Landscape Ecology **15:** 661–678, 2000.

Landscape patterns simulation with a modified random clusters method

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Received 19 February 1999; Revised 20 July 1999; Accepted 23 July 1999

Key words: landscape models, landscape patterns, percolation, spatial patterns, stochastic spatial simulation, thematic and categorical maps

Abstract

A new modified random clusters method for the simulation of landscape the matic spatial patterns is presented. It produces more realistic and general results than landscape models that have been commonly used to date in the field of landscape ecology. Simulated patterns are said to be realistic, apart from their patchy and irregular appearance, because the values of the spatial indices as a function of habitat abundance measured in real landscape patterns (number of patches, edge length and patch cohesion index) can be replicated with the proposed landscape model. It allows a wide range of spatial patterns to be obtained, in which fragmentation and habitat abundance can be systematically and independently varied. Furthermore, a degree of control over the irregularity of the shapes of the simulated landscapes can be achieved, and it is also possible to simulate patterns with anisotropy. The proposed method is easy to implement and requires little computation time, which enhances the practical possibilities of this method in different areas of landscape ecology.

Introduction

The development of methods for the simulation of landscapes and other categorical spatial data patterns has focused the attention of many researchers in the past years (Gardner et al. 1987; Gardner et al. 1991; O'Neill et al. 1992; Gustafson and Parker 1992; Li et al. 1993; Li and Reynolds 1994; Gotway and Rutherford 1996; Moloney and Levin 1996; Myers 1996; Srivastava 1996; With et al. 1997; With and King 1997; Hargis et al. 1998), mainly due to their potential usefulness in different areas of landscape ecology. However, the results are often partial and non realistic, and a general model that accounts for the different broad-scale landscape patterns that exist in reality is still lacking. This paper presents a new simulation method that provides more general and realistic results than commonly used landscape models.

The objective of a landscape pattern simulation method is not to reproduce the exact location of the habitat types of the pattern, but to generate realizations that account for the information that is considered relevant for the process under study (Gotway and Rutherford 1996). The spatial patterning of landscapes influences many ecological phenomena (the processes under study), like animal population dispersal and abundance, biodiversity, wildland fire spread, disturbance spread, etc. (e.g., Franklin and Forman 1987; Fahrig and Merriam 1985; Wilcox and Murphy 1985; Dorp and Opdam 1987; Andrén 1994; Wiens et al. 1997), and the information considered relevant for those processes can be summarized in different landscape metrics, such as those relating to connectivity, fragmentation, size and shape of the patches, habitat abundance, and other spatial indices. A successful landscape model should be able to provide patterns that replicate the values of the spatial indices observed in real landscapes.

Simulated patterns can be used as an input for other modeling steps (Myers 1996), making it possible to detect which component of spatial heterogeneity is relevant for the phenomena under study. There are many modeling studies in which artificially generated patterns have been used to explore the relationships between landscape pattern and ecological processes (Gardner et al. 1989, 1991; Turner et al. 1989a, 1991; Palmer 1992; Green 1994; Lavorel et al. 1994, 1995; With and Crist 1995; Gustafson and Gardner 1996; With et al. 1997). Artificially generated patterns have also been used to develop, evaluate, and compare indices of landscape pattern, as well as to detect correlation between them (Turner et al. 1989b; Li and Reynolds 1993, 1994; Plotnick et al. 1993; Hargis et al. 1998). A more detailed description of applications of landscape models in ecology can be found in the review by With and King (1997), including the use of simulated patterns as neutral landscape models. Many other applications, not necessarily in the field of landscape ecology, like the evaluation and comparison of techniques for integrating and analysing spatial categorical data and the development and evaluation of sampling designs, can produce relevant insights from the use of simulated patterns (e.g., Zöhrer 1978; Brus and Gruijter 1997).

However, the validity of these applications depends upon the realism and generality of the landscape model used. In so far as landscape models provide partial and non realistic results, studies where they are used are likely to produce non robust or misleading results.

But, why should simulated maps be used for those purposes instead of real landscape patterns? Li et al. (1993) used computer simulation because field experimental and chronological approaches were not feasible due to expense, time requirements, lack of experimental controls, and difficulties of finding suitable study sites. Lam (1990) stated that images simulating remote sensed data would be especially useful for benchmark or theoretical studies which may involve a large number of images. Besides the time and money requirements that the use of real images may involve, the results obtained from the landscape patterns of a concrete area may not be applicable to other areas with different spatial characteristics nor comparable with the results of other authors at other study sites. That is to say, the use of some particular data could limit the scope of application of the modeling results.

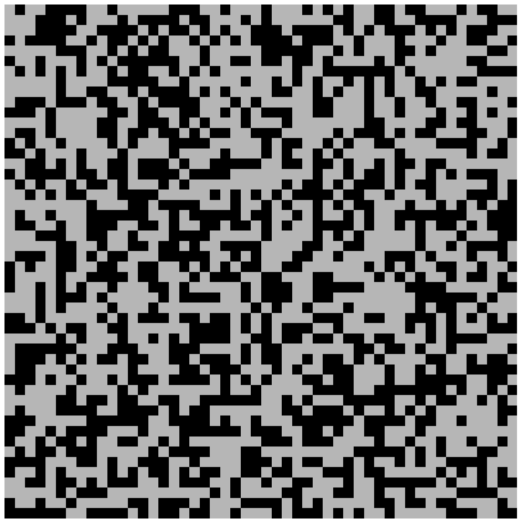


Figure 1. Percolation map for $p = 0.55$ (marked pixels are shown in lighter color).

A brief review of existing landscape simulation methods

It is not the purpose of this study to give a detailed description of these methods, but following are the main characteristics of the different available approaches. Existing simulation methods can be roughly classified in three groups: neutral landscape models, explicit simulation models and geostatistical simulation methods.

Neutral landscape models

Neutral landscape models have been defined as those that produce an expected pattern in the absence of specific landscape processes (Gardner et al. 1987; With and King 1997). According to this definition, the proposed modified random clusters simulation method (hereafter MRC) can be considered a neutral model, as it does not include any explanatory process of the resultant spatial patterns.

Among the models included in this category (With and King 1997), percolation maps have been the most widely used (Gardner et al. 1987, 1989, 1991; O'Neill et al. 1988; Turner et al. 1989a, 1991; Gardner and O'Neill 1991; Gustafson and Parker 1992; Plotnick et al. 1993; Andrén 1994; With and Crist 1995; Gustafson and Gardner 1996; Wiens et al. 1997; With et al. 1997). Percolation maps (simple random maps) are grids in which each location is occupied with a certain probability p (Figure 1); they were proposed as a neutral model for binary landscape mosaics (Gardner et al. 1987).

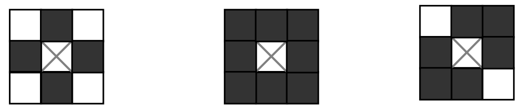
However, simple random maps are not at all adequate models of landscape patterns, as has been clearly shown when compared with real landscapes. Percolation maps have much more edge length and larger number of patches than real patterns (Gardner et al. 1991); comparisons of patch cohesion are dramatically different (Schumaker 1996), and also the cumulative frequency distributions are clearly divergent (Gardner et al. 1987). As stated by Srivastava (1996), one of the criteria in choosing a simulation method is the visual appeal of the final result, and in the case of percolation maps this is not very high (Figure 1). In general, visual inspection is valuable because it may anticipate the results of more detailed analysis based on spatial indices, which are of course needed for a non-subjective comparison of spatial patterns.

The main limitation of simple random maps is their complete spatial independence. In percolation maps, the habitat type present in a pixel is statistically independent of the habitat type present in neighborhood locations. However, real landscapes show positive spatial autocorrelation (spatial dependence), which means that if at a point of the landscape a certain habitat type exists, it is more probable that the same type is the one existing in the neighborhood locations (Palmer 1992). Percolation maps have proved useful to detect the differences between real landscapes and random patterns (Gardner et al. 1987), but they should not be used as landscape models because of their deficiencies in this respect.

Other simulation methods created to address specific questions of landscape pattern often do not appear realistic, probably because various aspects of landscape pattern were purposefully controlled, like maps with contagion (Gardner and O'Neill 1991), random clumps (Gustafson and Parker 1992), and hierarchical maps (O'Neill et al. 1992).

A more recent approach is the use of the midpoint displacement fractal algorithm (Saupe 1988). This can be adapted to obtain thematic patterns with a patchy appearance in which, according to With et al. (1997) and With and King (1997), abundance and spatial contagion of the habitat can be easily and systematically varied.

Hargis et al. (1998) describe a simulation approach that generates landscape patterns by adding patches from a data base to a map and placing them at random locations until the desired percentage of occupancy is reached. The patches included in that data base were 109 actual timber clearcut harvest patches from the Uinta Mountains of Northern Utah (USA), which may limit the results of the analysis to that particular kind of landscape patterns.



4-Neighborhood *8-Neighborhood* *Asymmetric Neighborhood*

Figure 2. Three different neighborhood criteria for identifying clusters in step B of the simulation. Pixels considered neighbors of the central pixel (x) are shown in darker color.

Explicit landscape models

These simulation models reproduce the landscape patterns resulting from the actuation of certain processes that are explicitly included in the model. Thus, these are explanatory models, unlike the neutral models described earlier. Examples of this category are the model by Moloney and Levin (1996) that simulates the spatial and temporal ecological dynamics occurring in a specific annual serpentine grassland in California, or the one developed by Li et al. (1993) to simulate the landscape fragmentation resulting from different forest cutting patterns.

Geostatistical simulation methods

The spatial simulation methods developed in the field of geostatistics to simulate the spatial distribution of categorical variables (Deutsch and Journel 1992; Gotway and Rutherford 1996) are included in this group. These methods require fairly comprehensive information about the statistical properties of the pattern to be simulated, such as variograms, covariance functions, etc.

One of the most interesting characteristics of the MRC method (and also of some of the neutral models mentioned before) is that it allows simulating complex structures with simple algorithms that require little or no previous information. This is what Guzmán et al. (1993) call 'simplicity of construction and complex appearance of the final result'. Also, computation times required to produce one simulation may be important to evaluate the performance of a simulation method. In this sense, some of the geostatistical methods cannot be considered fast at all: 'Though all methods are workable in practice, some require several days of run-time on fast computers to produce a single realization despite their author's enthusiastic claims of speed. Such procedures cannot be a practical basis for producing many realizations.' (Srivastava, 1996).

Methods

Description of the modified random clusters simulation method

The modified random clusters simulation method (MRC) is a grid-based model that generates thematic spatial patterns on squared lattices, which in the following description will be assumed to have L^2 cells (where L is the linear dimension of the map). Although it could be used for the simulation of any categorical spatial data, it has been developed for its potential interest as a landscape model. The MRC simulation method comprises the following four steps.

(A) *Percolation map generation*
The parameter that controls this step is the initial probability p. For each of the L^2 pixels of the image a random number x ($0 < x < 1$), taken from a uniform distribution, is compared with p, and if $x < p$, then the pixel is marked. Thus, a map is obtained in which approximately $p \cdot L^2$ pixels are marked (Figure 1). These simple random maps have been the subject of intensive studies in the context of percolation theory, where they have been used as a model for different physical properties, and their characteristics, which change as a function of p, are well known (Stauffer 1985; Feder 1988; Bunde and Havlin 1991). They have also been used as landscape models, but they have severe limitations in this respect, mainly due to their complete spatial independence, as noted earlier. In MRC, percolation maps are only the first step of the simulation, and its characteristics are considerably modified in the following steps.

(B) *Clusters identification*
In this step, clusters composed of pixels marked in step A are identified. A cluster is defined as a set of pixels that have some neighborhood relation between them. Depending on the neighborhood criterion used, clusters will be very different, and so this is another parameter that influences simulation results. The criterion used to generate all the MRC patterns shown in this paper (except landscape 3 in Figure 15) is the 4-neighbourhood rule: pixels are considered to belong to the same cluster if they are adjacent horizontal or vertically, but not along the diagonals (Figures 2 and 4). Other criteria can also be used (e.g., 8-neigbourhood (Figure 2), which also considers pixels along the diagonals to be neighbors), but no relevant differences in the simulated patterns are produced by the use of different symmetric criteria, in the sense that no significant increase in the variety of the simulated patterns is achieved (Saura 1998).

However, the use of asymmetric neighborhood criteria (Figure 2) leads to patterns with anisotropy, that is, with patches orientated in certain direction (Figure 15, landscape 3). The ability to reproduce this kind of non isotropic thematic patterns is of great interest, as they often appear in land cover or geological maps.

(C) *Clusters type assignation*
In this step, one type (class or category) is assigned to each of the clusters that were identified in the previous step. The objective is to transform a map with hundreds or thousands of clusters in a map with n types (Figure 4), each of them occupying a percentage of the area of the map $A_i (i = 1 \ldots n, \sum_{i=1}^{i=n} A_i = 100)$. In this step types are assigned only to the $p \cdot L^2$ pixels that were marked in step A of the simulation, thus obtaining the A_i percentages with respect to those $p \cdot L^2$ cells.

When clusters are small, types can easily be assigned in such a way that $p \cdot L^2 \cdot A_i$ pixels belong to category i of the thematic image. However, in percolation maps the size of the clusters increases with p. In particular, the size of the largest cluster of the map dramatically increases near the percolation threshold (p_c), and for $p > p_c$ a large cluster appears connecting opposite sides of the lattice and occupying most of the area of the map, as shown in Figure 3 (for the 4-neighborhood rule and large maps $p \cong 0.5928$ (Stauffer 1985; Ziff 1986)). Thus, all the possible combinations of A_i values can only be achieved for $p < p_c$. This is by no means a limitation for the generality of simulation results, as will become apparent later.

In the computer program where the MRC simulation method has been implemented (SIMMAP, Saura 1998), steps B and C take place simultaneously, assigning types to the clusters at the same time as they are being identified.

(D) *Filling in the image*
This is a key step of the simulation that makes it possible to obtain simulated landscape patterns with the necessary degree of spatial dependence, which look patchy like real landscapes.

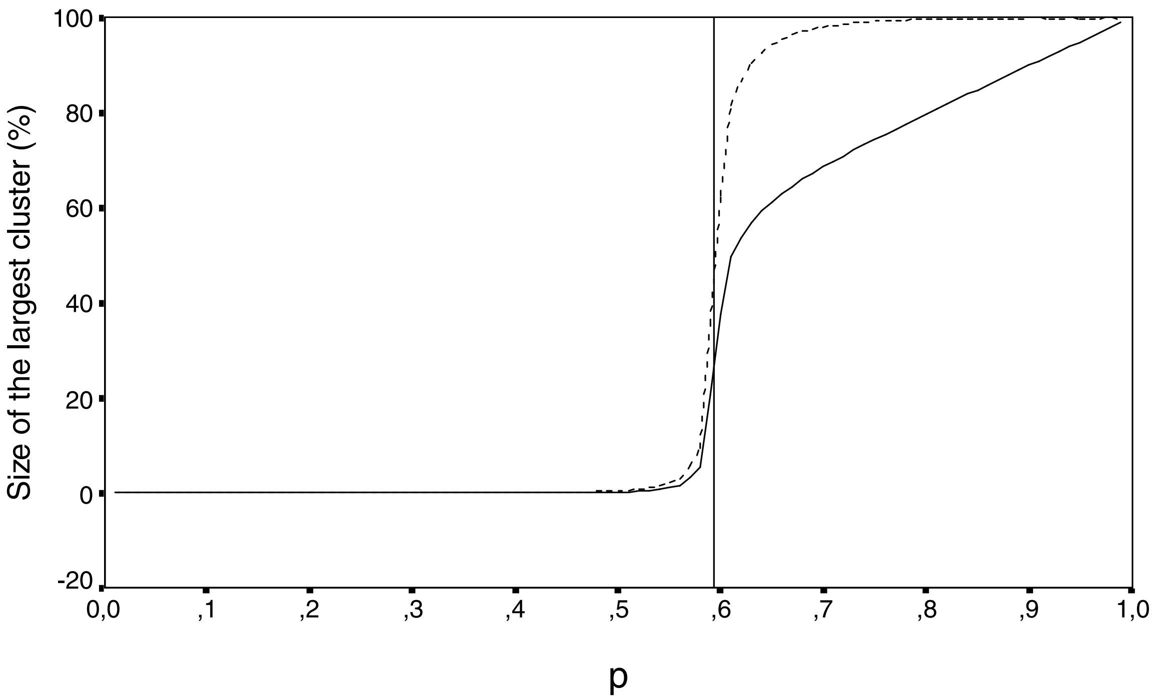


Figure 3. Size of the largest cluster as a function of p for $L = 400$, expressed as percent of the area occupied with respect to the total L^2 pixels of the map (continuous line) or with respect to the $p \cdot L^2$ marked pixels (dashed line). Percolation threshold ($p_c \cong 0.593$ for the 4-neighborhood criteria) is marked by the vertical line.

After the previous three steps an image has been obtained in which approximately $p \cdot L^2$ pixels have been assigned to one of the n types, while the rest ($(1 - p) \cdot L^2$) have no category assigned as yet. In this step, the most frequent type among the 8 neighborhood cells is assigned to each of those $(1 - p) \cdot L^2$ cells (notice that not all neighbor pixels may have a type assigned before step D. These unclassified pixels are not included in the frequencies count). In case of a tie between two types, one of them is randomly assigned. This is similar to 3×3 modal filters used in digital image processing techniques (Thomas 1980; Chuvieco 1990; Homer et al. 1997).

Thus, categories are assigned depending on those existing in the neighborhood pixels (spatial dependence). If none of the 8 neighborhood pixels has any type assigned before step D (that, is none of them was marked in step A of the simulation, which occurs when p is low) one of the types in the map is randomly assigned, but the probability of assigning each type is equal to its percentage of occupancy (A_i). This ensures that in the resulting map approximately $A_i \cdot L^2$ pixels will belong to each of the categories.

Other rules for 'filling in' the images were also tested but either did not show significant differences from the one described above or provided results that did not address the objectives of the simulation method (Saura 1998).

After this step the simulation process is complete (Figure 4), and a pattern composed of patches with an intermediate level of spatial dependence is obtained (note that we use the term 'patches' to denominate the patterns obtained after step D and 'clusters' to denominate patterns prior to step D).

Simulation parameters in the modified random clusters method

The parameters that control simulation results in MRC method are:

- Initial probability p (step A).
- Neighborhood criteria (step B).
- Number of types (classes) of the thematic pattern (n) and percentage of area of the map occupied by each of them (A_i).

And, if there is no interest in simulating patterns with anisotropy, the neighborhood criteria can be set to 4-neighborhood with no significant loss of vari-

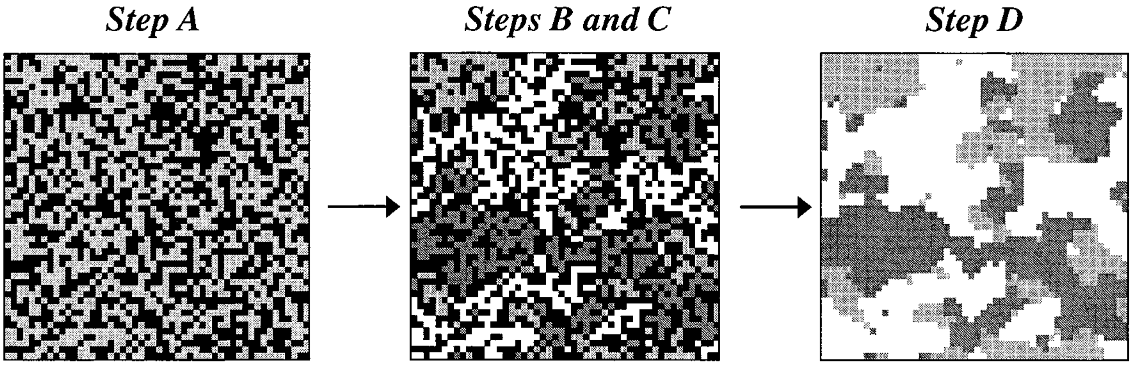


Figure 4. An example to illustrate the simulation steps that make up the modified random clusters method ($p = 0.52$, 4-neigborhood criteria, $n = 3$, $L = 50$ pixels). Pixels with no class assigned before step Dare shown in black.

ety of the simulated patterns. It is, then, a simple simulation method, controlled by a small number of simulation parameters and easy to implement for any of the purposes described in the introduction.

In MRC the initial probability p is *not* related to the abundance of the types in the map, as percentages of occupancy are determined by cluster type assignation (step C). This is the opposite of what occurs in percolation maps, and so special care should be taken in order to avoid confusion. In MRC p controls the degree of fragmentation or aggregation of the patches, as is clearly shown in Figure 5. When p is small, patches are more numerous and smaller, and thus patterns are more fragmented. As p increases, the number of patches decreases and its mean and maximum size increase, resulting in more aggregated landscapes. As shown in Figure 5, the increase in the size of the patches as a function of p is not linear, but more rapid as p is nearer $p_c(p_c \cong 0.593$ for the 4-neighborhood criteria).

As explained before, any desired percentages of occupancy of the n habitat types (A_i) can be obtained for any $p < p_c$. There is no need to use values of $p > p_c$, because maps with a dominant type (a type that occupies most of the area of the map) can be generated for any value of p by fixing the A_i values accordingly. Furthermore, this makes it possible to control the degree of fragmentation of the patches embedded in the dominant matrix, by simulating patterns with the same A_i but different initial probability p, as shown in Figure 6. This differentiation of abundance of the classes of the thematic pattern and probability p is one of the keys of the improvements in this method, as it allows separate control of fragmentation and habitat abundance, which in percolation maps are mixed and confused.

In MRC, percolation maps are only the first step of the simulation, and its characteristics are considerably modified by the following steps. In fact, very different thematic images can be obtained from the same percolation map. Figure 15 clearly shows how the modified random clusters simulation method expands and improves the simulation possibilities of simple random maps.

Simple random maps are just an extreme case of the MRC patterns, characterized by complete spatial independence, that are obtained when $p = 0$. In this case type assignation is done entirely at random in step D (steps A, B and C do not take place), producing a map in which the type existing in a particular pixel is not related statistically to those existing in the neighborhood cells. At the other extreme, there is maximum spatial dependence in a categorical map when all the pixels of a certain category belong to the same patch. Between these unrealistic extremes all the intermediate degrees of spatial dependence can be obtained by varying the initial probability p, so that spatial dependence is higher as p increases.

It should be noted that MRC is a stochastic simulation method, that is, multiple random realizations can be obtained for the same set of simulation parameters, which differ in the exact location of the types of the pattern but are similar in their overall spatial structure.

Landscape metrics for the quantification of simulation results

As Figures 5, 6, 12, 13, 14 and 15 show, patterns generated with the modified random clusters method are remarkably realistic, in the sense that they look patchy and irregular as real landscapes usually do.

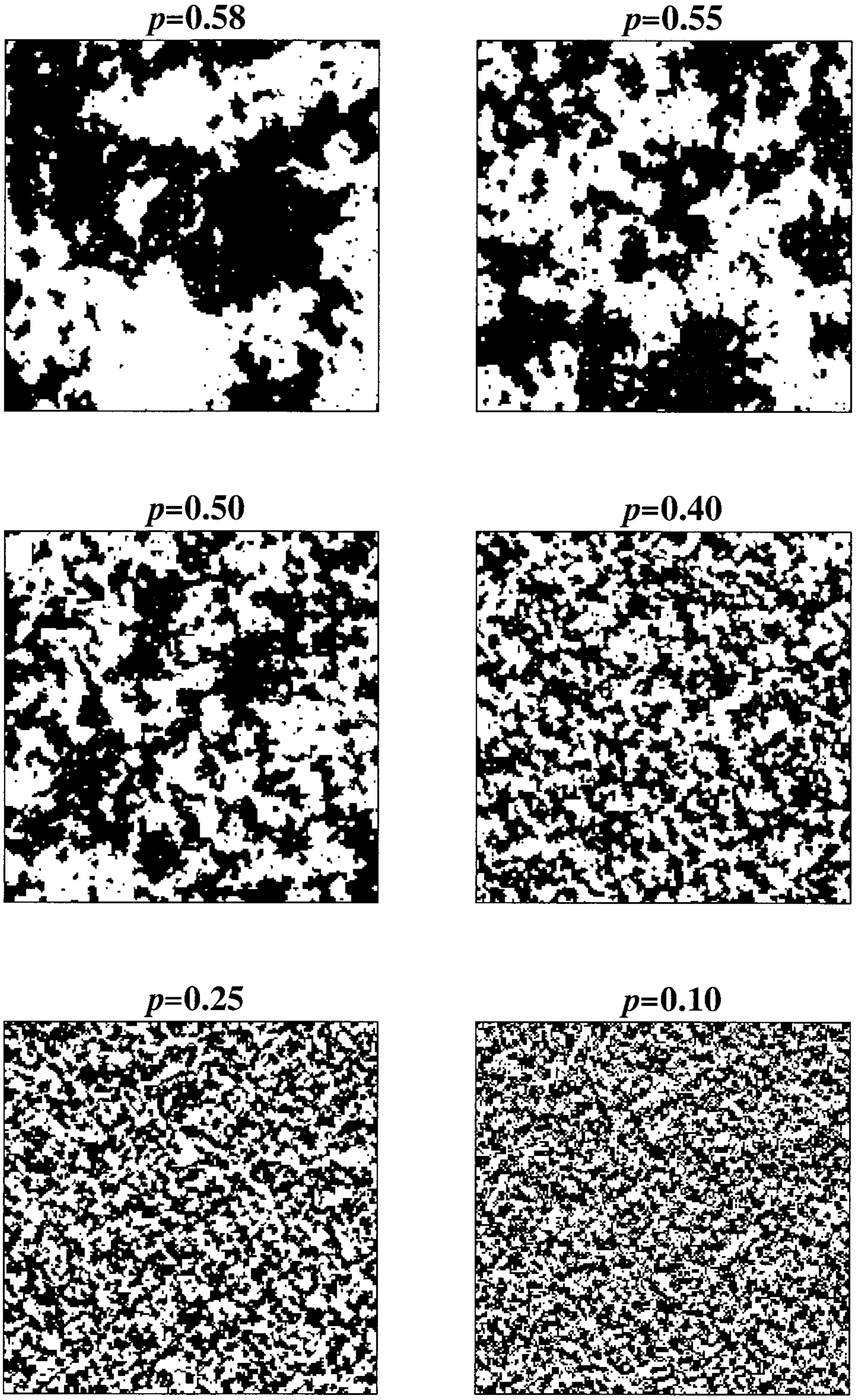


Figure 5. Six simulated binary landscapes ($n = 2$) with the same percentages of occupancy ($A_1 = A_2 = 50\%$) but generated for different values of the initial probability p. In all the images $L = 200$ pixels.

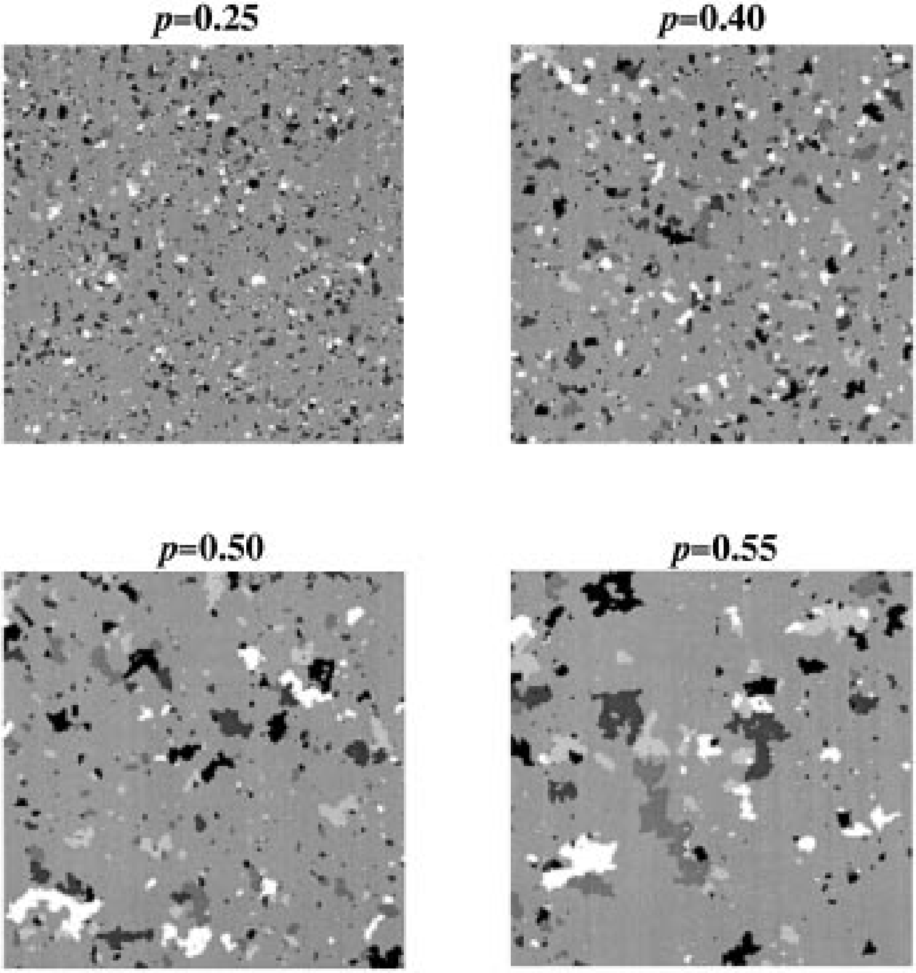


Figure 6. Four simulated landscapes in which the dominant habitat type occupies 80% of the area, but each of them generated for different values of p. The four patterns have 6 habitat types and their size is 200×200 pixels.

To evaluate the realism of the simulations in quantitative and non subjective terms, we generated a set of MRC binary simulated patterns ($n = 2$) and computed the values of number of patches (NP), edge length (EL), patch cohesion index (PC) and area weighted mean shape index (AWMSI) corresponding to patches of class 1. These indices were selected because MRC results could be compared with other simulation methods and published real landscape data and were particularly suitable for discriminating between simple random patterns and MRC maps.

All simulated patterns were 400×400 pixels and the clusters were identified using the 4-neighborhood criterion (step B of the simulation). The percentage of occupancy (A_1, $A_2 = 100 - A_1$) was varied from 1% to 99% in steps of 1% (99 cases) and the initial probability p ranged from 0.01 to 0.6 in steps of 0.01 (60 cases). In all, 5940 landscapes were simulated, in which percentage of occupancy and degree of fragmentation were independently and systematically varied. Also, 400×400 pixel percolation maps were generated with the same proportions of habitat (that is, from 1% to 99% in steps of 1%), and 10 replications for each of the 99 cases, making a total of 990 maps. Patches in the landscape were defined using the 4-neighborhood rule, which is the one used by most authors when computing landscape metrics (e.g., Gardner et al. 1987, 1991; Turner and Ruscher 1988; With et al. 1997), although some others have used the 8-neighborhood rule (Schumaker 1996; Hargis et al. 1998).

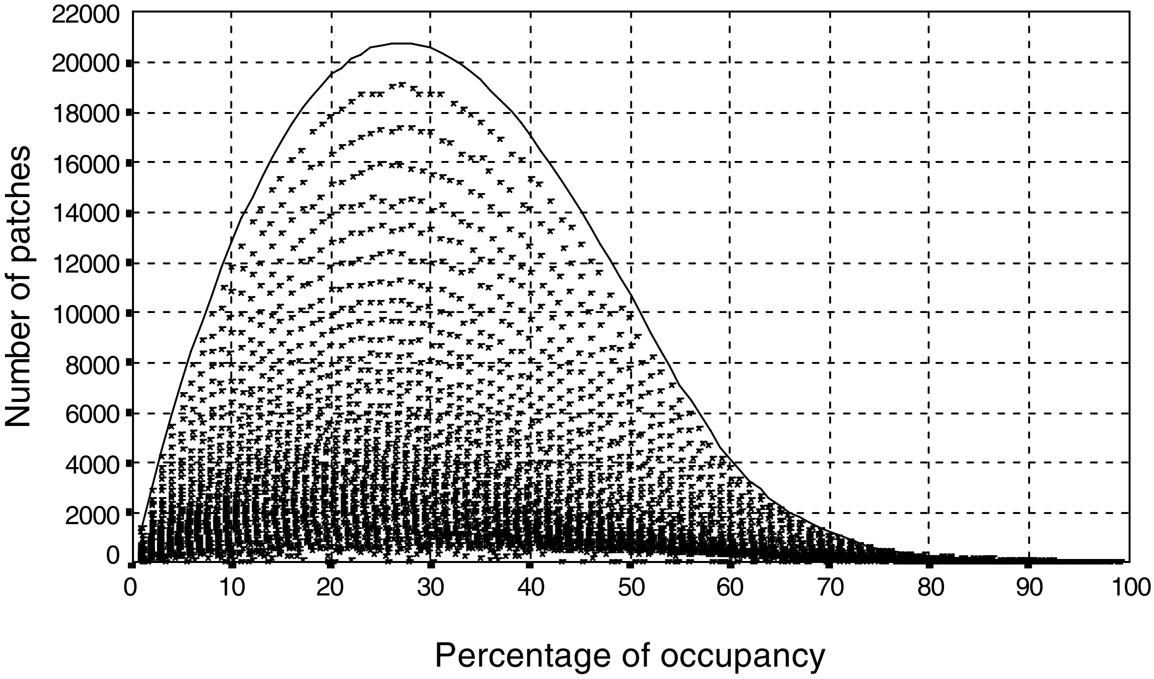


Figure 7. Number of patches as a function of percentage of occupancy (A_1) for the set of MRC simulated patterns.

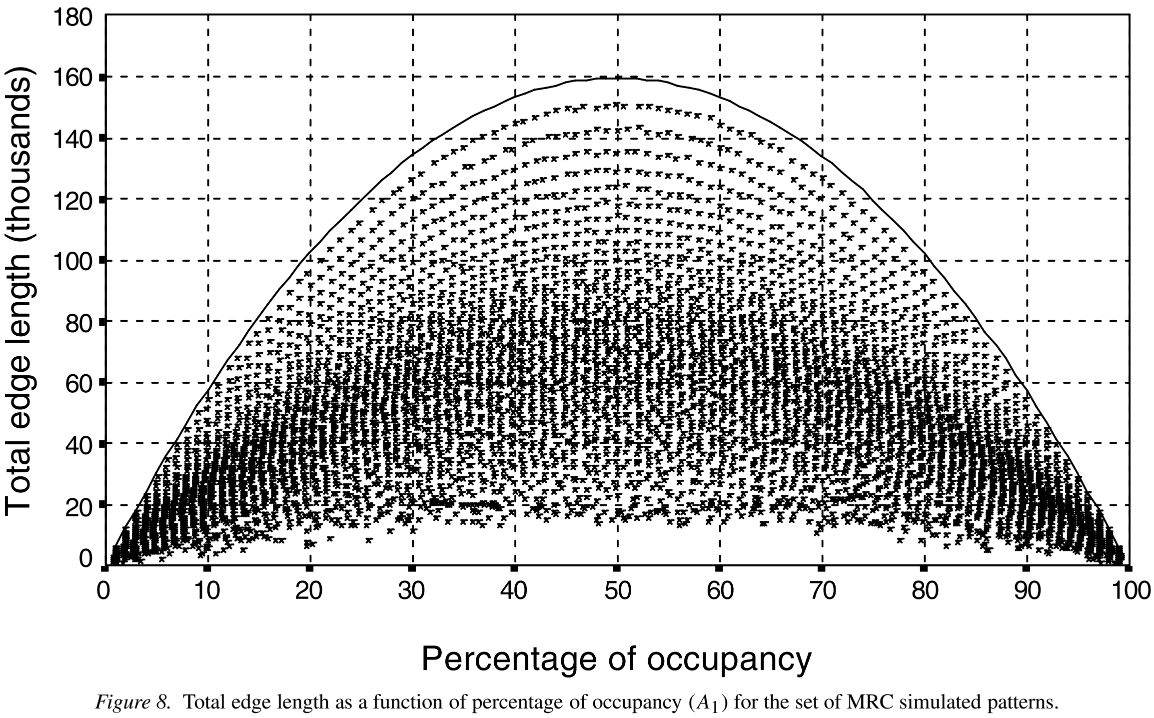


Figure 8. Total edge length as a function of percentage of occupancy (A_1) for the set of MRC simulated patterns.

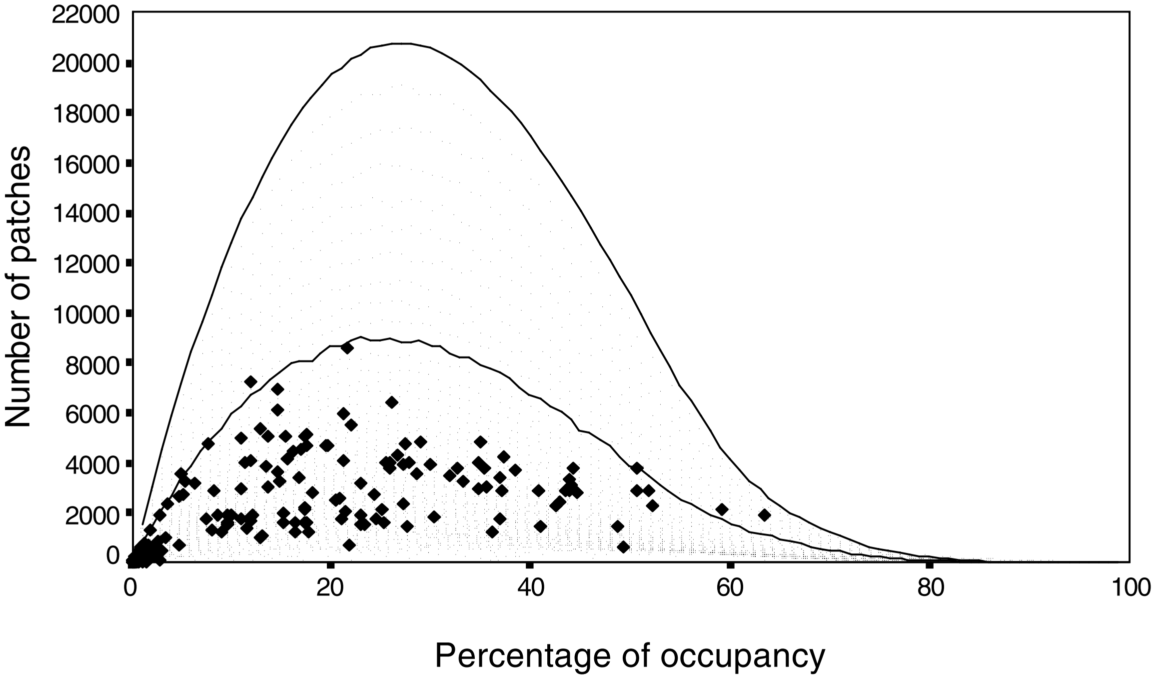


Figure 9. Comparison between the number of patches of real landscapes in Georgia (large rhombs) and the simulated patterns. The upper continuous line corresponds to simple random maps ($p = 0$) and the lower one to the simulated patterns obtained for $p = 0.1$.

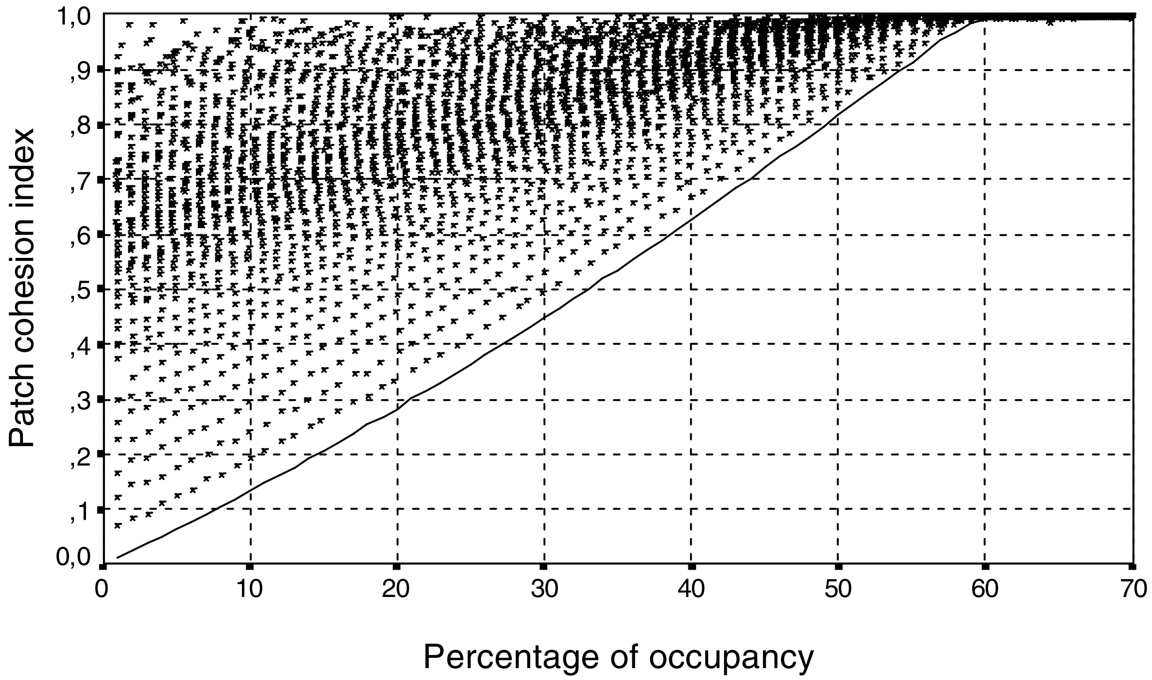


Figure 10. Patch cohesion index (PC) as a function of percentage of occupancy (A_1) for the set of MRC patterns. The continuous line corresponds to the PC values for simple random maps ($p = 0$).

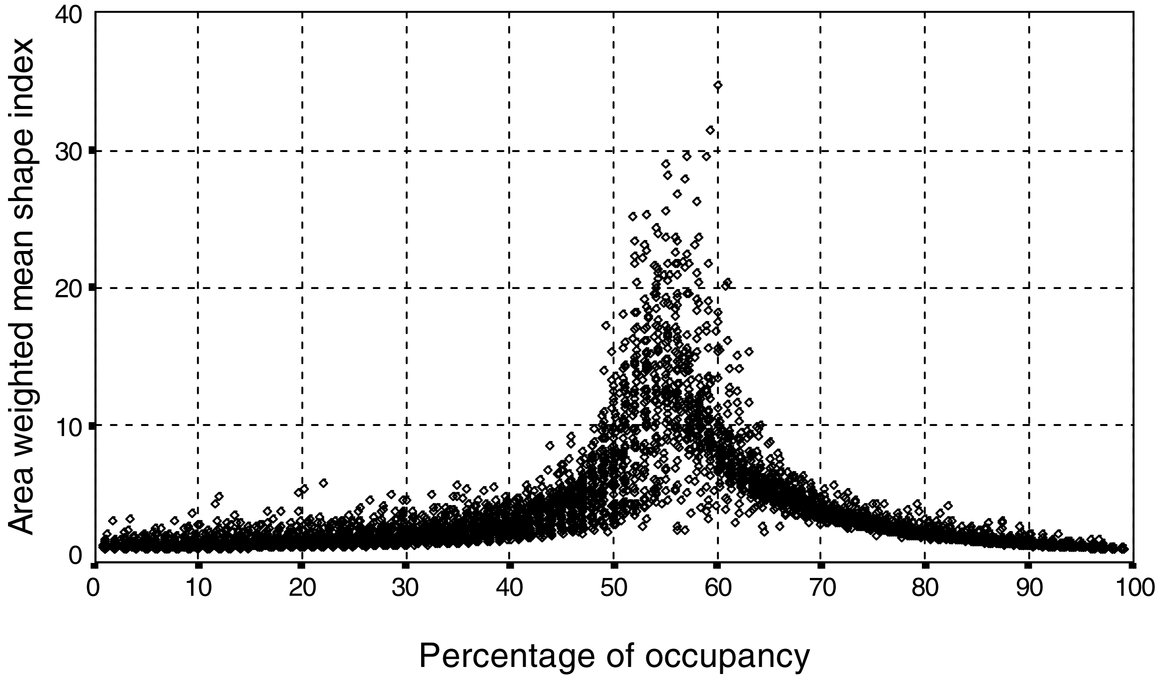


Figure 11. Area weighted mean shape index as a function of percentage of occupancy (A_1) for the set of MRC simulated patterns.

Edge length is the sum of all the edges between cells that are horizontally or vertically adjacent and belong to different habitat types. EL is a good index of fragmentation (Li et al. 1993), taking lower values as the pattern is more aggregated.

The patch cohesion (PC) index (Schumaker 1996), has the following expression:

$$PC = \left[1 - \frac{\sum_{i=1}^{i=m} p_i}{\sum_{i=1}^{i=m} p_i \cdot \sqrt{a_i}} \right] \cdot \left[1 - \frac{1}{\sqrt{N}} \right]^{-1},$$

where p_i and a_i are respectively the perimeter and the area of each of the m patches of the habitat class of interest, and N the total number of pixels in the landscape (L^2). The PC value is minimum (PC = 0) when all patches of habitat are confined to single isolated pixels, and maximum (PC = 1) when every pixel is included in a single patch that fills the landscape (Schumaker 1996).

The area weighted mean shape index (AWMSI) has the following expression:

$$\text{AWMSI} = \frac{\sum_{i=1}^{i=m} \frac{p_i}{4\sqrt{a_i}} \cdot a_i}{\sum_{i=1}^{i=m} a_i} = \frac{\sum_{i=1}^{i=m} p_i \sqrt{a_i}}{4 \sum_{i=1}^{i=m} a_i},$$

where p_i and a_i are respectively the perimeter and the area of each of the m patches of the class of interest in the landscape. AWMSI measures the irregularity or complexity of the shapes of the patches, and its value is minimum (AWMSI = 1) for perfect square patches. This index uses patch area as a weighting factor because larger patches are assumed to have more effect on overall landscape structure (Li et al. 1993; Schumaker 1996).

Results and discussion

The results for number of patches (NP) and total edge length (EL) are shown in Figures 7 and 8, where values corresponding to percolation maps are shown in a continuous line. Simple random maps, which are obtained as a particular case when $p = 0$, produce the most fragmented patterns of any that can be generated with the MRC method. Below this upper limit, all degrees of fragmentation can be obtained by varying the initial probability p. The upper limit for NP and EL of

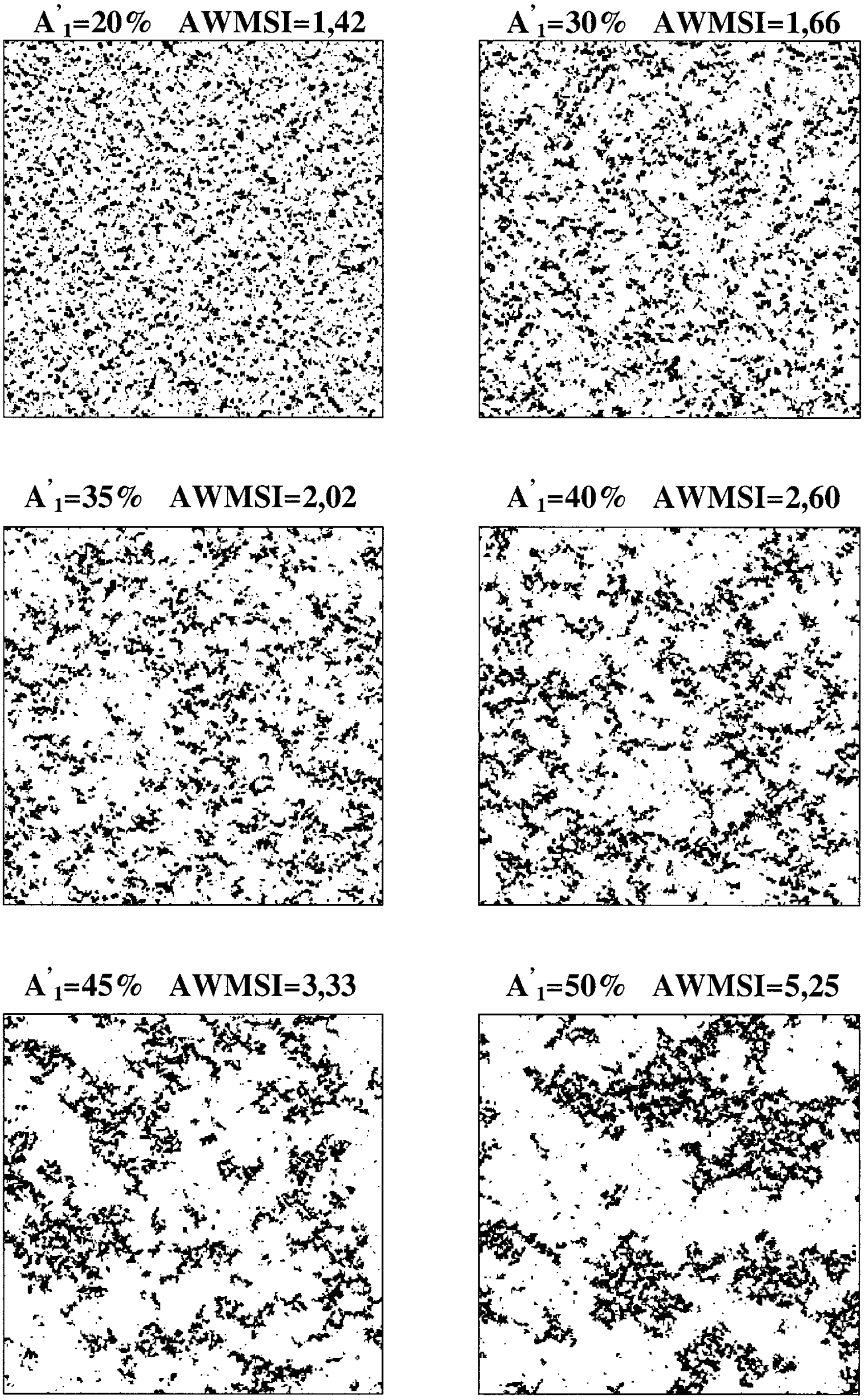


Figure 12. Six binary simulated patterns with the same habitat abundance (20%) and for the same initial probability ($p = 0.2$), but generated under different initial A'_1 values, with patches of type 1 later assigned to habitat type 2 until 20% of occupancy is reached. The nearer the initial A'_1 is to 50–60%, the more irregular and convoluted are the shapes of the patches. In each simulated pattern the initial A'_1 value and the area weighted mean shape index (AWMSI) of the obtained pattern are indicated. Obviously, in the case $A'_1 = 20\%$ (upper left), no reassignment of patches was needed.

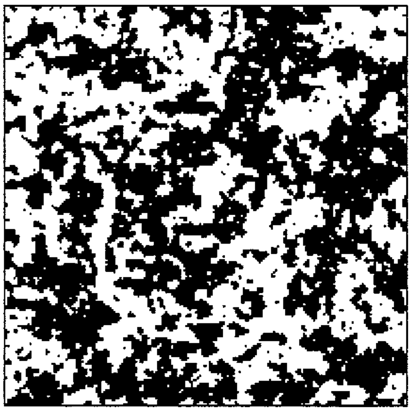
MRC simulated patterns by no means limits its use as a landscape model; Gardner et al. (1991) showed that real landscapes have much less edge length and number of patches than percolation maps with the same percentage of occupancy. The values of EL and NP as a function of the percentage of occupancy for 27 forest/non-forest binary landscapes can be reproduced with the modified random clusters method, as is apparent from a comparison of Figures 7 and 8 in this paper with figure 5 in Gardner et al. (1991).

To support this observation, values for the number of patches as a function of the percentage of occupancy for real landscapes were taken from Turner and Ruscher (1988) and Turner (1990) and compared with results for the MRC simulation method. Those landscape patterns were obtained from black and white aerial photography of nine counties of Georgia (USA), with scales ranging from 1:20.000 to 1:60.000. In all, 177 cases were taken from those data, which included eight land cover categories (urban, agricultural, transitional, improved pasture, coniferous forest, upper deciduous forest, lower deciduous forest and water), and four different physiographic regions (mountains, piedmont, upper and lower coastal plain). In order to render the NP values comparable with one another and with the 400×400 cell simulated patterns, the number of patches was multiplied by the quotient between 400×400 and the number of cells of each of the 177 raster maps (with sizes varying from 12.696 to 38.088 cells, each cell representing one hectare). In spite of the variety of the data, MRC was effective for all the values of the number of patches observed in these landscapes (see Figure 9). In this figure, the number of patches corresponding to $p = 0.1$ is presented in a continuous line, to emphasize that with $p >= 0.1$ we could account for 173 of the 177 cases (97,7%). This indicates that too low values of the initial probability p are not adequate for landscape simulation, as they are more fragmented than they appear in reality. In fact, very low values of p produce results too close to complete spatial independence; in the limit case ($p = 0$) the result was simple random maps which bore little resemblance to real landscapes (Figure 9). The same is true of total edge length, as a comparison of Figure 8 with Figure 5 in Gardner et al. (1991) demonstrates. The maximum edge length is achieved for 50% of habitat abundance (Figure 8), just as has been shown to occur in real data from remote sensing in the north of Costa Rica (Traub 1997).

No landscape model that produces a single value of EL or NP for a fixed percentage of occupancy can account for the diversity of cases that exist in real landscapes, because a range of values can occur for the same habitat abundance (see the data for Georgia landscapes in Figure 9 and other landscape data, e.g., Traub 1997). In this sense, MRC provides a continuum variation of the values of those spatial indices, which is a significant improvement on some of the previously existing landscape models.

However, these two indices (NP and EL) may correlate only weakly with some ecological processes like animal population dispersal, because pattern indices that ignore habitat area are considerably biased by small patches that contribute little or nothing to dispersal success (Schumaker 1996). Schumaker proposed the patch cohesion index (PC) which, according to the dispersal model used, correlated better with dispersal success than any other of the commonly used landscape metrics. He computed the values of PC for old-growth forests in the National Forests of the Pacific Northwest of USA (a total of 2100 randomly selected landscapes), with percentages of occupancy ranging from 1% up to 33.4%. The observed PC values were in most cases over 0.9, and lower values of PC were obtained only for sparse habitat, but always over 0.8. PC values for MRC simulated patterns are shown in Figure 10. The figure illustrates how simulated landscapes with high patch cohesion for all the percentages of occupancy can be obtained, just as occurs in the real patterns examined by Schumaker. The MRC method, then, is able to generate the values of spatial metrics existing in real landscapes for indices that seem to correlate strongly with ecological processes. Again, PC values for simple random maps are very different from those observed in landscapes (Figure 10), as noted by Schumaker (1996). The difference in the slope for PC values corresponding to percolation maps in Figure 10 in the present paper and figure 9 in Schumaker (1996) is due to the different criteria used to define patches here (4-neighborhood) and by Schumaker (8-neighborhood). Each of the lines tends to equal 1 near the percolation threshold, which occurs at different values in both cases (around 59.3% of occupancy for 4-neighborhood and 40.7% for 8-neighborhood). Patch cohesion index is not sensitive to landscape changes when a large percentage of the landscape is occupied (Figure 10), which could be a limitation for its use in that range of occupancy percentages.

The results for the area weighted mean shape index covered a wide range of values, as shown in Figure 11. However, there is a clear dependence of AWMSI with



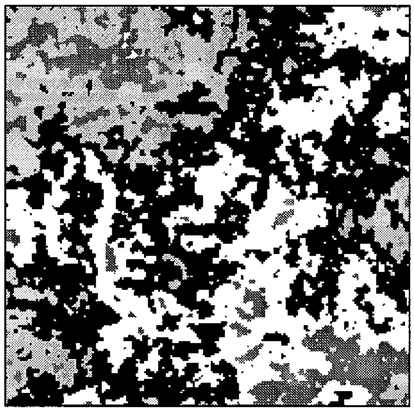
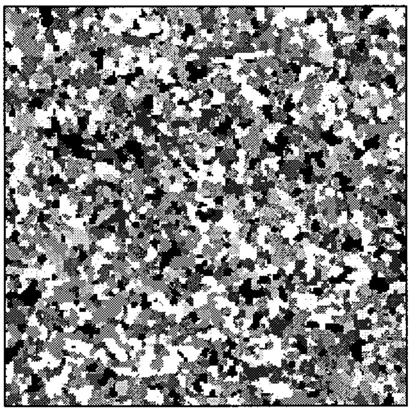


Figure 13. A pattern with four habitat types (right, $n = 4$) is obtained after splitting the patch types of a binary landscape (left, $n = 2$).



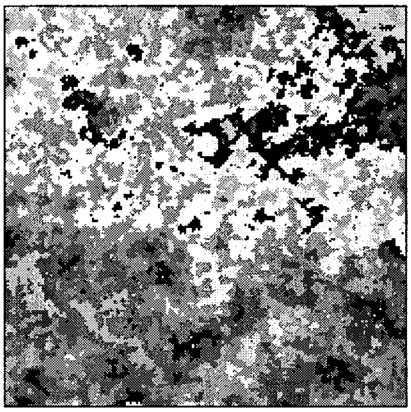


Figure 14. Two simulated patterns with the same habitat proportions ($n = 6$) and obtained for the same initial probability $p = 0.4$ ($L = 200$ cells). However, the one on the right was generated by splitting the patch types of a binary pattern ($n = 2$) with $A_1 = A_2 = 50\%$.

A_1 and the greatest complexity of shapes is given by habitat abundance around 55%. Of course, when habitat is either very abundant or sparse patterns are not complex; in extreme cases where all the habitat is confined to single isolated pixels or where all the landscape is occupied by the same habitat type, AWMSI would yield its minimum value (AWMSI = 1).

More general results as to patch shape index are readily obtained: landscapes with a high AWMSI can be generated (this occurs for A_1 near 55%) and the habitat abundance decreased later by reassigning the type 1 patches to type 2 until the desired occupancy percentage is reached. This is only possible if p is not too close to p_c (as in Figure 12, where $p = 0.2$). In this way A_1 is fixed depending more on the irregularity of the shapes to be obtained than on the habitat abundance, which can later be rearranged until the desired percentage of occupancy is attained (Figure 12). When simulating patterns with multiple types ($n > 2$), similar devices can be used to have more control over the complexity of patch shapes. By generating a binary map ($n = 2$) for $A_1 = A_2 = 50\%$ (high AWMSI) and splitting the patches in each of the two categories into two new types (Figure 13), a four-type map ($n = 4$) can be produced in which patch shapes are more complex and less isodiametric than if the map was simply simulated by fixing the desired n and A_i in step C (Figure 14). That is, maps can be generated with a value of A_i for which a high AWMSI is obtained, and patches can later be reclassified to obtain the desired number of categories and proportions, resulting in patterns with the high AWMSI corresponding to the initial A_i. This was also the method used to generate landscape 2 in Figure 15. These methods increase the variety of the simulated patterns that can be obtained with the MRC, allowing more independent control of the patch shapes of the simulated patterns than is possible by simple variation of the initial probability p.

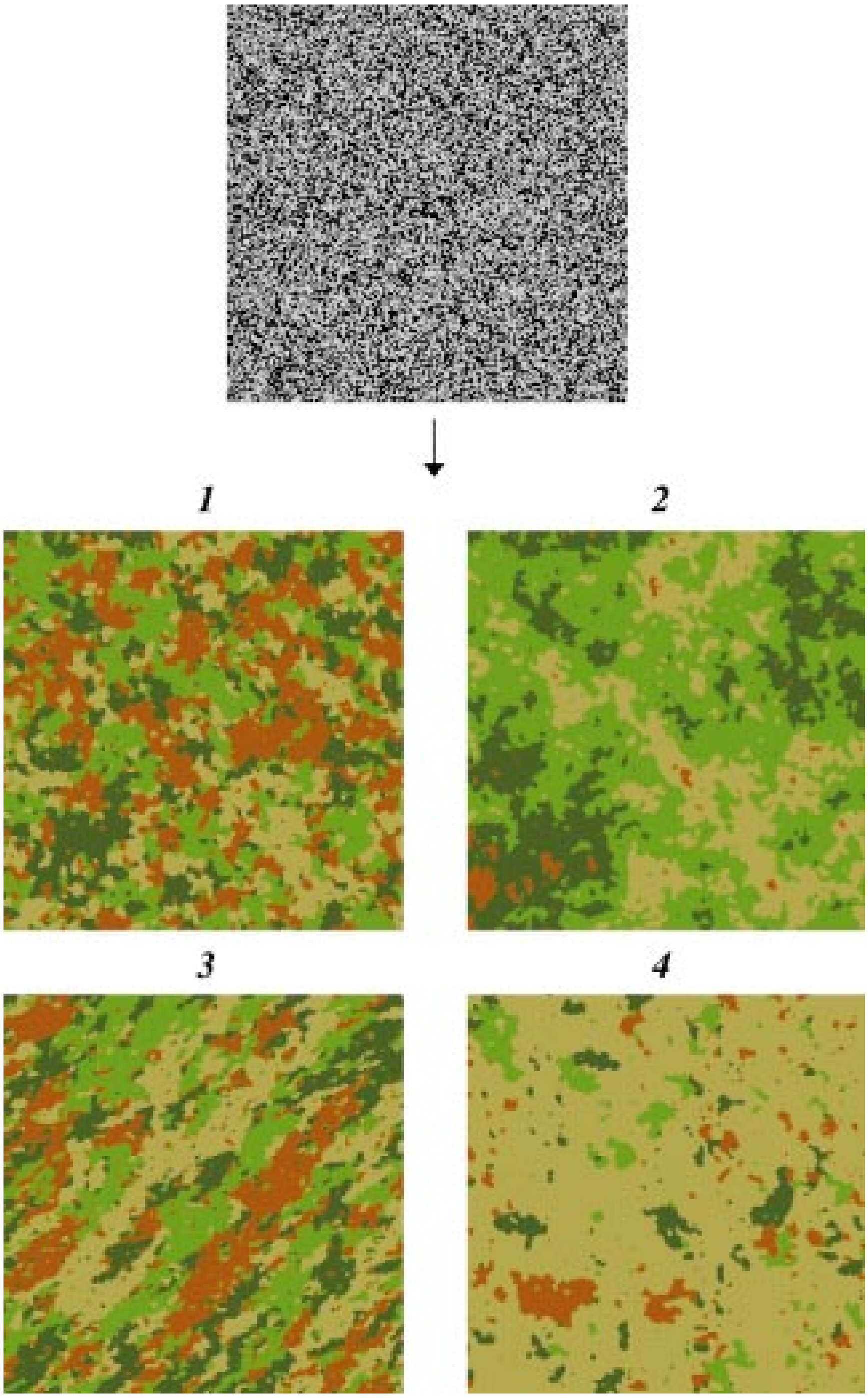


Figure 15. Four simulated thematic patterns obtained from the same percolation map (up, $p = 0.5$). All have four habitat types ($n = 4$) and a size of 200×200 pixels. The rest of the simulation parameters are: (1) $A_1 = A_2 = 22\%$, $A_3 = A_4 = 28\%$. (2) Initially $n = 2$ and $A_1 = 45\%$ $A_2 = 55\%$, but patches were split into four habitat types ($n = 4$) with $A_1 = 23\%$ $A_2 = 22\%$ $A_3 = 53\%$ $A_4 = 2\%$. (3) Asymmetric neighborhood criteria, $A_1 = A_4 = 28\%$ $A_2 = A_3 = 22\%$ (4) $A_1 = 79\%$ $A_2 = A_3 = A_4 = 7\%$.

All the algorithms required for the simulation of thematic patterns with the proposed MRC method were implemented on a specific software, SIMMAP (Saura 1998), with which all the simulated landscape patterns presented in this paper can be generated. SIMMAP also computes the indices described in Landscape metrics for quantification of simulation results section, as well as several others. As noted earlier, the computational effort required to produce one realization may be an important aspect to consider when evaluating the performance of a simulation method. MRC requires low computation times to generate one simulated landscape pattern: as implemented on the SIMMAP program, and running on a standard PC at 200 MHz, times per realization are around 1 s (100×100 pixels landscapes), 4 s (200×200 pixels) and 16 s (400×400 pixels).

Conclusion

Many of the landscape models that have been used in landscape ecology provide results that are partial and often unrealistic. It is not surprising that Schumaker (1996), comparing the patch cohesion of landscapes with the values corresponding to percolation maps, stated that "this analysis suggests that the relationship observed here between patch cohesion and dispersal success derives from a characteristic property of real landscapes that is not found in simple artificial landscapes, and that studies of simulated habitat pattern may thus provide little insight into the extent to which habitat fragmentation actually alters connectivity (. . .).

These observations suggest that the use of computer-generated landscapes could both inflate the value of poor predictors of ecological quality and diminish the power of useful indices".

Indeed, in so far as landscape models are unable to reproduce the values of the landscape metrics that are found in reality, studies where they are used are likely to produce non robust or misleading results.

The proposed modified random clusters simulation method may be a significant improvement in this sense, in that it provides more general and realistic results than previous landscape models. It is more realistic because the results presented in this study show that MRC accounts for the values of the landscape metrics that have been observed in landscapes as a function of percent of occupancy; and it is more general in that the results of some other landscape models are or may be considered particular cases of the wide array of patterns that can be generated with the proposed method.

MRC makes it possible to simulate landscapes with every possible degree of fragmentation and spatial dependence, ranging from the unrealistic extreme of simple random maps to higher degrees of spatial dependence and aggregation as the initial probability *p* increases. Patterns with multiple habitat classes and any abundance of each of the categories can be generated. Furthermore, it is possible to simulate patterns with anisotropy, and to achieve some control over the irregularity of the shapes of the simulated landscapes.

These results are achieved with simple algorithms that are easily implemented and low time consuming. This enhances the practical possibilities of this method for modeling the effects of landscape configuration on ecological processes and for the other purposes mentioned in the introduction.

Acknowledgements

This work is based on the study 'Simulación de mapas temáticos mediante conglomerados aleatorios' (E.T.S. Ingenieros de Montes, Universidad Politécnica de Madrid), which received the 'D. Bemardo de la Torre Rojas' award from the Asociación y Colegio de Ingenieros de Montes (Spain). The initial idea of this paper was developed under a grant funded by the European Union project 'Development and Harmonization of Monitoring Systems for Forest Resources Management in Europe' (AIR3-CT94-2327). Two anonymous reviewers made valuable comments on an earlier version of this manuscript.

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