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Interactions between landcover pattern and geospatial processing methods: Effects on landscape metrics and classification accuracy

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ABSTRACT

Remote sensing data is routinely used in ecology to investigate the relationship between landscape pattern as characterised by land use and land cover maps, and ecological processes. Multiple factors related to the representation of geographic phenomenon have been shown to affect characterisation of landscape pattern resulting in spatial uncertainty. This study investigated the effect of the interaction between landscape spatial pattern and geospatial processing methods statistically; unlike most papers which consider the effect of each factor in isolation only. This is important since data used to calculate landscape metrics typically undergo a series of data abstraction processing tasks and are rarely performed in isolation. The geospatial processing methods tested were the *aggregation method* and the choice of *pixel size* used to aggregate data. These were compared to two components of landscape pattern, spatial heterogeneity and the proportion of landcover class area. The interactions and their effect on the final landcover map were described using landscape metrics to measure landscape pattern and classification accuracy (response variables). All landscape metrics and classification accuracy were shown to be affected by both landscape pattern and by processing methods. Large variability in the response of those variables and interactions between the explanatory variables were observed. However, even though interactions occurred, this only affected the magnitude of the difference in landscape metric values. Thus, provided that the same processing methods are used, landscapes should retain their ranking when their landscape metrics are compared. For example, highly fragmented landscapes will always have larger values for the landscape metric "number of patches" than less fragmented landscapes. But the magnitude of difference between the landscapes may change and therefore absolute values of landscape metrics may need to be interpreted with caution. The explanatory variables which had the largest effects were spatial heterogeneity and pixel size. These explanatory variables tended to result in large main effects and large interactions. The high variability in the response variables and the interaction of the explanatory variables indicate it would be difficult to make generalisations about the impact of processing on landscape pattern as only two processing methods were tested and it is likely that untested processing methods will potentially result in even greater spatial uncertainty.

1. Introduction

Land use and land cover maps (LULC) derived from remote sensing sources are routinely used in ecology to investigate the relationship between landscape pattern and ecological processes (Gergel, 2007; Lechner et al., 2012a; Wiens, 2002). LULC maps are used to support the identification of vegetation types and to describe habitat for ecological analyses including the derivation of landscape metrics (Griffith et al., 2000), change detection analysis (Kennedy et al., 2009), habitat suitability/prediction (Guisan and Zimmermann, 2000; Leyequien et al., 2007), population viability analysis (Southwell et al., 2008), and conservation planning (Margules and Pressey, 2000). The outcome of such spatial analyses, however, depends not only on the landscapes themselves but also on the way they are represented. In other words, the methods used to observe and process these landscapes influences the outcome of spatial analyses (Friedl et al., 2001; Gergel, 2007; Gustafson, 1998; Lechner et al., 2012a).

Quantifying uncertainty that results from the abstraction of the real world is critical for ecological analyses that use remote sensing data (Hess, 1994; Lam et al., 2005; Lechner et al., 2012a) to

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understand the potential implications for management decisions. The characterisation of uncertainty is essential to provide data users with confidence in the results of analyses using spatial data. Multiple factors related to the depiction of real geographic phenomenon have been shown to affect the representation of mapped landscapes causing spatial uncertainty. For example, there are numerous scale-dependent factors such as pixel size (e.g. Saura and Castro, 2007; Wickham and Riitters, 1995), the application of a minimum mappable unit (MMU) (e.g. Kendall and Miller, 2008; Prada et al., 2008; Shen et al., 2004; Thompson and Gergel, 2008) and thematic resolution (Bailey et al., 2007; Buyantuyev and Wu, 2007) which all affect the characterisation of spatial patterns in LULC maps (Lechner et al., 2012a).

There are many ways in which the choices made during the map creation process can affect the characterisation of landscapes and the ecological analyses conducted with that data. For example, the commonly used European LULC CORINE mapping product has specific characteristics (factors) which affect how it represents landscape such as its mapping scale (1:100,000) and its MMU (25 hectares) (European Environment Agency, 1994). Many studies investigate the sensitivity of the characterisation of land cover and/or ecological analysis to these characteristics, however, these studies usually test a single factor or two factors in isolation by fixing all other factors except the one's under investigation (e.g. Buyantuyev and Wu, 2007; Lechner et al., 2012b; Wickham and Riitters, 1995). Often the interaction between factors is not investigated. If factors interact, studies that consider a single factor in isolation may produce a result that could otherwise differ when other factors are fixed at different levels. There are many examples of studies that have tested multiple factors (e.g. Kendall and Miller, 2008; Lechner et al., 2008; Saura and Martinez-Millan, 2001; Wu, 2004; Wu et al., 2002), but in most cases implicitly, without explicitly testing for interactions using statistical methods.

The aim of this study was to *explicitly* investigate the interaction between factors affecting the representation of landscape pattern, including geospatial processing methods and the spatial characteristics of the underlying landscapes. In terms of geospatial processing methods that affect the representation of geographic data, we investigated the effects of aggregation methods and the choice of pixel sizes - common tasks in remote sensing data preparation. The term *processing method* has been used in this paper to describe both geospatial processing tasks (e.g. resampling) and related input parameters (e.g. pixel size). These processing methods were tested in relation to the true landscape pattern as described by the spatial autocorrelation and percentage landcover class area at the landscape scale (henceforth class proportion) of generated synthetic landscapes. Multiple synthetic landscapes were generated with known spatial patterns with a large sample size to provide the statistical power to allow for generalisations to be made. The interactions were described using landscape metrics to measure landscape pattern and classification accuracy (Fig. 1). It is critical to understand the interaction between true landscape pattern and the processing methods to determine whether a specific factor (e.g. aggregation method) has the same effect in all landscapes, or whether certain types of landscapes (e.g. those with high *spatial heterogeneity*) are more affected by these processing methods compared to other landscapes. Furthermore, it is important to assess if these interactions are statistically significant and to assess the magnitude and types of these interactions.

An additional aim of this study was to investigate the effect of aggregation method on the representation of landscape pattern, a rarely tested source of spatial uncertainty. The aggregation methods that are used to change pixel sizes for multi-scale studies, are commonly assumed to have no effect and few studies consider how the method of aggregating to coarser pixel sizes may affect the representation of the same landscape at other pixel sizes (but see

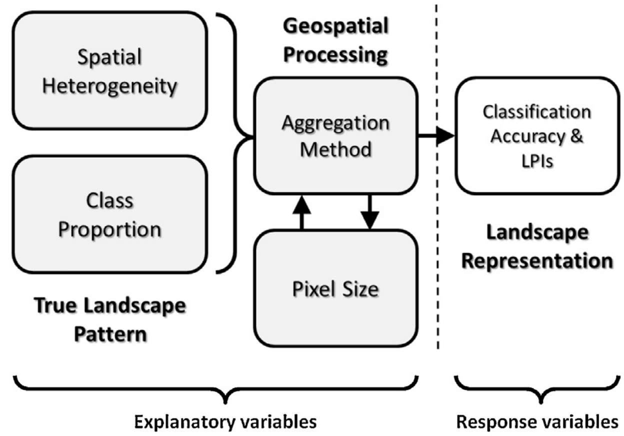

Fig. 1. Conceptual diagram showing the relationship between true landscape pattern and geospatial processes, and their effect on the representation of landscapes as described by Landscape Pattern Indices (LPI) / landscape metrics and classification accuracy.

Bian and Butler, 1999; Gardner et al., 2008). This assumption that aggregation method has no effect need to be tested in order to validate studies that aggregated data to multiple pixel sizes to test for the sensitivity of an ecological analyses to pixel size or describe an ecological phenomenon at multiple scales (e.g. Cain et al., 1997; Lechner et al., 2008, 2012b; O'Neill et al., 1996; Wickham and Riitters, 1995; Wu, 2004; Wu et al., 2002). In the spatial sciences community, it is common practice for remote sensing data to be aggregated when historical data of low or medium spatial resolution from satellites such as Landsat are combined with higher resolution data from newer satellites such as Ikonos and Quickbird for cross comparison or change detection analyses.

There are numerous methods that can be used to spatially aggregate remote sensing data and each has the potential to affect landscape characterisation. Remote sensing data in its raw format represents the radiometric reflectance values of surface objects. In order to create LULC maps these raw values are converted into land cover information classes (e.g. urban vs. forest) with a classification algorithm. To aggregate remote sensing data to a new pixel size there are two possible strategies: (i) the raw data is aggregated and then classified or (ii) the raw data is classified at the original pixel size and then aggregated. Furthermore, the aggregation process may be performed using a number of standard methods such as a majority filter, nearest neighbour or average filter. The question of whether all aggregation methods produce equivalent land cover patterns has important consequences for studies using multiple pixel sizes, or where original pixel sizes have been changed, and for between studies which use different methods.

2. Methods

Using synthetic landscapes we tested for the effects of processing method and real spatial pattern on classification accuracy and the characterisation of spatial pattern. The process involved four steps: (i) generating synthetic landscapes with a range of spatial heterogeneity, (ii) aggregating data using one of three methods, (iii) calculating landscape pattern indices and classification accuracy and (iv) conducting statistical analysis. For the statistical analysis, we applied a multivariate analysis of variance (MANOVA) along with an analysis of variance (ANOVA) for specific response variables.

2.1. Landscape generation

The synthetic landscapes used in the model were continuous gray scale fractal landscapes, generated using Saupe's (1988)