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Selecting landscape metrics as indicators of spatial heterogeneity—A comparison among Greek landscapes

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ABSTRACT

This paper investigates the spatial heterogeneity of three landscapes along an altitudinal gradient and different human land use. The main aim was the identification of appropriate landscape indicators using different extents. ASTER image was used to create a land cover map consisting of three landscapes which differed in altitude and land use. A number of landscape metrics quantifying patch complexity, configuration, diversity and connectivity were derived from the thematic map at the landscape level. There were significant differences among the three landscapes regarding these four aspects of landscape heterogeneity. The analysis revealed a specific pattern of land use where lowlands are being increasingly utilized by humans (percentage of agricultural land = 65.84%) characterized by physical connectedness (high values of Patch Cohesion Index) and relatively simple geometries (low values of fractal dimension index). The landscape pattern of uplands was found to be highly diverse based upon the Shannon Diversity index. After selecting the scale (600 ha) where metrics values stabilized, it was shown that metrics were more correlated at the small scale of 60 ha. From the original 24 metrics, 14 individual metrics with high Spearman correlation coefficient and Variance Inflation Factor criterion were eliminated, leaving 10 representative metrics for subsequent analysis. Data reduction analysis showed that Patch Density, Area-Weighted Mean Fractal Dimension Index and Patch Cohesion Index are suitable to describe landscape patterns irrespective of the scale. A systematic screening of these metrics could enhance a deeper understanding of the results obtained by them and contribute to a sustainable landscape management of Mediterranean landscapes.

1. Introduction

Landscape patterns are formed by various interacting abiotic and biotic processes (Levin, 1978; Forman and Godron, 1986; Turner, 2005). Not only topographical determinants, such as altitude (Bolliger, 2002), but also human activities have been proved as driving forces in shaping landscapes (Blondel and Aronson, 1995; Blondel, 2006; Bürgi et al., 2007; Serra et al., 2008) by inserting novel patches into landscapes (Proulx and Fahrig, 2010), creating land division and settlement patterns (Corry and Nassauer, 2002), introducing mechanization into agriculture (Wood and Handley, 2001; Rühl et al., 2005) and causing urban-sprawl (Van Eetvelde and Antrop, 2004). Other studies have also argued that human land use play a crucial role in landscape heterogeneity (Farina, 1998; Wu and Hobbs, 2002). Gao et al. (2009) have also shown that human presence strongly affects the local landscape structure resulting in different land uses, for example in mountain villages of Beijing in China, where altitude was a crucial factor.

The quantification of spatial heterogeneity is a key topic in landscape ecology due to its influence on many ecological processes (Turner, 1989; Braimoh, 2006). When dealing with heterogeneity it is important to discriminate between different types of heterogeneity, recognize its causes and consider scale effects (Levin, 1992; Wiens, 2000; Turner et al., 2001; Wu, 2004). Changes in either extent or grain (Forman and Godron, 1986) or comparisons among different scales, affects landscape pattern index values (Turner et al., 2001; Li and Wu, 2004). Due to landscape heterogeneity and nonlinearity, scaling is often a difficult task and understanding the

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scale multiplicity in pattern and process is a key to the success of scaling (Wu, 1999), as it has been widely recognized that spatial pattern is scale-dependent (Wu et al., 2002).

A characterization of the shape, size and spatial arrangement of different habitat patches within a landscape can be used to connect the detected spatial patterns to the driving forces generating them, such as natural ecological processes or human management practices (De Blois et al., 2002; Corry and Nassauer, 2005). Landscape metrics are useful in applying the concepts of landscape ecology in landscape monitoring and planning (Botequilha Leitão and Ahern, 2002; Zhang and Wang, 2006; Lin et al., 2007; Wrbka et al., 2008), providing an objective description of different aspects of landscape structure and patterns (McGarigal and Marks, 1995). In addition, landscape metrics have been used to compare the spatial heterogeneity among different landscapes (Hulshoff, 1995; Trani and Giles, 1999; Corry and Lafortezza, 2007). However, metrics differ in their range of values (some are range-limited, while others are not) and may be unit-less, or reported as percentages or map units. Comparing metrics with different units or ranges can be difficult and determining an ecologically significant change in index values is challenging (Lafortezza et al., 2005). In the past, several studies have used factor analysis (FA) and principal component analysis (PCA) to reduce the multitude of available landscape pattern metrics to a meaningful subset for the respective application (Rogers, 1993; Riitters et al., 1995; Cain et al., 1997; Tinker et al., 1998). Cushman et al. (2008) identified 13 landscape metrics as independent components of landscape structure and grouped them to describe the major attributes at the landscape level. However, no single metric can adequately capture the pattern on a given landscape.

The patterns of Mediterranean landscapes have been carved out over thousands of years by livestock grazing, deforestation for cultivation and other anthropogenic disturbances (Farina, 1998). Analysis of Mediterranean landscapes undeniably needs further research as the entire Mediterranean Basin is one of the most significantly altered hotspots on earth hosting many endemic species (Quezel, 1985; Myers et al., 2000). The special characteristics of these hotspots are the result of internal environmental heterogeneity, including dissected mountainous landscapes, a high degree of natural disturbance (Archibold, 1995; Allen, 2001) like naturally occurring fires (Pignatti et al., 2002), topographical characteristics (Geri et al., 2010) and a remarkable degree of human activity, especially agriculture, as a major pressure on landscape shaping (Blondel and Aronson, 1999; Vogiatzakis et al., 2006).

A delineation of the landscape into discrete patches serves as a basis for calculating metrics that describe landscape fragmentation, connectivity or human influences (Ivits et al., 2005). Remote sensing data is increasingly used to derive such landscape classification, especially in Mediterranean countries, where good weather conditions allow for the provision of critical information in real time (Karydas et al., 2009). Relevant studies have already proposed a core set of metrics that is most useful to detect the local drivers of biodiversity in the Mediterranean area (Botequilha Leitão and Ahern, 2002). Other studies have calculated landscape metrics for an entire study area such as Dadia National Park (Schindler et al., 2008), Lake Koronia (Chouvardas, 2007) and the island of Lesvos (Koukoulas et al., 2008) and analyzed the temporal land use/cover changes, based on scenarios (Chouvardas and Vrahnakis, 2009) or in relation to socioeconomic changes (Zomeni et al., 2008; Kizos et al., 2010). But there is still need for further research on different aspects of landscape heterogeneity. Firstly, it is important to identify and describe the different landscape patterns that may exist in an area characterized by topographical factors that are responsible for the landscape formations. Secondly, it is useful to determine landscape metrics which are insensitive to both components of spatial scale: grain and extent.

The aim of this study was to analyze spatial heterogeneity of different landscapes in a multiscale approach. The specific objectives of the study were to: (1) calculate different landscape metrics and discriminate a minimal subset of them appropriate for describing the landscape heterogeneity, (2) investigate the scale effect on these metrics and identify those which are to a lesser extent – dependent and (3) try to connect the detected spatial heterogeneity to the driving forces generating them, either altitude or human land use.

2. Study area

The study was carried out in the Prefecture of Trikala, central Greece (Fig. 1). The study area has an extent of 615 km^2 and is located at an altitude from 150 to 1130 m. It is part of the NATURA 2000 network of the protected areas in Europe (Dafis et al., 1996), due to its importance for the conservation of 163 bird species (Meliadis and Kassioumis, 2001). The climate is sub-Mediterranean throughout the majority of the territory.

Based on the altitude, the study area was divided into three sub-landscapes (Fig. 1). The first landscape covers an area of approximately 249 km^2. It has altitudes ranging from 100 to 150 m and is dominated by agricultural land use. The cultivated area is composed of a mosaic of mixed and relatively small fields of cereal, corn and cotton and a few permanent crops, such as vineyards (Meliadis et al., 2010). The second landscape is semi-mountainous with altitudes ranging from 200 to 750 m and with a total area of 193 km^2. Land cover is rather variable, with a typical patchwork landscape structure. It is dominated by shrub species such as *Pyrus amygdaloformis*, *Quercus coccifera*, *Carpinus orientalis* and *Cotinus coggygria*. The third landscape is mountainous with altitudes ranging from 780 to 1130 m and has an approximate area of 163 km^2. It is dominated by forest vegetation composed of *Quercus pubescens* stands mixed with *Q. ithaburensis var. cerris* and *Q. frainetto*, whereas *Fagus sylvatica* dominates the highest elevations. Hereafter, the three landscapes will be called lowland, midland and upland. Livestock husbandry is one of the main sources of income for the local population of the midland and upland area, which are dominated by rangelands, meaning either grasslands or shrublands.

3. Materials and methods

3.1. Image classification and land cover data set

In the present study the visible and near infrared (VNIR) data of ASTER satellite image, derived from the Earth Remote Sensing Data Analysis Center (ERSDAC), and acquired in July 2008 with a spatial resolution of 15 m was used to obtain the land cover map. The ASTER (VNIR) images contain three multispectral bands (0.52–0.86 μm) corresponding to green (G), red (R) and near infrared (NIR). The land cover map was produced by performing a supervised classification using the software ENVI (Environment for Visualizing Images 4.7, ITT Visual Information Solutions) and applying a Maximum Likelihood algorithm (Richards, 1994).

Training samples were used to determine the land cover classes on the ground and then train the algorithm with that information. Over 1000 ground-truthing points were collected by a hand-held GARMIN global positioning system (eTrex Vista HCx). The resulting land cover map was merged into ten categories: dense forest (DF) (canopy density of 70% and above), open forest (OF) (canopy density < 70%), dense shrublands (DS), open shrublands (OS), grasslands (G), agricultural land (AL), urban areas (UR), bare land (BL), water (W) and unclassified (UN) (Ghossoub, 2003). If a pixel is not