Self-similar land cover heterogeneity of temperate and tropical landscapes

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ABSTRACT

Landsapes are complex objects often showing self-similar properties. For example, some power law exponents and fractal dimensions have been extensively used as global metrics for describing spatial arrangements of landscape land covers. This paper presents some newly found invariance properties for rural landscapes, with the hope to prepare further theory capable to link these properties mechanistically with generating processes. For this purpose, I propose a new surface-pattern analysis computing heterogeneity metrics into moving windows in a specific way. This generic method provides Multiscale Heterogeneity Maps (MHMs) and Heterogeneity Profiles (HPs) of almost any kind of landscape. Six landscapes, covering a wide range of observed mosaics have been analyzed by this way: four of them exhibit strong self-similar evenness/diversity heterogeneity over two orders of magnitude with an apparent universality of the power law exponents ($\gamma = 0.19 \pm 0.02$). Such landscape self-organization is interpreted in terms of spatial arrangements of numerous land covers and fine scale patchy mosaics. This study suggests that most of terrestrial landscapes could exhibit power law behaviors in terms of evenness heterogeneity and could be the result of a hidden optimization of ecological and/or socioeconomic processes.

1. Introduction

Rural landscapes are complex objects in the sense that they display non-linear and far-from-equilibrium dynamics. Landscape can be defined as a set of elements of various nature continuously interacting in space and time at different scales (Forman and Godron, 1986; Turner and Gardner, 1991). Therefore, mosaic attributes or land covers interplay in a way that mosaic is often highly heterogeneous. Heterogeneity is indeed the central concept of landscape ecology, dealing for a long time with landscape structure and functioning. Heterogeneity takes various forms, such as connectivity, diversity and fragmentation, all of major importance to define landscape patterns or to interpret population dynamics in heterogeneous landscapes (Pielou, 1977; Hanski and Ovaskainen, 2000). Important works have mentioned some specific properties of rural landscapes. In particular, some power laws behaviors, also called fractal or self-similar properties, have been illustrated (O'Neill et al., 1988; Milne, 1998; Rietkerk et al., 2002; Chen et al., 2005). Fractal dimensions for example, have been used extensively as global landscape metrics for describing the spatial distribution of various habitats, on either pixel-based or patchy mosaics (Li, 2000; Chen et al., 2005). Yet, there is presently little theory to link these properties mechanistically with generating processes. For this purpose, we would benefit of a generic method aiming at computing some multiscale heterogeneity observed within any kind of landscape (Gaucherel, 2006). In a second stage only, we should be able to analyze the multiscale behavior of real landscapes and detect departures from theoretical power laws. Many given ecological processes could produce self-similar behaviors, among which are multiscale randomness, diffusion-limited aggregation or self-organized criticality. More recently, it has been shown that power laws can be interpreted as a preferential attachment, which is nothing else than a kind of optimization (D'Souza et al., 2007).

Yet, no landscape is strictly fractal over a range of scales considered. Even with departures from power laws scaling, extrapolations can be made if the departures are systematic and predictable (Halley et al., 2004). This work makes the central assumption that many rural landscapes exhibit self-similar properties. Landscapes considered for this purpose are vegetation spatial distributions or land covers of various natures (agricultural, forested, anthropized or non-anthropized mosaics). To build a consistent theory giving the interpretation of such self-organization (confirmed by self-similarities) is out of the scope of this paper. Our objective is rather to demonstrate that most rural landscapes have generic self-similar behaviors. At least should it be true and demonstrated for a certain range of scales and with generic enough heterogeneity indices. This generic character of Shannon-related indices used here is our main hypothesis (Pielou, 1977; Halley et al., 2004).

The present work is based upon a new methodology to analyze in depth multiscale behaviors, further illustrated on several neutral

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landscape models. This methodology, called MMH (for Multiscale Heterogeneity Map (MMH) and Heterogeneity Profile (HP), Gaucherel, 2006), will then be used to explore self-similarities of a large panel of observed landscapes. This method is inspired from two different current of spatial analysis: the gliding or moving box algorithm to study the lacunarity of fractal structures (Plotnick et al., 1996) and the scale-dependent textural analyses of FRAGSTAT programs (Cushman and McGarigal, 2002) among others. The dominant feature of the MMH method is to allow a detailed quantification of the multiscale behavior of various heterogeneity indices: it synthetically offers a map of heterogeneity's spatial modulations as well as the corresponding Heterogeneity Profile. By this way, the multiscale properties of six observed landscapes are presented within a spatially explicit scheme, such that departures to the self-similarity are easier to trigger and to interpret. These six observed landscapes were chosen in order to cover a wide panel of landscape types, ranging from a rater airborne to categorical (patchy) mosaics, from tropical to temperate landscapes and from numerous land covers to a binary hedgerow network. Four landscapes among the six studied exhibit persistent diversity (heterogeneity) self-similarity, thus suggesting landscape functioning that could have been hidden up to now.

2. Materials and method

2.1. Principle of the method

Heterogeneity indices such as contagion or evenness are capable to offer synthetic information about a landscape. Conversely, they have numerous disadvantages: sensitivity to the scale, insensitivity to the classes/types order, insensitivity to second-order spatial neighborhood or to directional information, etc. (Li and Reynolds, 1994; Li, 2000; Halley et al., 2004). In a previous work (Gaucherel, 2006), I proposed to draw Multiscale Heterogeneity Maps to bypass most of these limits and to keep local as well as global heterogeneity information. This method has been extensively described in the previous reference and used in various ecological studies. Landscape structure is further quantified with a slightly modified measure of the evenness heterogeneity (Li and Reynolds, 1994):

\[ E = \frac{-100 \ln \left( \sum_{i} p_i^2 \right)}{\ln(n)} \quad \text{with} \quad p_i = \frac{n_i}{\sum n_i} \]

where \( p_i \) is the probability that a randomly chosen pixel belongs to class type \( i \) (including background) and \( n_i \) the number of pixels of type \( i \). Everywhere in this paper, \( \ln \) is the Neperian logarithm. The heterogeneity parameter \( H = -E/100 \) will be used here for easier comparison and visual comfort. The evenness index responds to the number of class types and their respective proportions in the mosaic. Hence, it could also be called diversity index.

The successive steps of the multiscale method used in this article are illustrated in Fig. 1 with a simple patchy neutral model (a tesselated mosaic, see further). The principle of such map is to compute the heterogeneity index value within a small size window moving/gliding over the whole image and associate the resulting value to the central pixel of the window (Fig. 1a, see Gaucherel, 2006 for details). Repeating this operation for each pixel leads to the construction of a new image of approximately the same size, with the local index variations. The size of the calculation window is varying from \( \pm 1 \) to \( \pm L \) pixels around the central one, while its shape has been kept circular to avoid directional effects. Hence, \( L \) is the window radius and defines the analysis scale. We avoided border effects, by computing index at a distance greater than \( L \) pixels from the edges of the original image. These borders are visualized as null pixels zones, but are never included in the following calculations. All the evenness maps (one for each scale) could be synthesized into a final multiscale evenness map (Fig. 1c). The averaged maps (a map built with pixels carrying the averaged values of the corresponding pixels in each scale image) or other combining operations can be used for this synthesis. In this example, we computed indices on observed landscapes up to \( L = \pm 30 \) pixels, the averaged correlation image is then about 36% of the original surface. It is then possible to build a curve (the Heterogeneity Profile, similar to a scalogram, Legendre and Legendre, 1998) of the mean index value over the whole resulting image as a function of the scale (Fig. 1b). Error bars are also specified but are rather neglectable in this work due to the high number of points used in every landscape. Note that fine scale values (i.e. for moving windows having less than 50 pixels) are likely to present unreliable heterogeneity statistics. Since the underlying evenness probability changes with the number of pixels inside the window, one needs to normalize each index value in order to compare them later (Gaucherel, 2006). This dividing factor \( \ln(n_i) \) is related to the number \( n_i \) of pixel used within the moving window. This normalization is distinct and complementary to the one always made for the \( n \) classes of the original image ('dividing factor \( \ln(n) \))'. The final scaling curve is usually slowly decreasing, indicating more homogenous structures at broader scales than at finer ones. In a categorical landscape such as the one used for illustration, the profile reaches a second maximum around \( \pm 26 \) pixels, precisely corresponding to the inter-patch distance and to relatively higher (diversity) heterogeneity. Note that the multiscale map greatly helps interpreting global heterogeneity detected by the profile by precisely locating the intra-patch and inter-patch structures (Fig. 1c).

2.2. Simulated landscapes

In order to better interpret self-similar behaviors observed in the Heterogeneity Profiles, neutral landscape models are useful. Theoretical landscapes were simulated by arranging seed cells of patches according to a Poisson process, and then carrying out a tessellation (Hug and Schneider, 2004) also called a nearest neighbor interpolation. The five patch categories (classes) were randomly attributed. Configurations simulated are square landscapes of \( 100 \times 100 \) pixels, containing \( n \) patches with \( n \) being successively equal to 20, 50, 100, 200 and 500. This choice is guided by the aim to better understand the patch-size structure effect in heterogeneity measures. A fully random raster landscape (called the reference landscape) and a landscape made of 200 patches with only three categories, both of size \( 100 \times 100 \) pixels, were added to help interpret finest grain mosaic as well as landscapes of variable category numbers. I did not need to replicate any of these categorical landscapes as qualitative and even quantitative conclusions deduced from HP are very robust (very low standard deviations of evenness values for each scale). Yet, MMH maps are not as robust as they are highly sensitive to local heterogeneity modulations (their power). Note that such landscapes are not self-similar as they are generated using random configurations and random compositions. No fractal process is used to mimic fractal properties. The goal here is not to search for self-similarities in simulated landscapes rather than to help interpreting HP.

2.3. Observed landscapes

This is not the objective of such landscape sampling to fully analyze specific landscape features, rather than to compare various landscapes and their potential self-similar behaviors. For this reason, it will not be necessary to compute detailed confidence level on heterogeneity measures. To know that fully random mosaics (see simulated landscape profiles) always have higher heterogeneity/evenness values is sufficient. The way to proceed then is to interpret relative heterogeneity values and curve shapes. To achieve this goal, I selected six different mosaics expected to
cover a wide range of landscape types and compared their HP. These landscapes are either fully or partly anthropized and come from tropical (India, L1-L3) and temperate (France, L4-L6) areas (Fig. 2): (L1) airborne image of Cayenne suburbs, (L2) a mixed anthropized/non-anthropized landscape and (L3) the same mixed landscape aggregated within six dominant land covers (classes), (L4) an extended agricultural landscape displaying various spatial structures, (L5) the hedgerow network extracted from the previous landscape and (L6) a categorical zoom of the same agricultural landscape.

The first studied site is a raster airborne image of Remire-Montjoly, a Cayenne City – French Guiana capital suburb. It covers 1.9 km × 2.5 km (375 × 500 pixels) and handles 255 radiometric gray levels. Its fine spatial resolution allows visualizing very small landscape features, such as houses or tracks, as well as broad structures of this tropical suburb. The two following landscapes are images of the same site in central Kerala, South of India. This landscape is composed of a wide range of land use types classified here in 40 categories for L2 and 5 categories for L3, plus the background (missing information, class 0). Both landscapes cover 53.6% of the 38 km × 45 km site, transformed for analysis into a raster mode image of 1073 × 1278 pixels (Fig. 2). Categories cover primary wet evergreen to semi-evergreen forests, primary moist deciduous forests and their respective degraded stages, as well as plantations. Anthropized part of the landscape is located in the South-Western part of it and the interface with more untouched areas is roughly parallel to the (North–West/South–East) border of the landscape. L5 landscape consist in aggregation of these 40
categories within the following simplified classes: evergreen forests, semi-evergreen forests, moist deciduous forests, various swamps and grasslands, teak plantations, secondary or degraded forest stages and others (mainly rivers, roads or buildings). These aggregations were chosen for their relevance to wild fauna in an older study and to get an extended categorical landscape. Land cover interpretations consisting of manually tracing inferred boundaries on aerial photography have been made and subsequently ground truthed.

The next three studied sites are located north of Ille-et-Vilaine (Brittany, Western France). L4 called Pleine-Fougères has a contrasted landscape structure and covers 62.2% of the 10 km × 14.9 km site. L5 and L6 are extracted from the southern part of L4 because they still have a rather dense network of hedges with a high density of trees, many small permanent grasslands, and small woodlands. The northern part of L4 went under a reallocation program in 1992. In L4, farming systems are exclusively oriented toward dairy production in this landscape; a
high proportion of the Umed Agricultural Area (UAA) is covered by grasslands and fodder crops and milk cows predominate in livestock. Data were collected for a European project GREENVINE targeting to analyze the effects of agriculture intensification and greening on biodiversity. Aerial photographs have been transformed in raster mode with a ~20 m optimized pixel size: final images have $745 \times 500, 529 \times 558$ and $252 \times 558$ pixel sizes for L4–L6 sites, respectively (Fig. 2). L4 land covers are for year 2001, hedges of L5 are in a binary state (presence or absence of hedge in year 2001) and L6 landscape is composed of 1996 land covers categorized within 12 different classes, the dominant being: maize, cereals, other crop productions, permanent and temporary grasslands, forests, fresh waters, roads and farm buildings.

3. Results

3.1. Simulated landscapes

Heterogeneity Profiles of simulated landscapes showed progressive shape evolutions (Fig. 3). From random reference landscape to categorical landscape with coarse patch structure, we observed a slowly decreasing HP. Hence, the broader the spatial structure, the more homogeneous the landscape (Fig. 3, insets). By construction, none of these landscapes were self-similar, while they could mimic partial self-similar behaviors considering a reduced range of scales. Profiles all show higher heterogeneity at fine scales, which was due to, uncorrelated pixels arrangements at fine scales. A second maximum was visible on almost all profiles (circles): it corresponded to the dominant patchy structure simulated. At lower scales, below this maximum, a homogeneous behavior was caused by intra-patch zones, while at higher scales, beyond this maximum, landscape started to behave as broad multi-patch structures. In this latter case, patches started to replace pixels for the raster (reference) landscape and went closer and closer to self-similar heterogeneity property. Linear fit in loglog plot is not recommended to quantify the scaling behavior, as points of the curves are not independent. Yet, reduced self-similar behaviors can be triggered either for broad scale structures (i.e. higher than the dominant one) or for fine scales (lower). The slope of such fits is directly linked to the fact that the self-similar part of the profile is inner or outer landscape patches. Reducing the category numbers tended to increase the overall landscape heterogeneity (due to the more frequent landscape type changes) with a less marked second maximum (dominant structure) as the profile went closer to the reference landscape.

3.2. Observed landscapes

Some observed landscape profiles were self-similar (L1, L2, L4 and L5), some others were not (Fig. 4). No dominant characteristic seemed to be linked to these self-similarities, as some of these landscapes are tropical (L1 and L2), some are in raster mode (L1 and L5), some have a quite high number of classes (L1 and L2). The loglog slopes were equal to $\gamma = -0.180, -0.213, -0.157$ and $-0.194$ for L1, L2, L4 and L5, respectively. Such values were much lower than a five-class random landscape by the same method order one second of magnitude ($\gamma = -0.37$). Note that this reference landscape would not be self-similar over two orders of magnitude. Landscapes L3 and L6 were not at all self-similar, highlighting the role of the landscape characterization (Fig. 4, dotted lines). Even when forgetting the finest scales (i.e. the left part of the curves), these two profiles showed features close to simulated categorical ones, with a secondary maximum for instance. Yet, the identified profile self-similarities hided important local features that a detailed heterogeneity map could enhance (Fig. 5). I displayed here the three most interesting MIMs of self-similar landscapes L2, L4 and L5. A local MIM analysis on the L2 raster landscape led to homogeneous zones mainly at the border between agricultural/natural boundary (Fig. 5 dashed line on L2). This highlighted land cover diversity of such landscape interfaces that HP profile would not be able to quantify and locate. A local MIM analysis on the L4 categorical landscape led to quite homogeneous zones in place of forests (Fig. 5, right side of the L4 landscape) and relatively high heterogeneities for mixed crop agriculture close to some villages (middle). The land cover diversity of these zones was quantified by the evenness values and their local variations, while the MIM multiscale map intended to capture heterogeneity redundancies across scales. MIM tool appeared to be efficient as well for hedgerow networks as illustrated with L5 landscape (Fig. 5, L5). Other regions showed disparities, such as gradients between north

![Fig. 3. Heterogeneity evenness Profiles (background) of the seven simulated landscapes (insets). 100 x 100 pixels landscapes are, from bottom to top profiles: categorical mosaic with 20, 50, 100, 200, 200-3 classes, 500 patches respectively and finally raster random mosaic (first, third, fifth and sixth landscapes are shown as insets). All the landscapes have five classes (with a common gray scale) except the 200-3 classes one, also having a dotted profile. Second maximums of profiles, highlighting the dominant structure of each landscape, are plotted as circles when possible.](image1)

![Fig. 4. Heterogeneity evenness Profiles of the six simulated landscapes of Fig. 2 in a loglog plot. Landscapes L1, L2, L4 and L5 show self-similar heterogeneities (black circles), while L3 and L6 not (blue lines for visual comfort). Linear fits (mean-square minimization) of the first four landscapes are plotted in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)](image2)
and south of the hedgerow network, that would have needed otherwise specific tools to be analyzed and above all quantified.

4. Discussions

It was proposed a generic methodology to quantify possible power law behaviors based here on the heterogeneity spatial variations of a landscape. This approach has been tested and illustrated with six observed landscapes of very different natures. Four mosaics of the studied sample have shown highly self-similar evenness profiles, suggesting slightly progressive gains of structural information with increasing scales (a decreasing profile slope, Fig. 4). Self-similar properties analyzed exhibited power law exponent close to $\gamma = -0.19 \pm 0.02$ over up to two magnitude of orders (moving windows from $\pm 1$ to $\pm 170$ pixels at best). This scaling range is rather low, but it has to be reminded how this methodology is highly constrained by the ratio between spatial extend and resolution of each landscape (here around three orders of magnitude at best). The two landscapes not showing any self-similar property combined patchy characteristics with a weak number of land covers, as suggested by the second maximum of their profile. These two characteristics were generating spatial structures, particularly at broad scales, finding their origin in various class aggregations. These results are in good agreement with previous studies focusing on specific self-similar landscapes (Rielkerk et al., 2002; Chen et al., 2005). Past studies usually use raster mode (grid-based) for describing analyzed mosaics.
combined with informational entropy or clustering analysis in order to demonstrate self-similar behaviors of grasslands and savannas. I intended here to analyze a wider range of landscapes that may furthermore be patchy, as it has already been suggested in the past (Li, 2000). This work led to similar behaviors on some of our patchy landscapes.

The Heterogeneity Profile helped to quantify departures from a perfect self-similar behavior, while the MMH allowed precisely locating them, for example along anthropized/non-anthropized interfaces or close to villages (Fig. 5). Self-similar properties detected in this work seemed to be quite sensitive to the multiscale computation. This is the reason why I have computed diversity index with the most rigorous scheme: using combined normalization stages (upon landscape classes as well as scales, to make them comparable), with a landscape mask (i.e. ignoring the landscape background) and a circular moving window to avoid directional biases. We should also not forget that a linear behavior in log-log plot could not be rigorously fitted using a mean-square error minimization, because points are not independent. Nevertheless, such linear behavior is related to some power law property that has to be interpreted. Other heterogeneity indices, such as contagion index, are not showing any self-similar behaviors for the same six landscapes (not shown). This is the clue that land cover diversity could be self-organized while their connectivity not and thus that self-organization is highly dependent on the metrics.

While self-organizations observed in this work still have to be confirmed, the MMH and the associated HP have demonstrated their ability to simultaneously study spatial and scaling structures (Gauchercel, 2006). This methodology offers rapid quantification of most of the spatial structures that can be encountered in ecology such as anisotropy, aggregation or edge effects in environmental factors distributions (Plotnick et al., 1996; Milne, 1998). In a sense, this method proposes a merge or a synthesis of older fractal and lacunarity measures, as it computes fractal dimensions of heterogeneity/lacunarity patterns in a specific way. In addition, the MMH approach does not require the condition of second-order stationarity to be satisfied (contrary to many surface-pattern analyses) (Legendre and Legendre, 1998). The links of heterogeneity indices with the diversity notion (inspired from the Shannon information index) indirectly gives a larger extend to the MMH methodology: the mapping method could in theory be extrapolated to a wide range of data types or space and time dimensions.

It is still difficult to interpret such landscape self-organization in terms of ecological processes. The objective in explaining the γ exponent significatiion for example would need new landscape modeling and is still in progress. At least, we could interpret the general scaling pattern of Heterogeneity Profiles computed in this study. Landscape is not a physical system on which we can straightforwardly apply principles such as energy or matter conservation. Some recent works about self-organization and power law properties within a system may open new ways for interpretation (D’Souza et al., 2007): self-similar behaviors could be the result of preferential attachments or of a kind of system optimization. Heterogeneity, indeed, cannot be cumulated along to scales as usually done for other self-similar properties (O’Neill et al., 1988).

In this work, heterogeneity (diversity) self-similarity could refer to some spatial auto-correlations progressively scaling at broader scales. A decreasing HP for example is quantifying the way in which landscape is more and more homogeneous on larger surfaces (and not distances, Fig. 4). In agricultural landscapes, with airborne or satellite image resolutions, fine scales are linked to field margin and road network structures; intermediate scales concern crop rotation systems and field allocation structures; and broad scales are progressively connected to soil covers and climate region structures or to cultural heritage (Fig. 5). These various spatial factors have no chance to be linked in a self-similar manner, except if considering a widely generic property such as heterogeneity. Diversity for example highlights how landscape states (land cover units) are distributed: their neighborhood and alternative distribution within large landscapes are driven by many different factors that could act in a common direction as in an optimized functioning.

Heterogeneity Profiles of this study emphasized the regular way a landscape is built: every scale appeared to be slightly more homogeneous than its finer scale, except if some dominant patchy structure emerges. This difference between broad and fine scales heterogeneity probably has to be related to the fact that landscape driving factors are not easily generating sharp boundaries and regular land covers in space at broad scales. It probably costs less energy to create regular gradients that are not self-similar, although this point may be checked. Finally, landscape systems are precisely this kind of system where different units and their neighborhoods are linked in a way which cannot be understood by studying the individual components in isolation and where the holistic view offered by self-organization may be of great use in future.

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