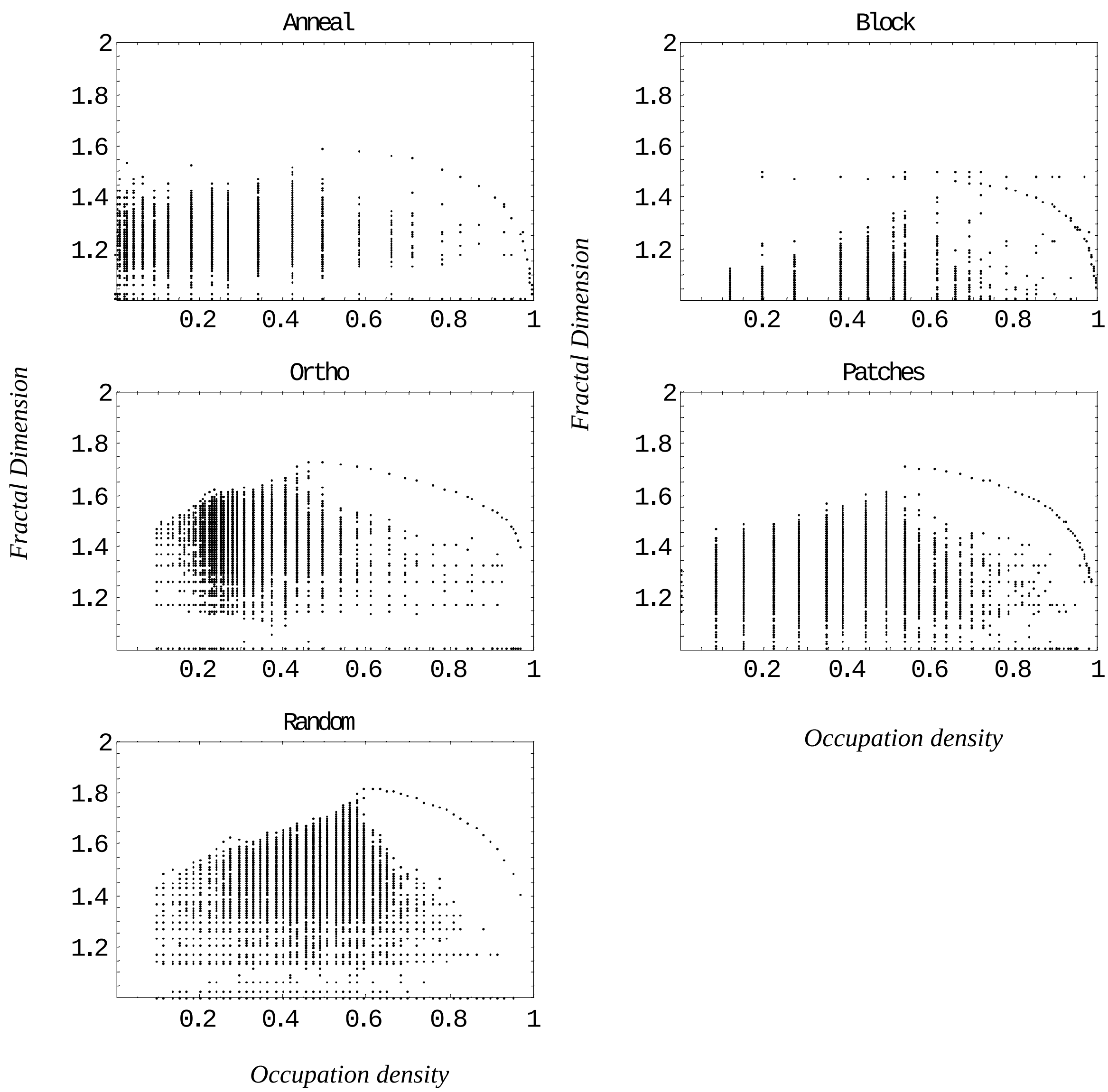


Figure 8. a-e) Perimeter area fractal dimension for every patch, as a function of occupation density. The line shows the mean Fractal dimension commonly used to describe the whole landscape.

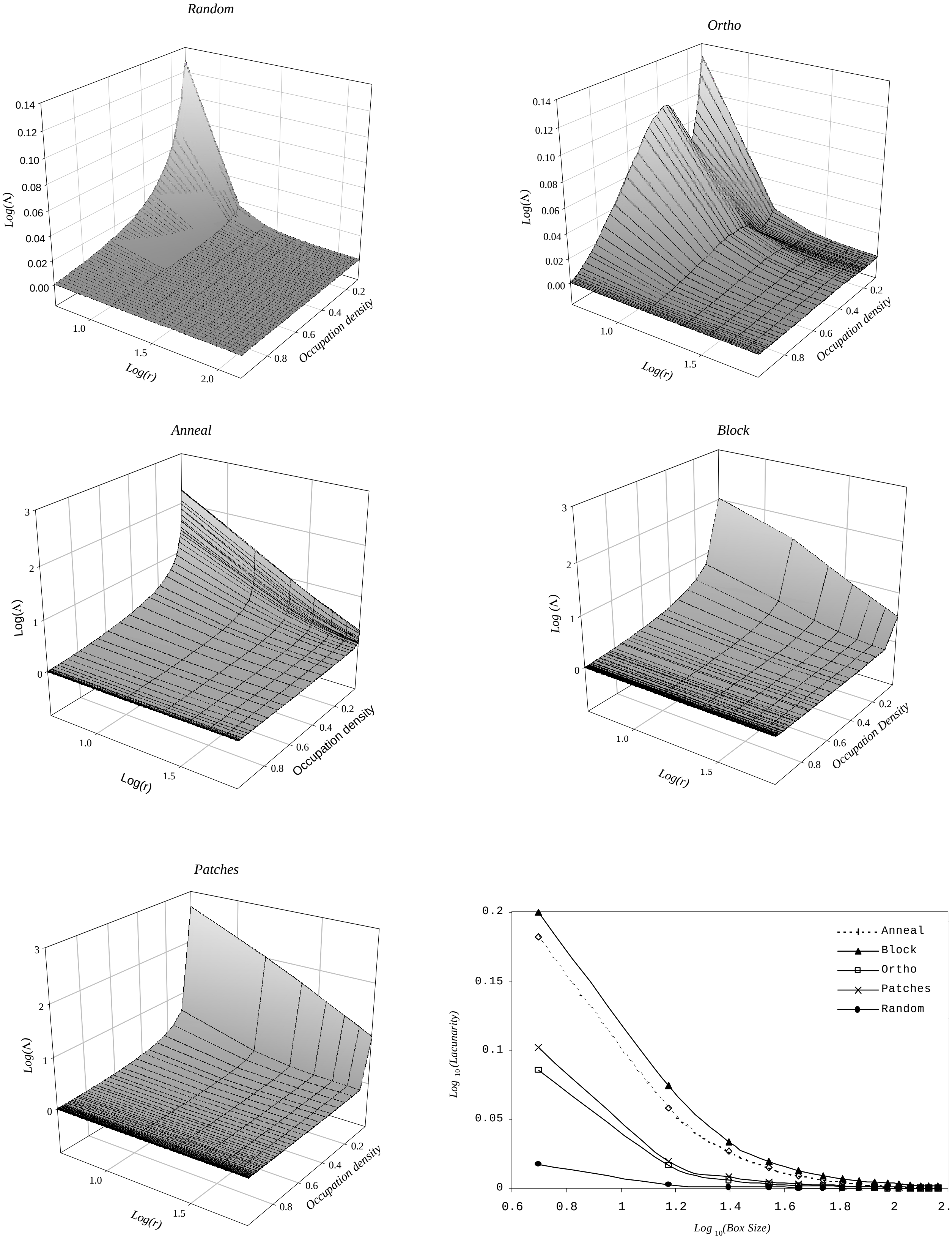


Figure 9. Logarithm of Lacunarity (Λ) as a function of the logarithm of box size (r) and occupation density for the artificial landscapes: a) random, b) ortho, c) anneal, d) block and e) patches, f) Lacunarity (log) as a function of box size with 0.5 occupation density.

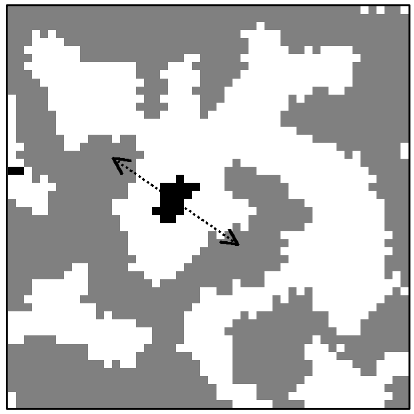


Figure 10. A sample 50x50 window of the anneal landscape at percolation density (around 0.52). The small black patch, although it is disconnected from the percolating cluster, is surrounded by it, increasing the probability of restoration of connectivity.