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Research paper

Detection of landscape heterogeneity at multiple scales: Use of the Quadratic Entropy Index

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HIGHLIGHTS

- Use of the Quadratic Entropy Index (Q) as a multiscale heterogeneity index was tested.
- A semantic criterion was included to improve the information obtained.
- Q detected differences between maps in the spatial distribution of heterogeneity.
- Q enabled identification of scale invariance levels in the spatial pattern.
- Q can be used as a support tool for landscape planning and design.

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ABSTRACT

Understanding landscape heterogeneity is essential for developing reliable landscape planning and design methods. Nevertheless, despite the many advances made in recent years regarding the analysis of landscape heterogeneity, methods that produce useful results that can be applied to design, planning and management schemes are still required. In this study, we explore the use of the Quadratic Entropy Index (Q) as a measure of landscape heterogeneity. Although the Q metric is derived from information theory, the inclusion of a dissimilarity component in the calculation enables analysis beyond the syntactic content of the information and the inclusion of semantic content. Adoption of a multiscale approach to the calculation fulfils the desirable characteristics for a heterogeneity measure, while also producing spatially-explicit results. Application of the index to three landscape areas in NW Spain with different characteristics clearly demonstrated the capacity of the index to differentiate levels of heterogeneity, and their dependence on scale, and to detect scale invariance. The close fit of Weibull II logistic regression enables prediction of pattern-scale relationships beyond the area of analysis. The findings show that Q is a potentially useful support tool for design, planning and management procedures.

1. Introduction

It is generally accepted that the study of ecological heterogeneity and its organization at different scales is essential for understanding ecosystems and landscapes (Chave, 2013; Levin, 1992; Pickett & Cadenasso, 1995; Turner, 1989). Landscapes and their constituent ecosystems behave as complex adaptive systems (Ingegnoli, 2011; Naveh, 2004) with heterogeneity being one of the key elements, together with non-linearity, flows and hierarchical organization, among others (Levin, 1998, 1999). Such systems reveal emergent properties that are directly related to their spatial organization and the relationships between their component elements (Ingegnoli, 2002). Differences in heterogeneity will therefore lead to changes in system functions such as movement of organisms, materials, energy and information. Heterogeneity is also directly related to ecosystem resilience and sustainability (Levin, 1999; Wu, 2013; Zurlini, Petrosillo, Jones, & Zaccarelli, 2012).

The study of landscape heterogeneity has progressed in recent decades through the use of methods based on the application of

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landscape metrics (Uuemaa, Antrop, Roosaare, Marja, & Mander, 2009; Uuemma, Mander, & Marja, 2013) and spatial statistics (Fortin, James, MacKenzie, Melles, & Rayfield, 2012). The main goals of such studies are to clarify the relationship between pattern and process, and to integrate the information thus obtained in planning and management procedures (Botequilha Leitao, Miller, Ahern, & McGarigal, 2006; Botequilha-Leitao & Ahern, 2002). In fact, recent perspectives emphasize the integration of design in pattern-process comprehension (Musacchio, 2009, 2011; Nassauer, 2006; Nassauer & Opdam, 2008), while acknowledging the importance of spatial and functional heterogeneity in the design process.

Despite these important efforts, practical methods of assessing landscape heterogeneity and complexity are still required. Indeed, Loehle (2004) remarked that although spatial pattern has received more attention than other components of complexity, the description and quantification of spatial patterns remain poorly developed. This may be due to the inherent complexity of the systems, which makes it difficult to develop specific or general methods of study. As 'medium-number systems' (King, 1997; O'Neill, DeAngelis, Waide, & Allen, 1986), landscapes are characterised by too many components for modelling and too few components to enable description of the system using statistical (e.g. averaging) systems. It is also difficult to establish common definitions of heterogeneity and complexity, because of the dependence of these concepts on specific research questions (Li & Reynolds, 1995). Solutions may be given by the definition of the heterogeneity components to be addressed. In this sense, Feagin (2005) identified five components for describing and analysing heterogeneity in the distribution of any variable: Vector (L), corresponding to the size of the system; Richness (K); Evenness (S); Difference (D), or the mutual differences between the diverse forms of the variable; and finally Scaling (R), which defines scale-dependent covariance. These components show an increasing degree of specificity regarding the distribution of one variable, and they can be used to define a reference framework to assess the reliability of an indicator to account for the heterogeneity of a system.

2. Information indices as heterogeneity metrics

Indices derived from information theory (i.e. Shannon, Simpson) have been extensively used to analyse the diversity of landscape heterogeneity (see e.g. Eiden et al., 2000; Legendre & Fortin, 1989). Following Feagin's rationale, these indices are functions of the L, K, and S components of heterogeneity: although this author uses the evenness (S) component P_i only with Shannon entropy, it can be found in other indices following Rènyi's generalized entropy of order α (Hill, 1973; Pielou, 1975; Ricotta, 2000), as expressed in the following formula:

$$H_{\propto} = \frac{log \sum_{i=1}^{n} p_i^{\propto}}{1 - \propto} \quad (1)$$

where α is an arbitrary real number representing the order of the entropy, and P_i is the proportion of area covered by patch type (land cover class) i. For instance, when $\alpha = 1$, we would apply the Shannon-Wiener Index, and when $\alpha = 2$ we would obtain the expression for the Simpson Index (S) (See, Pielou, 1975; Ricotta, 2000). Nevertheless, fulfilment of the usefulness of indices derived from information theory would then depend on two additional heterogeneity components (D and R). The first, reporting for dissimilarity, can be taken into consideration with the application, at landscape level, of a special case of Rènyi's generalized entropy (Expression (1) for $\alpha = 1$): the Quantitative Entropy Index (Q) (Rao, 1982; Ricotta & Szeidl, 2006). The application of this index to landscapes can be defined as the expected distance between two randomly selected ecosystems:

$$Q = \sum_{i=1}^{s} \sum_{j=1}^{s} d_{ij} p_i p_j \quad (2)$$

where d_{ij} is the distance between ecosystems i and j, and p is the above-described evenness factor. However, the application of this index differs in two important aspects relative to commonly used information indices. The first difference is related to the relative independence of the concepts of heterogeneity and richness. Indeed, in an application of Q for detecting plant functional diversity, Botta-Dukat (2005) pointed out that an unexpected property of Q is that its value may decrease as richness increases, due to the dual influence of abundance and between-species differences. This is considered by the author as an improvement, because one of the main shortcomings of Simpson and other information indices is their inability to consider the relative importance of each ecosystem (Nagendra, 2002). The second difference is related to the capacity of the index to interpret the information content represented by the index values. For a better understanding, we should take into account that from a semiotic perspective, information theories can be classified as syntactic, semantic and pragmatic (Brier, 2014). *Syntactic* perspectives focus on calculating information by the probability of occurrence of signs in their respective contexts: *semantic* perspectives seek to calculate the amount of meaningful content in a message; and *pragmatic* perspectives consider data only if it conveys new, true, meaningful, and understandable information, thus including feedback between informer and receiver. These perspectives correspond respectively to three different levels of communication problems (Shannon & Weaver, 1949): the technical problem (or 'how accurately the symbols of communication can be transmitted'); the semantic problem (or 'how precisely the transmitted symbols convey the desired meaning'); and the effectiveness problem (or 'how effectively the received meaning affects conduct in the desired way'). Well-founded perspectives in landscape ecology (Naveh, 2007; Naveh & Lieberman, 1994) underline the importance of the development of *information management*, transforming the knowledge derived from the semantic information produced into pragmatic information, thus enabling the information to produce real changes, for instance through landscape planning or ecosystem management. Indices such as Shannon's or Simpson's only deal with the technical problem (Naveh & Liebermann, 1994), as their early application in ecosystems were perceived as channels projecting information (i.e. proportion of the component subsystems such as species, taxa, etc.) to the future (Margalef, 1993). However, the Quantitative Entropy Index enables the inclusion of a semantic element in the calculation, through the dissimilarity distance component d_{ij} included in Expression (2). Although in studies with other ecological emphasis the calculation involves taxonomic, phylogenetic or functional differences (Izsak & Papp, 1995; Otto, Vasileiadis, Masin, & Zanin, 2012; Pavoine & Doledec, 2005; Pavoine & Ricotta, 2014), this component can also be measured by using a semantic distance metric (Ahlqvist & Shortridge, 2010; see below).

Finally, the scale component (R) can be integrated by calculating Q on categorical maps at multiple scales, by using a moving-window approach (Diaz-Varela, Marey-Perez, & Alvarez-Alvarez, 2009; Gaucherel, 2007). This involves using GIS to calculate the Q index for a set of windows of different sizes, each producing a different raster map of continuous values. Thus, instead of obtaining a unique, general value of the index for the whole landscape, the maps will represent the spatial distribution of landscape heterogeneity at different scales. The scaling aspect of the analysis is important in the study of complexity, as it reflects the hierarchical arrangement of the ecosystems (Kolasa, 2005; Loehle, 2004), acknowledged as essential in landscape analysis (Billeter et al.,