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Landscape and Urban Planning 62 (2003) 173–177

LANDSCAPE  
AND  
URBAN PLANNING

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## Beware of contagion!

Carlo Ricotta<sup>a,\*</sup>, Piermaria Corona<sup>b</sup>, Marco Marchetti<sup>c</sup>

<sup>a</sup> *Dipartimento di Biologia Vegetale, Università di Roma “La Sapienza”, Piazzale Aldo Moro 5, 00185 Roma, Italy*

<sup>b</sup> *Dipartimento di Scienze dell'Ambiente Forestale e delle sue Risorse, Università della Tuscia, Viterbo, Italy*

<sup>c</sup> *Dipartimento di Colture Arboree, Università di Palermo, Palermo, Italy*

Received 28 May 2002; accepted 1 July 2002

### Abstract

Landscape ecology starts from the assumption that diversity and spatial arrangement of ecosystem mosaics has ecological implications and tries to understand the interactions between diversity and structure of large spatially heterogeneous areas and its ecological functions. This approach implies effective use of earth observation techniques and geographic information systems, enabling a global view of the landscape mosaics. Consequently, a large number of indices has been used to quantify the structure of categorical maps as a surrogate of actual landscapes and correlate them to ecological processes. In particular, the entropy-based contagion index has been extensively used to summarize the amount of clumping or fragmentation of patches on raster categorical maps. However, despite its widespread application, the contagion index is very dependent on pixel resolution. This effect may render it inadequate as a meaningful measure of landscape structure. To overcome this major shortcoming, in this short note we propose to quantify pixel adjacency with a bivariate summary statistics that is not adversely influenced by pixel resolution.

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**Keywords:** Categorical maps; Evenness; Fragmentation; Shannon's entropy

### 1. Introduction

In the past 20 years, as the influence of global change became more prominent, ecological research has been conducted over larger and larger areas. Since terrestrial landscapes generally consist of mosaics of different ecosystems, as ecological analyses move from single ecosystems to entire landscapes, it becomes necessary to understand the ecological functions of large spatially heterogeneous areas. Landscape ecology is based on the premise that diversity and spatial arrangement of ecosystem mosaics

has ecological implications and tries to understand the interactions between diversity and structure of large spatially heterogeneous areas and its ecological functions (Forman, 1995). To enable a global view of landscape mosaics, effective use of earth observation techniques and geographic information systems (GIS) is required. In this view, the spatial variability of ecosystem mosaics is typically represented by categorical (i.e. thematic) maps that quantify this variability by identifying patches that are relatively homogeneous and that exhibit a relatively abrupt transition to adjacent areas (Gustafson, 1998). As a consequence, a large number of indices has been developed to summarize different aspects of categorical maps as a surrogate of landscape mosaics and correlate them to ecological processes (Baker and Cai,

\* Corresponding author. Tel.: +39-06-4991-2408;  
fax: +39-06-445-7540.  
E-mail address: [carlo.ricotta@uniroma1.it](mailto:carlo.ricotta@uniroma1.it) (C. Ricotta).

1992; MacGarigal and Marks, 1995; Riitters et al., 1995).

Within this context, entropy-based landscape metrics deriving their conceptual basis from Shannon (1948) information theory have a long history of use in landscape ecology (O'Neill et al., 1988; Li and Reynolds, 1993; Riitters et al., 1995; Ricotta et al., 1999).

Consider a pixel-based categorical map composed of  $N$  attribute classes where  $n_i$  is the number of pixels belonging to the  $i$ th class ( $i = 1, 2, \dots, N$ ), and let  $p_i$  denote the relative frequency of  $n_i$  ( $p_i = n_i / \sum_{i=1}^N n_i$ ) such that  $0 \leq p_i \leq 1$ , and  $\sum_{i=1}^N p_i = 1$ . According to Shannon (1948), the amount of statistical information (or Shannon's entropy  $H$ ) associated to the map is:

$$H = -\sum_{i=1}^N p_i \ln p_i \quad (1)$$

The entropy  $H$  of a given categorical map is a measure of uncertainty in predicting the relative abundance of attribute classes. It is easily demonstrated that the maximum value of Shannon's entropy  $H_{\max} = \ln N$  is obtained from an equiprobable distribution (i.e.  $p_i = p_j$  for all class pairs  $i \neq j$ ). Conversely, minimum entropy ( $H_{\min} = 0$ ) occurs if the map is composed of just one class. Normalization of  $H$  with respect to maximum entropy ( $J = H/H_{\max}$ ) is termed 'evenness' because it measures deviation from an even distribution of attribute classes (Pielou, 1969).

To summarize the spatial configuration of categorical maps with information-theoretic indices, O'Neill et al. (1988) and Li and Reynolds (1993) developed the contagion metric as:

$$C = \frac{2 \ln(N) + \sum_{i=1}^N \sum_{j=i}^N ((n_{ij}/M) \ln(n_{ij}/M))}{2 \ln(N)} \quad (2)$$

where  $n_{ij}$  is the number of shared pixel edges between attribute classes  $i$  and  $j$  and  $M$  is twice the number of total pixel edges since there is double counting of edges (i.e.  $ij$  and  $ji$  are counted twice).

The 'evenness-like' contagion index  $C$  measures the extent to which map pixels are aggregated or clumped into patches of the same attribute class in comparison to the case of random pairing when attribute frequencies are equal (Gustafson, 1998). Lower values of contagion may result from landscapes fragmented in many small patches. In this case, the proportion

of pixels being adjacent to a given attribute class are nearly equal. When pixel adjacency proportions are nearly equal, the double summation term of Eq. (2) approaches its absolute value maximum,  $2 \ln(N)$ , and contagion approaches zero. Conversely, higher values of contagion generally characterize landscapes with a few large patches. Contagion reaches its maximum of 1 with maximum clumping and minimum fragmentation when the landscape is composed of just one attribute class. In this case,  $n_{ii}/M = 1$ , and  $\ln(1) = 0$ . Consequently,  $C = 2 \ln(N)/2 \ln(N) = 1$  (Li and Reynolds, 1993; Frohn, 1998).

The contagion metric has been used extensively to relate the effects of clumping or fragmentation of attribute classes on a landscape to ecosystem processes such as habitat fragmentation, vegetation dispersal and animal movement (Turner and Ruscher, 1988; Turner, 1989, 1990a, 1990b; Graham et al., 1991; Gustafson and Parker, 1992; Li and Reynolds, 1993). Within this context, the Environmental Monitoring and Assessment Program (EMAP) of the United States Environmental Protection Agency (1994) proposed the contagion index as an effective indicator of (i) watershed integrity, (ii) landscape stability and resilience, and (iii) biotic integrity, whereas in a recent proposal for a standardized multiresource forest inventory, Köhl and Päivinen (1996) proposed the contagion index to measure the degree to which land cover units are clumped or aggregated. In addition, alternative methods have been described for calculating class-specific contagion measures to capture more of the information about class and pixel adjacency that is necessarily lost when using a single-valued summary statistics (Pastor and Broschart, 1990; Gardner and O'Neill, 1991). However, despite its widespread application, the contagion index has a major shortcoming that may render it inadequate as a meaningful measure of landscape structure.

## 2. A major shortcoming of the contagion index

Interactions between landscape structure and ecological functions have a range of dynamics that is scale-dependent. Thus, parameters and processes important at one scale of observation are frequently not important or predictive at another scale (Turner et al., 1989). Nonetheless, especially for multitemporal mon-

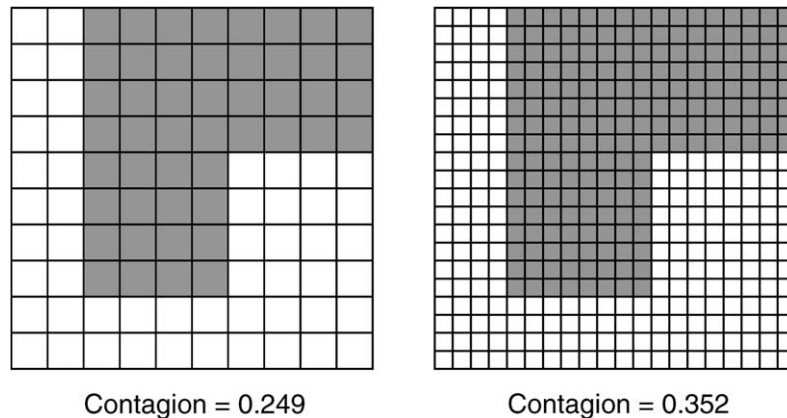


Fig. 1. The dependency of the contagion index on pixel size for identical categorical maps represented at different spatial resolutions.

itoring purposes, categorical maps at a given scale are generally derived from a variety of satellite data that generally slightly differ in pixel resolution. Furthermore, once acquired raster categorical maps can be represented at virtually unending pixel resolutions by simply resampling the original pixel dimension (Frohn, 1998). Consequently, since a pixel is not a true geographical or ecological object *per se* (Fisher, 1997), meaningful landscape metrics need to be preferably insensitive to changes in pixel resolution. Without such metrics, integrated investigations of landscape patterns that use data layer at multiple pixel resolutions may prove to be invalid.

The contagion index is based on pixel adjacency proportions. Therefore, it is very dependent on pixel resolution. For instance, within-class edges (i.e. edges between pixels belonging to the same attribute class) increase at an exponential rate following pixel replication, whereas inter-class edges (i.e. edges between pixels belonging to different attribute classes) increase at a linear rate. As a consequence, the rate of change in the value of contagion as a function of pixel resolution will depend on the proportion of within-class edges versus inter-class edges within the categorical map (Frohn, 1998). Fig. 1 shows the influence of pixel size on contagion for a small artificial map composed of two attribute classes. This artificial map may be considered as a small subset of a larger categorical map. In Fig. 1, both illustrations represent the same spatial structure, but halving the cell increases contagion from 0.249 to 0.352.

To overcome the dependency of contagion on pixel resolution, we propose to ‘unmix’ the information derived from the contagion index into two independent metrics: a first index that measures landscape fragmentation, such as average patch size or patch density, and a second entropy-based adjacency measure that summarizes the evenness of the edge types without considering the relative abundances of the same-type edges (Wickham et al., 1996):

$$J = \frac{-\sum_{i=1}^N \sum_{j=1}^N ((n_{ij}/M) \ln(n_{ij}/M))}{2 \ln(N)} \quad (3)$$

where  $i \neq j$ . It is easily demonstrated that, unlike contagion, traditional fragmentation measures and edge-type evenness  $J$  are both insensitive to (artificial) changes in pixel resolution obtained by simply halving the original pixel dimension as shown in Fig. 1.

Given such a bivariate measure, a convenient graphical display is possible if the analyzed categorical map is represented by a point in the fragmentation-evenness plane. If a large number of maps need to be compared, the resulting scatter diagram might be analyzed using the well-known techniques of classification and ordination (Orlóci, 1978; Podani, 1994). A more radical solution would be to focus solely on edge-type evenness as represented by Eq. (3) without considering landscape fragmentation. Nevertheless, since in doing so, a considerable amount of information on landscape structure is lost, this is like throwing the baby out along with the bathwater.

### 3. Conclusion

In this paper, we proposed a bivariate measure of edge-type evenness and landscape fragmentation to overcome the dependency of the contagion index on pixel resolution. However, it should be clear that the problem of measuring the degree of aggregation of land cover units remains very much open and the proposed solution is not satisfactory in all respects. For example, by reducing the spatial arrangement of landscapes into a bivariate measure, information is necessarily lost, and there is no ideal function capable of collapsing all aspects of pixel adjacency into few summary statistics. Another shortcoming of landscape indices is that they are going to depend both on the classification scheme adopted for constructing the categorical maps and on the extent of the area analyzed. Therefore, in analyzing the ecological implications of large spatially heterogeneous regions, a landscape classification scheme is needed that provides ecologically meaningful units for quantifying different aspects of landscape mosaics and correlate them to ecological processes.

### Acknowledgements

This paper has been carried out with the financial support from the Commission of the European Communities, Agriculture and Fisheries (FAIR) specific RTD programme, CT98-4045, “Scale dependent monitoring of non-timber forest resources based on indicators assessed in various data sources”. The content of this paper does not represent the views of the Commission or its services and in no way anticipates the Commission’s future policy in this area.

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**Carlo Ricotta** is adjunct researcher in plant ecology at the University of Rome "La Sapienza". His current research interests include the extraction of spatial information from remotely sensed imagery and environmental databases to study vegetation dynamics and conservation ecology.

**Piermaria Corona** is full professor of forest management at the University of Viterbo. Prof. Corona is deputy leader of IUFRO 4.02.06 working unit (Resource Data in the Boreal and Temperate Regions) and member of the Italian Academy of Forest Sciences. Forest resources monitoring and management is his main research field.

**Marco Marchetti** is associate professor of silviculture and forest inventories at the University of Palermo. Much of his work is concentrated on spatial statistics and remote sensing applications for multipurpose forest inventories.