Neutral models for polygonal landscapes with linear networks

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ABSTRACT
Dynamical mosaic models are very useful in ecology to study the influence of patterns on some ecological processes. Examples of such mosaics are patches of agricultural or forested landscapes. They are often built on the basis of either explicit processes or on neutral approaches using random or almost random element generation. Yet, most of the latter, called neutral landscape models, use a grid-based scheme and simulate pixel mosaics that are autonomous and/or independent. This scheme is not perfectly adapted to anthropogenic patchy landscapes made of contiguous and uniform polygons. Landscape ecology for example explains how a landscape may be seen as a complex mosaic of patches and corridors, with dynamical compositions (the patch attributes) and configurations (their shapes and neighbourhoods). This work presents three neutral landscape models dedicated to manipulations of polygonal patchy mosaic configurations as compared to an observed one. These models have respective advantages that can be summarised in an increasing ability to simulate realistic anthropogenic landscape mosaics. The tessellation approach is simple and rapid, but very much constrained by the patch shapes and positions. The Gibbs algorithm method adapted to landscapes is powerful to manipulate patch positions, with still a weak control on patch shapes. The last method based on a Delaunay triangulation technique offers the opportunity to modulate patch shapes and can still be combined with the Gibbs method to optimise the patch positions. With such neutral landscape models, it is possible to explore ecological hypotheses using a wide range of controlled patchy mosaics.

1. Introduction
To model patchy mosaics is useful in ecology. It serves either to understand landscape dynamics for themselves or to offer mosaics able to support various phenomena. Landscape models may help simulating dispersions of vegetation, genes and fire (He and Mladenoff, 1999; Colin, 2002; Manel et al., 2003) or to better understand land cover and land use distributions and changes (Lambin et al., 2000; Veldkamp and Verburg, 2004). Among the landscape models available are spatial interpolations, such as those used in geostatistics (Kyriakidis, 2003) or in geographical information systems (Dungan, 2003), explicit process models (Baker, 1989; Sklar and Costanza, 1991; Gaucherel et al., 2006b) and neutral landscape models. Neutral landscape models (NLM, sensu Gardner et al., 1997; Gardner, 1999), not to be confused with ecological neutral theories, simulate landscapes by generating spatial patterns expected in the absence of the studied process, and are complementary to models explicitly implementing the ecological processes being studied. Hence, NLM are kind of null hypothesis tests, ranging from “hard” neutral models when only using random functions to “weak” neutral models when parameters

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are added to constraint these random functions (Gardner and O'Neill, 1991; With and King, 1997). NLM act on the landscape composition (the patch/unit attributes or land covers) as well as the configuration (the patch shapes/geometry and patch neighbourhoods/topology) and greatly helped in the past quantifying ecological processes (abundance or animal dispersion, forest fire or biodiversity studies, etc. (With and King, 1999; Kirkpatrick and Weishampel, 2005)).

Yet, most of the existing NLM work with a grid basis (i.e., in a raster mode, with pixels) and simulate pixel mosaics (Gardner, 1999; Saura and Martinez-Millan, 2000). First, this is inappropriate for most of the anthropogenic landscapes such as agricultural or forested mosaics often displaying patchy structures: a rural landscape for example have been described by landscape ecology as "a mosaic composed of corridors and patches, showing a uniform surface, with rather sharp adjacent boundaries with the neighbourhood" (Forman and Godron, 1981; Kotliar and Wiens, 1990; Levin et al., 1993; Saura and Martinez-Millan, 2000). Second, landscapes are often made of contiguous polygons, with rectilinear boundaries and a limited number of neighbours that are difficult, or even impossible, to simulate with pixel-based models. Third, NLM generally focus on the landscape composition or generate land use or land cover changes (LUCC) on the basis of a fixed mosaic (Veldkamp and Verburg, 2004). Changing the landscape composition simultaneously modifies the landscape spatial organisation, while it is often useful to also modify the patch shapes and sizes (the configuration) (Li and Reynolds, 1994). The objective of this work was to design NLM able to automatically generate or modify patchy landscape configurations and to compare them. I did not intend to investigate the effects of generated landscapes on ecological processes, but rather to preliminary show how to generate them with basic properties of observed landscapes.

To achieve this goal, several models dedicated to patchy landscapes have been tested, among which three are detailed and compared here. They were all based on point-pattern analysis methods, combining manipulations of germs (i.e., patch centres) and interpolation techniques such as tessellation. Point pattern analysis involves the ability to describe patterns of locations of point (or germ) events and test whether there is a significant occurrence of clustering of points in a particular area (Ripley, 1981; Cressie, 1993). As it would be rather difficult to compare these NLM handling polygonal patches to existing pixel-based NLM, a classical tessellation (nearest-neighbour) interpolation served here as a NLM reference (Okabe et al., 1992). The second is an adaptation of the Gibbs algorithm (first developed in physics, also called Gibbs process in point-pattern analyses, and recently applied to ecological domains (Stoyan and Stoyan, 1998)) to patchy landscapes. This model, optimizing a set of germs according to a local germ-interaction rule, has already proven its power with landscape composition modelling (Gaucherel et al., 2006a), where the patch shapes are fixed but the main attributes may change. After listing limits of these two former methods in generating realistic rural landscapes, a third method based on the Delaunay triangulation has been developed. Germs in this case, are not anymore defining patch centres, rather than patch summits. Simulated landscapes using these three methods are compared between each others, as well as with an observed landscape, with the help of landscape pattern indices (LPI). Principles of each method are described, with detailed sensitivity analyses.

2. Methods

The following hypotheses define the simulated landscapes: (a) landscapes should be patchy; (b) ecological interactions occur between adjacent polygonal patches (i.e., that can be described by a specific inter-patch function); (c) interactions can be either additive or geometrical. Real landscapes following these criteria show specific properties that our models should simulate automatically and efficiently (rapidly, about on second, and with low standard errors). All NLM have been developed under the Matlab® software in vector mode.

2.1 Tessellation method

A tessellation covers (maps) a surface area with geometrical figures, without any gap or superimposition (Fig. 1a). The most common technique uses the Voronoi diagrams to map this surface (Barrett, 1997; Haydon and Planka, 1999). This technique is implemented by generating a set of points (the tessellation germs) from which a polygon is built with the condition that each germ is the nearest neighbour of every germ belonging to its polygon (Okabe et al., 1992). A surface tessellation can be computed by different algorithms such as the Thiessen polygons using the intersections between the biggest disk around each germ to define the polygon boundaries or the Delaunay triangles to draw bisectors between each germ couple and define the polygon angles. Delaunay triangles and Voronoi diagrams have narrow links, as the centre of each circle that confines the triangles is one the polygon summits of the diagram.

2.2 Gibbs algorithm method

It is possible to improve this simple method of surface mapping by controlling the tessellation germ positions. This second method is more complicated to apply due to numerous degrees of freedom added, but it takes advantage on this aspect of the whole point-pattern analyses of the literature (Ripley, 1981; Cressie, 1993). The Gibbs algorithm has already been successfully applied in ecology to plot trees in a forest or animals within a moving group (Stoyan and Stoyan, 1998; Gregoire and Chate, 2004). To describe the model-steady state, one makes the assumption that the more stable the system (the germ positions), the weaker the system energy. The energy is here defined as the sum of the germ potential (i.e., their interactions, often consisting in their inter-distance). By this way, called the Gibbs algorithm, it is possible to describe the global behaviour (the energy) of the closed system simply with a local rule (the potential also called the pair function) (Gaucherel et al., 2006a).

There is a close link between the Gibbs algorithm and Monte Carlo Markov chains (MCMCs) as the former is a MCMC for which the joint distribution probability is known (here, the potential relating the x and y spatial dimensions) and the jump
in the parameter space is random (Andrieu et al., 2003). There is also a strong link between the Gibbs algorithm and the minimum principle developed in the optimal control theory; it has been shown by Pontryagin in 1962 that a necessary condition for solving the optimal control problem, i.e., to find the best possible control for taking a dynamic system from one state to another in the presence of constraints for the state or input controls, is that the control should be chosen so as to minimize what is called here the potential function.

A forestry application of the Gibbs algorithm helped us introducing the method (Stoyan and Stoyan, 1998; Degenhardt, 1999) to find a realistic position for all the $n$ trees (represented by germs $\phi = (x_1, \ldots, x_n)$) within the mosaic. As a first stage, it was possible to plot germs according to a Poisson process, but also according to a more elaborated way using the Gibbs algorithm. In the latter case, it was convenient to define a potential function $\phi$ describing the interaction between pairs of germs and being summed to deduce the total landscape distribution function:

$$f(x_1, \ldots, x_n) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=i+1}^{n} e^{-\frac{\varepsilon}{2} \|x_i - x_j\|}$$

Eq. (1) presents the case where the potential function only depends on the Euclidean distance $\|x_i - x_j\|$ between germs of each pair $(x_i, x_j)$, with $Z$ a normalization constant (Fig. 1d). If two germs are relatively close together ($\|x_i - x_j\| < r_0$), then they have higher potential (repulsion) for interaction than if two germs are farther away from each other ($r_0 \leq \|x_i - x_j\| < r_m$, attraction). If two germs are very far away from each other, then the potential is negligible. This distribution is stationary and the inter-distances are fixed. Nevertheless, the potential would vary depending on the number of germs added or deleted in the pattern, yet the statistical distribution remains similar. This could be understood with a tree species having a heavy seed reproduction scheme. Schematically, observations show that this species has young trees quite close to the mother

Fig. 1 – Examples of neutral landscape models with the three methods studied: (a) by tessellation; (b) with the Gibbs algorithm; (c) the Delaunay triangle associations with linear networks (black lines). The landscape is $800 \times 800$ pixels, 11 classes/categories and 150 patches, except the Gibbs algorithm landscape using only 50 patches to enhance the vertical gradient in patch size. Not all the patch boundaries are visible. Example of a potential (pair function, $d$) as a function of germ inter-distances used in the Gibbs algorithm applied to forestry. In this case, the potential value depends only on the distance between associated germs or trees. (For interpretation of the references to colour in text, the reader is referred to the web version of the article.)
Fig. 2 – Example of an observed patchy landscape in Brittany (western France, a). This observed landscape is made of 1471 patches (woods/colour 7, grassland/9, maize/10 and wheat/11 fields and roads/2) with a 534 × 717 pixel-mosaic. The histogram (b) shows the distribution of neighbour numbers per landscape unit. (For interpretation of the references to colour in text, the reader is referred to the web version of the article.)

tial value is equal to +2 (corresponding to unfavourable interaction).
• If the distance between two patch centres is comprised between 5 and 50 pixels, the (favourable) potential is equal to −1 if patches have the same attribute or +1 otherwise.

As a second stage, we may use the "depletion/replacement" method to obtain the landscape configuration associated to this potential function. This method is a minimization approach, thus favouring lower potential values, corresponding to intermediate inter-distances with the previous potential function. We proceeded as follows:

1) The landscape size, the number of patches and attribute classes (categories) are chosen.
2) The landscape germs (with the same number as the number of needed patches) are then plotted according to a Poisson process for the first step (the method used here is not crucial as the Gibbs algorithm rapidly moves these germs), each germ being associated to a randomly chosen attribute class.
3) The landscape "energy" of this first germ configuration is computed from the potential values of all pairs of the mosaic.
4) A germ is randomly chosen and its position randomly changed. The new landscape energy is computed. If this energy is lower to the previous one, the new configuration is retained, otherwise the old configuration is kept.
5) Step 4 is repeated as much as necessary, according to a chosen stopping criterion defining the algorithm convergence.
6) The landscape is then generated using the tessellation method based on the final germ configuration.

The depletion/replacement technique on germs led to a progressive re-organisation of the landscape in agreement to the spatial criteria imposed by the potential function (Fig. 1b). In the particular case described here, we got more heterogeneous patch shapes; while it was possible to modify the landscape according to other properties (the number of required class clusters for example). For example, Fig. 1b shows a neutral landscape model with a vertical patch size gradient, which was the result of a marked Gibbs algorithm: larger polygons were generated towards the bottom of the gradient and smaller polygons were generated at the top. The previous algorithm is known to have a high convergence rate (Stoyan and Stoyan, 1998) and the choice of the stopping criteria is most of the time a maximum number of iterations or a minimum energy variation (or both). In the present study, it was systematically equal to one hundred successive iterations with no energy decrease.

Results of this work present the tests of some potential functions able to homogenise patch shapes (similar size, perimeter and number of edges), and based on the patch inter-distances r. Definitions of these five potential functions P are the following:

1) \( P = 1/r; \)
2) \( P = 1/r^2; \)
3) \( P = 1 \text{ if } r < 5; \quad P = -1 \text{ if } 5 \leq r < 100; \quad P = 0 \text{ if } r > 100; \)
For each potential function defined here, hundred landscapes have been simulated. Mean and standard deviations of following indices have been estimated and compared to 100 tessellation landscapes having the same default landscape characteristics as above (see Section 2.4).

2.3. Delaunay triangle method

A third method has been developed to improve previous ones. The patch boundary control in the second method was weak due to tessellation constraints. For example, it is not possible to choose the number of patch edges, even with an accurate potential function choice, as this is not a parameter of the Gibbs algorithm. One of the best ways to bypass this observation was to work with the polygon summits (vertices) instead of the polygon centres/germs (Fig. 10). Considering the Delaunay/Voronoi technique links already mentioned (i.e., they are called dual structures), our purpose suggested to work with the Delaunay triangles themselves to build the patch polygons (Yamamoto et al., 1996; Anupam, 1998). Germs in this case, are not anymore defining patch centres, rather than patch summits. In addition, this method allows integrating a crucial component of real landscapes (yet not studied here): linear networks. Here are the following stages to elaborate a patchy landscape with Delaunay triangles:

1. To place a set of germs in the mosaic with the Poisson or a specific Gibbs method.
2. To compute the Delaunay triangles, adding the four mosaic summits to the previous set of germs, to better confine the landscape. Squared landscape boundaries have been chosen for simplicity, even if it slightly biases the edge numbers at the landscape border.
3. To generate the linear networks needed (that could be several) with two simple rules:
   a. starting from a mosaic boundary and crossing the landscape to another boundary;
   b. moving through the landscape with a random angle (between old and new directions) lower than a chosen angle, for example 90°, which is always possible due to the Delaunay triangles.
4. To generate patches by randomly combining a chosen number of triangles if they are on the same side of the linear network(s).

The results of this work investigate the main advantage of this method, namely the opportunity to impose the number of triangles (3 edges) associations required among three kinds of algorithms: (i) classical tessellation without any triangle association; (ii–iii) every triangle is associated (aggregated) with one, two or three of its neighbour triangles with a controlled probability p. Association probabilities further used were p = 0.5; 0.9 and p = 0.99, while the standard deviation used was the p = 0.9 one (quite stable). In this method, no tessellation method was needed as the patch edges come from the neighbouring germ associations. It is always possible to adjust the germ positions with the Gibbs algorithm involved in the first step (not explored here).

2.4. Landscape pattern indices

To compare these methods, the literature offers a wide range of landscape pattern indices (LPI (Gustafson, 1998; Forlin et al., 2003), here dedicated to landscape configuration analyses and different from the composition landscape indices. I retained three indices:

(a) The contagion heterogeneity Hc is defined as (Li and Reynolds, 1994):

\[
H_c = 1 + \sum \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \quad \text{with}
\]

\[
H_c = 1 + \sum \sum_{i=1}^{n} p_{ij} \ln(p_{ij})
\]

where \(p_{ij}\) is the probability of type j being adjacent to patch type i and \(n_{ij}\) is the number of adjacencies (joins) between pixels of type i and j. It is related to the intensity of the patch aggregation and connectivity within the landscape and is sensitive to landscape configuration as well as composition. It is widely used in landscape analyses. A high value of Hc indicates that the mosaic has relatively few patches, of bigger size and more aggregated than for a lower Hc value. Further in the study, the constant (equals to one) in the original formula has been omitted to have comparable indices between each other;

(b) the edge numbers of patches Ne is one of the main features of real/observed landscapes;

(c) the area weighted mean shape index (AWMSI) is used to quantify the shape of landscape patches (Gustafson, 1998):

\[
AWMSI = \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \frac{p_{ij}}{\sqrt{a_{ij}}} \right) \left( \frac{a_{ij}}{A} \right)
\]

This index is equal to the patch shape index (perimeter/area) average weighted by the patch area, where A is the total landscape area. It is greater or equal to one. As the biggest patches have a higher contribution (weight) in the shape index, the AWMSI allows standardizing their influence and globally quantifying the patch shapes of the simulated landscape.

2.5. Comparison methodology

As a matter of comparison, same LPI have been estimated on a typical brittany agricultural landscape having roughly similar characteristics of our simulations. This observed landscape is agricultural and located in the north-western France; it is made of 1471 patches (Fig. 2a, woods/colour no. 7, grassland/9, maize/10 and wheat/11 fields and roads/2) over a 534 x 717 pixel-mosaic, with a surface area approximately equal to 10.9 km².
It was relevant to understand the effect of some "basic" parameters on the landscape configuration, in the sense that no additional process to the tessellation is required. They concern the number of landscape patches $n_p$, the number of different attributive classes $n_c$ and the total width of the squared landscape mosaic $t_p$. One hundred landscapes have been simulated by the Monte Carlo technique. Their LPI means and standard deviations have been computed, with the following permutations:

(a) Landscape dimensions $t_p$ varies from $50 \times 50$ pixels to $500 \times 500$ pixels with a discrete step of 50, with $n_p$ equal to 20 and $n_c$ equal to 5. Changing the landscape size (the pixel number) without changing the patch number indeed, is equivalent to change pixel size (resolution).
(b) Number of classes $n_c$ varies from 2 to 20 classes with a discrete step of 1, with $t_p$ equal to 200 and $n_p$ equal to 20.
(c) Number of patches $n_p$ varies from 5 to 200 patches with a discrete step of 10, with $t_p$ equal to 200 and $n_c$ equal to 5.

Hence, the default values (used in particular for tessellation references) are $t_p = 200; n_p = 20; n_c = 5$. The study of the linear network properties is a heavy task in itself and no specific works have been performed in this sense here. Nevertheless, this study mentions when appropriate if linear networks can be generated with the NLM studied here.

3. Results

The tessellation method helped elucidating the effect of changing basic model parameters on the configuration of patches in generated landscapes. Fig. 3 only showed the index curves with a significant effect (i.e., with LPI variations higher than their standard deviation). The landscape size was the parameter with the highest influence on the normalized contagion index. As expected, such heterogeneity significantly decreased with the size of the landscape (Fig. 3a) and increased with the patch number (Fig. 3b) (no significant effect of the class number observed because of its normalization). Only the patch number significantly influenced the edge number per patch, roughly increasing from 4.5 to 5.5 with a constant landscape size (Fig. 3c). Such values indeed remained below the theoretical limit of the Voronoi diagram maximal edge number equal to 6. This patch number also influenced the AWMSI index (Fig. 3e), slowly decreasing to a 3.7 plateau and showing more regular patch shapes (i.e., closer to the disk shape). The variance of this index was also decreasing with the patch...
number. The class number appeared to have almost no impact on the landscape configuration (except on the contagion variance, not shown).

The Gibbs algorithm may then be compared to tessellation, depending on the potential (pair) function chosen. When focusing on the potential functions with influences on patch shapes, it was relevant to estimate the core and interaction distances upon the configuration. Five potential functions able to homogenize the patch shapes (abscisses 1–5 in Fig. 4) have been tested and compared to tessellation landscape having the default landscape values (abscissa 0), with hundred runs each. We observed that the potential function definition had a weak impact on the contagion heterogeneity (Fig. 4a). However, the potential function curve had stronger influences on the other configuration indices (Fig. 4b and c). Potential function curves, one and two, tended to homogenize the patch shapes in average; the others increased the shape diversity. The second potential was more efficient than the first one to homogenize, while the third and the fifth had similar behaviour. Hence, hard core and interaction distances seemed to be of great importance for the final landscape configurations.

The third method using Delaunay triangles to generate patchy landscapes may be compared to tessellation (abscissa 0) with the same LPI indices. This method allows controlling some of landscape properties such as the edge number, according to the three algorithms detailed in the method section (abscises 1–3 in Fig. 5). LPI values are plotted according to the number of associated triangles and to the association probability were \( p = 0.5 \) (circles in Fig. 5), \( p = 0.9 \) (squares) and \( p = 0.99 \) (triangles). Contagion was quite stable across the successive triangle associations (Fig. 5a). AWMSI is low and predictably increasing (Fig. 5c); this method did not attempt to impact this patch property. At the counterpart, the edge number was interestingly evolving (Fig. 5b): the whole range of values between 5 and 6 edges was covered, depending on the number and the probability of triangle associations. Hence, this method offered the opportunity to finely tune the edge number at a selected value.

An observed agricultural mosaic such as the one observed in Fig. 2b gives commensurable LPI values. Contagion, edge number and AWMSI are equal to \( Hc \sim 0.0393 \), \( Ne \sim 6.1 \pm 2.26 \) and \( AWMSI \sim 1.016 \), respectively.

\[ \text{Fig. 4 - Influences of the five potentials or local functions of the Gibbs method on the three landscape pattern indices: (a) contagion heterogeneity; (b) edge number; (c) AWMSI. The potential no. 0 is a classical tessellation taken as a reference. Index values resulting from 100 Monte Carlo simulations are plotted.} \]
Fig. 5 – Influences of the two triangle associations of the Delaunay method on the three landscape pattern indices (LPI), with increasing association probabilities (a) contagion heterogeneity; (b) edge number; (c) AWMSI. The nil abacuse taken as a reference corresponds to the absence of triangle association, while the other abacuses concern the algorithms for which every triangle in the mosaic is associated (aggregated) with one, two or three of its neighbour triangles. Index values resulting from hundred Monte Carlo simulations are plotted with the p = 0.9 standard deviation (except for the tessellation values), roughly similar to the others. Dashed lines feature LPI values of the observed landscape seen Fig. 2.

4. Discussion

4.1. NLM efficiencies

Most of two-dimensional anthropogenic (and many natural) landscapes are made of contiguous polygons. This study presents an attempt to automatically generate such patchy mosaics with neutral landscape models (NLM, sensu Gardner et al., 1987; Gardner, 1999) in order to simulate a large number of landscapes having similar (or not) properties to those observed. Namely, it compared three NLM of increasing complexity to generate more realistic patchy landscapes than, to my knowledge, do not exist. This study analyzed a few dominant landscape properties (contagion, edge numbers and area weighted mean shape) of fully controlled simulations to compare them to values computed on an observed landscape. The tessellation method is widely used, is easy to understand (the nearest-neighbours interpolation principle) and to implement. Yet, it failed here to mimic realistic patchy landscapes because patch boundaries were not at all controlled, thus leading to low edge numbers and high AWMSI values (Fig. 3). The Gibbs algorithm method also uses the tessellation method, but allowed a powerful control on the patch centres (the tessellation germs). It was then possible to tune centre aggregations, their spatial regularity, with or without marks related to the patch attributes (their land cover). This marked-Gibbs method offered the opportunity to generate a spatial gradient within the landscape, to aggregate patches around a village or to mimic geological features.

Yet, combined with the tessellation method, the Gibbs method also led to low edge numbers and high AWMSI values (Fig. 4). To produce the right number of patch edges, and to build rather rectilinear networks along the patch boundaries, it is recommended avoiding the tessellation method and rather manipulating the patch summits. The main idea of the
third method explored here was to use the Delaunay triangles, not as a skeleton of the Voronoi diagrams as usually done, but as a final mosaic mapping. To work with triangles ensured to start building patches with a low number of edges. It is then always possible to aggregate triangles to increase the edge numbers per patch. While higher contagion and edge number values may be reached by triangle associations with quite high probabilities, AWMSI values remain much higher than an observed landscape one (AWMSI = 1.01, with a much higher patch number, Fig. 5c). Finally, if such elaborated NLM is not the panacea, it allows at least controlling some of the most important landscape properties as well as easily generating linear networks (Fig. 1c). None of the three methods presented here were controlling the area per landscape class. Such feature could be easily modelled using additional parameters, with an obvious neutrality loss of the resulting model.

4.2. Conceptual limits

From this study arose some limits on the way anthropogenic landscapes are perceived and simulated. The second NLM assumed that the landscape modelled was at steady-state. This state is quite hard to assume for spatial mosaics well known to have non-linear behaviours (due to natural processes or human decisions) and to be far from (thermodynamical) equilibrium (Gauchere et al., 2006a). This could be one of the perspectives to develop Gibbs algorithms mimicking non-equilibrium mosaics. In addition, Euclidean inter-distance was supposed to be a good surrogate for interaction between patch centres. This assumption allowed manipulating patch polygons with point-pattern and tessellation techniques, hence indirectly controlling their sizes, shapes and neighbourhoods. Yet, this is only one possible way compared to techniques explicitly handling every patch (Gauchere et al., 2006b). Patch properties may be controlled by ecological processes and patch interactions: patch splitting and patch merging are common in agricultural landscapes due to farmer managements, while patch dilution and patch erosion rather concern forested landscape under natural colonisation and/or competition processes. Finally, the calculation of the landscape energy (to be defined in ecological terms) related to other thermodynamic variables is therefore a possible step towards analytical and physical descriptions of patchy mosaics.

4.3. Neutral models and landscape realism

There is a gradation of virtual landscapes, from the one obtained by neutral models (Gardner and O'Neill, 1991; With and King, 1997; Kirkpatrick and Weishampel, 2005) up to the nearly explicit models (Sklar and Costanza, 1991; Gauchere et al., 2006c), and NLM of this study are located right in between. The random model, the simplest (and the only purely) neutral model, is performed by associating each pixel/patch with a probability of belonging to one of the landscape classes. Such model, without spatial correlations, is useful for example to control the landscape composition (Gauchere et al., 2006b) and not configuration. Other sophisticated models define not only the probability that a pixel belongs to a class, but also to a directional adjacency matrix Q (Gardner, 1999). This Qij elements translate the probability of a pixel belonging to type i being adjacent to a pixel of type j, the notion of adjacency being defined according to direction and distance. These models can be refined by the modified random cluster method which can control the shapes of simulated types (Gaur and Martinez-Millan, 2000). Most of neutral models today found in literature deal with landscape as a continuous entity in raster mode, where the pixel is an autonomous (not always independent) entity, while most ecological studies use patchy landscape maps in which areas are considered homogeneous from the point of view of the ecological process studied (Forman and Godron, 1981; Kotlar and Wiens, 1990; Levin et al., 1993). This becomes vital in anthropogenic landscapes and strongly justify developments new NLM (or almost neutral models) such as those of this study.

In a further stage for the triangle-association NLM, several improvements such as the patch convexity, the edge directions after associations, and so on, can be explored to constrain triangle associations in a more realistic (and less neutral) way. Another important advantage of this third method was that, patches being fixed at the beginning of the landscape generation, it was possible to “follow” the network germs (the patch summits) to build linear networks then becoming a constraint for triangle associations. Many techniques to generate such networks can be investigated; here, I imposed to rotate by an angle lower than 90° when following the summit network (Fig. 1c). This method finally produced quite realistic landscapes (in terms of the three properties being quantified), but was more difficult to implement and needed a deep knowledge of its parameter influences (i.e., sensitivity analysis such as in this paper). With the goal to generate more realistic rural landscapes, it is critical to impose to these NLM at least: a realistic edge number (6 in average) and size distribution (patch centre inter-distances), realistic linear networks (their length, possible intersections, directions, etc.); and realistic edge parallelism (that should be controlled with additional LIF). Each NLM method presented here can be modified on specific steps, the chosen geomorphology, and so on, to follow these observed landscape constraints.

5. Conclusion

This work offers various ecological perspectives, depending on the chosen objective. The main idea behind these models is to offer randomising specific polygonal patches to better understand ecological processes operating in patchy landscapes. Considering the usual “universality” of NLM, it is probable that such methods could also offer interesting opportunities to model most of the two-dimensional mosaics encountered in ecology. Influences of spatial patterns due to anthropogenic landscapes on population dynamics and genetic distributions may for example be explored with NLM.

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