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Original Article

Towards more predictable and consistent landscape metrics across spatial scales

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ABSTRACT

Habitat change and fragmentation are considered key drivers of environmental change and biodiversity loss. To understand and mitigate the effects of such spatial disturbances on biological systems, it is critical to quantify changes in landscape pattern. However, the characterization of spatial patterns remains complicated in part because most widely used landscape metrics vary with the amount of usable habitat available in the landscape, and vary with the scale of the spatial data used to calculate them. In this study, we investigate the nature of the relationship between intrinsic characteristics of spatial pattern and extrinsic scale-dependent factors that affect the characterization of landscape patterns. To do so, we used techniques from modern multivariate statistics to disentangle widely used landscape metrics with respect to four landscape components: extent (E), resolution (R), percentage of suitable habitat cover (P), and spatial autocorrelation level (H). Our results highlight those metrics that are less sensitive to change in spatial scale and those that are less correlated. We found, however, significant and complex interactions between intrinsic and extrinsic characteristics of landscape patterns that will always complicate researcher's ability to isolate purely landscape pattern driven effects from the effects of changing spatial scale. As such, our study illustrates the need for a more systematic investigation of the relationship between intrinsic characteristics and extrinsic properties to accurately characterize observed landscape patterns.

1. Introduction

Landscape pattern refers to discrete landscape features of an ecosystem (composition) and their spatial arrangement (configuration) within the landscape. Biotic and abiotic determinants, as well as human activities, have been shown as driving forces that shape landscape patterns (Turner, 1990). Furthermore, the rate, extent and magnitude of human alteration of the earth's terrestrial surface is greater now than ever in history, driving unprecedented change in ecosystem processes (Lambin et al., 2001). Such changes range from biodiversity loss and climate change to important modification of ecosystem services (Foley et al., 2005). Accurately quantifying and characterizing landscape pattern has therefore become a major priority for addressing a wide range of spatial analysis applications (Turner, 2005).

In this regard, a plethora of quantitative metrics have been developed to ostensibly provide simple quantitative measurements of the composition and configuration of a landscape (Baker and Cai, 1992; McGarigal and Marks, 1995; O'Neill et al., 1988; Turner, 1990). In general, the calculation of these landscape metrics requires the use of a categorical map, often indicating land-cover or land-use. Typically, these metrics are then used to investigate the relationship between landscape pattern and ecological processes, or as an indicator of ecological condition and risk (O'Neill et al., 1997; Uuemaa et al., 2013). They are also of key importance for identifying or detecting critical spatial and temporal changes in landscape patterns to anticipate abrupt ecological transition (Johnson and Patil, 2007). The outcome of such spatial analyses, however, remains limited by constraints in our ability to quantify the changes in landscape pattern (Turner, 2005; Uuemaa et al., 2013). In particular, the characterization of landscape patterns depends not only on the patterns themselves but also on the way they are represented (Wu, 2013).

Multiple scale-dependent factors can affect the characterization of a landscape pattern. For example, most landscape metrics are sensitive to changes in the resolution (grain size) of the spatial data (Frohn and Hao, 2006; He et al., 2000; Li et al., 2005; Saura, 2004; Wickham and Rhtters, 1995; Wu, 2004), the extent of

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the area under investigation (Frohn and Hao, 2006; Li et al., 2005; Saura and Martinez-Millan, 2001; Szab et al., 2014; Wu, 2004; Wu et al., 2002), or the classification scheme of categorical maps (Bailey et al., 2007; Buyantuyev and Wu, 2007; Castilla et al., 2009; Li et al., 2005; Peng et al., 2010). There are many examples of studies that have investigated the sensitivity of landscape metrics to change in spatial scales (Saura and Martinez-Millan, 2001; Wu, 2004; Wu et al., 2002). Such studies typically target a small set of landscape metrics and base conclusions about the effect of spatial scale on landscape metrics on unique case studies, investigating a single or two scale-dependent factors in isolation (Lechner et al., 2013). Thus far, limited consideration has been given to the vexing question of interaction between scale dependent-factors and change in the landscape patterns (Lechner et al., 2013; Peng et al., 2010).

Additionally, the use and application of landscape metrics is hampered by several characteristics of the metrics themselves (Uuemaa et al., 2013). Many landscape metrics are strongly correlated with the proportion of habitat cover on the landscape (Neel et al., 2004). As a consequence, metrics used to characterize particular aspects of the configuration of the landscape pattern cannot be easily interpreted if the proportion of habitat cover on the landscape is different (Neel et al., 2004; Remmel and Csillag, 2003; Wang and Cumming, 2011). Furthermore, no single metric can fully capture and describe intricate landscape pattern. On the other hand, reducing the number of metrics by correlation and ordination techniques has failed to render the ecological meaning of the latent metric to the practitioner (Turner, 2005). Several suggestions have been made for a minimum set of metrics that capture independent elements of the variation in observed landscape patterns while minimizing redundancy and capturing the desired qualities (Riitters et al., 1995; Cushman et al., 2008). Nonetheless, no general framework exists that permits a particular component of landscape patterns to be unambiguously linked to specific landscape metrics.

To address these persistent challenges, most previous research has been directed toward developing a more rigorous statistical interpretation of landscape metrics. The development of the neutral landscape model (Gardner et al., 1987; With et al., 1997) has provided a framework for generating replicated landscape patterns with partially controllable spatial properties, particularly with respect to their composition and configuration of components (Turner, 2005). Inspection of the relationships among landscape metrics revealed that many were nonlinear and often not monotonic across composition and configuration scenarios (Neel et al., 2004; Remmel and Csillag, 2003). However, most of these studies were limited to maps of the same spatial extent and resolution to avoid the confounding effects of these extrinsic scale-dependent factors. There is dearth of studies that explicitly assess the relative importance of scale-dependent factors versus changes in intrinsic characteristics of landscape patterns on the characterization of spatial patterns (Estreguil et al., 2014; Lechner et al., 2013). Yet, it is critical to determine whether a change in spatial scale has the same effect in all spatial patterns or whether particular types of spatial patterns (e.g. those with high fragmentation level) are more sensitive to a change in spatial scale than others.

The primary aim of this study was to investigate the nature of the relationship between intrinsic characteristics of spatial patterns and extrinsic scale-dependent factors that affect the characterization of landscape patterns. This research is motivated by the need to identify a set of key generic landscape metrics that enable concise characterization of independent aspects of spatial patterns regardless of the scale at which the patterns are represented (Lindenmayer et al., 2008). In terms of scale-dependent factors affecting the representation of landscape patterns, we investigated the role of spatial resolution (R) and spatial extent (E). These scale-dependent factors were tested in relation to the intrinsic characteristics of the landscape patterns themselves as described by the spatial autocorrelation (H) and the percentage of suitable habitat cover (P). We first tested the statistical significance of the interaction between landscape pattern and scale-dependent factors to assess the magnitude of these interactions and their statistical effect on landscape metrics. Second, we showed how a self-organizing map (SOM) can be used to identify less correlated subsets of landscape metrics thereby providing a robust alternative to traditional ordination techniques.

Table 1
List of predictor variables tested and values.

Predictor variables	Measures
Intrinsic characteristic	
Landscape spatial autocorrelation (Fragmentation)	H = 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1
Percentage of suitable habitat cover in a binary scheme	P = 5, 15, 25, 35, 45, 55, 65, 75, 85, 95%
Scale-dependent factor	
Spatial extent	E = 640, 1280, 2560 m^2
Spatial resolution or pixel size	R = 10, 20, 40 m

2. Materials and methods

2.1. Landscape patterns and landscape metrics generation

We used the computer program Qrule 4.2 to generate a wide range of landscape patterns, in which fragmentation (measured as the degree of spatial autocorrelation) and proportion of habitat cover can be systematically and independently controlled (Gardner, 1999; Gardner and Urban, 2007). We considered a binary distinction between suitable and unsuitable habitat type. Qrule uses a midpoint displacement algorithm (Saupe, 1988) to generate multi-fractal maps in which the degree of spatial autocorrelation among adjacent cells (H) can be controlled. We generated landscape patterns in a full factorial design across an 11-step gradient in spatial autocorrelation (H = 0–1 in increments of 0.1, 0 being close to random and 1 being completely clustered) and a 10-step gradient in proportion of suitable habitat habitat cover (P = 5–95% in 10% increments) with 100 replicate landscapes for each of the 110 factor combinations (Table 1). In order to analyse the influence of spatial extent and resolution on landscape metrics, we generated binary landscape patterns for 40, 20 and 10 m cell size raster and three different extents of 640 × 640, 1280 × 1280, and 2560 × 2560 m^2 (Table 1). We used independent realizations for each spatial scale to assure the statistical independence of the estimates corresponding to different resolution and extent.

For each sample landscape, we calculated 101 landscape metrics using the computer program FRAGSTATS 4.2 (McGarigal et al., 2012). The metrics were defined for the suitable habitat cover only and are commonly referred as class-level metrics. McGarigal et al. (2012) categorized these metrics into five groups corresponding to the aspect of landscape structure emphasized. These include area/edge/density, shape, core area, contrast and aggregation (Table 2). Metric calculation was based on a 80 m edge depth affecting metrics related to core area, a 400 m search radius affecting metrics based on the distribution of suitable habitat cells within a specified distance of a focal point and an eight-neighbour rule.

2.2. Permutational multivariate analysis of variance

To test the null hypothesis of no statistical difference between landscape metrics for four predictor variables, spatial extent (E), spatial resolution (R), percentage of suitable habitat cover (P), and spatial aggregation (H), we used the permutational multivariate analysis of variance (PERMANOVA) (Anderson, 2001). This