



# Modeling plant species richness using reflectance and texture data derived from QuickBird in a recently burned area of Central Spain

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## ABSTRACT

Species richness increases markedly during the first years after fire, driven mainly by the increase in the number of herbaceous species. However, such increase is variable in space and time, due to the role that the different plant life-forms can play after the fire disturbance. In addition, the absence of reliable species richness information can be a limitation for decision making when postfire management actions are needed. In this study we used QuickBird imagery to develop multiscale, spatially explicit predictive models of species richness in a burned area 1 year after a fire. The study area is an abandoned *dehesa* (a *Quercus suber* (cork oak) open woodland with shrubs) of central Spain, which had been affected by a large summer fire. Two  $90 \times 180$  m macroplots were established, where species richness and percentage cover of various plant life-forms were measured at three spatial scales (1, 25, and  $100 \text{ m}^2$ ). Total plant species richness was related to reflectance and spectral contrast derived from the multispectral bands of QuickBird and to the Normalized Difference Vegetation Index (NDVI), by using regression tree analysis (RTA) and boosted regression trees (BRT). Furthermore, for the biophysical support of such models, plant species richness was related to field-based compositional data, and life-form percentage cover to satellite data. Results indicated that the relationship between species richness, reflectance and spectral contrast was strong and scale-dependent ( $1 \text{ m}^2$ : adjusted  $R^2 = 0.50$ ;  $25 \text{ m}^2$ : adj.  $R^2 = 0.65$ ;  $100 \text{ m}^2$ : adj.  $R^2 = 0.79$ ), whereas NDVI played a minor role at all scales. At the finest sampling scale, a low range of species richness was related to a high variability of spectral and texture responses, due to the excess of spatial detail of the pixel size. At  $25 \text{ m}^2$ , a higher range of species richness was related to a low variability of spectral and texture responses; this was probably due to the fact that the sampling size only captured certain portions of plant individuals or life-form associations. At the largest sampling scale ( $100 \text{ m}^2$ ), the highest variability of species richness was adequately related to the spectral and texture responses, due to the spatial fit between the sampling plot size and both the pixel- and plant-sizes. Species richness was closely linked to life-form percentage cover (mainly to herbaceous plant cover), and life-form cover was adequately explained by satellite data, giving a biophysical support to our predictive models. Reflectance and spectral contrast were good predictive tools of total plant species richness at the largest sampling scale, but their predictive power diminished at the smaller scales. This was explained by the range of species richness measured at each scale, the spatial arrangement of species, and the ratio of the spatial resolution (both for pixels from satellite data and for ground sampling plots) to the size of the objects. These results contribute to improve our knowledge about the link between high spatial resolution remotely sensed data and species richness at different sampling scales.

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## 1. Introduction

Assessing patterns of plant species richness (number of species per unit area) is a central task of biodiversity assessment (Gaston, 2000). This is particularly relevant in landscapes subject to multiple drivers of change, and where plant biodiversity is very high, such as the Mediterranean region (Myers et al., 2000). Measuring plant species richness in the field is difficult and often time consuming.

Estimating species richness from remotely sensed data is challenging, because species richness is an aggregated measure of diversity that does not take explicitly into account either vegetation structure or composition, the two main vegetation properties that are more easily captured by remotely sensed data (Nagendra, 2001). Moreover, species richness estimation is scale-dependent; that is to say, inferences regarding species richness depend on the spatial scale of the analysis (i.e., spatial resolution of image pixels and/or field sampling sizes; and the extension of the study area) (Hortal & Lobo, 2005; Legendre et al., 2005), making predictive models very contextual and not comparable. In spite of these limitations, remote sensing data have been used to estimate species richness at several spatial and temporal

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scales by relating it to direct or indirect biophysical proxies such as resource availability and productivity, disturbance and/or spatial heterogeneity, among others (e.g., Gillespie et al., 2008; Nagendra, 2001).

Vegetation properties such as biomass, cover or primary productivity have been usually linked to the averaged or maximum normalized difference vegetation index (NDVI) (Parelo et al., 1997; Rosenzweig, 1995). The relationships between NDVI and plant species richness has been frequently assessed at broad scales (large extensions), by relating large ground-sampling areas (> 1 ha) with low–medium spatial resolution remote sensed data (i.e., NOAA-AVHRR, MODIS, Landsat TM, Landsat ETM+), and linking species richness to biomass or related variables across large environmental or disturbance gradients (Cayuela et al., 2006; Fairbanks & McGwire, 2004; Feeley et al., 2005; Foody & Cutler, 2003, 2006; Gillespie, 2005; Gillespie et al., 2009; Hernández-Stefanoni & Dupuy, 2007; John et al., 2008; McCosker et al., 2009; Saatchi et al., 2008). The use of high spatial resolution sensors (i.e., ASTER or QuickBird) (e.g., Levin et al., 2007), as well as the use of small sampling plots (<0.1 ha) (Foody & Cutler, 2003, 2006; Hernández-Stefanoni & Dupuy, 2007) has been less common in this kind of studies. In most cases, the relationship between NDVI and plant species richness was found to be life-form dependent (i.e., NDVI related positively to woody plant species richness and negatively to herbaceous plant species richness). Furthermore, the larger the environmental gradient considered, the greater the species richness variance explained (Mittelbach et al., 2001; Rosenzweig, 1995). Apart from biomass and productivity-related variables (i.e., NDVI), spatial heterogeneity-related variables derived from abiotic and biotic conditions could potentially influence patterns of species richness, and hence exploring their role from remotely sensed data is worth (Carlson et al., 2007; Carter et al., 2005; Lucas & Carter, 2008; Palmer et al., 2002; Rocchini et al., 2004, 2007).

More heterogeneous habitats, driven by marked gradients of abiotic (climate, topography and soil conditions) and biotic (vegetation composition and structure) factors, may support richer species assemblages than more homogeneous ones because of species niche differentiation (Grimme, 1979). Habitat heterogeneity has been linked to several spectral variation (or spectral heterogeneity) measures derived from remotely sensed data. For example, the variance and standard deviation of the NDVI or other multispectral bands (Gillespie et al., 2009; Gould, 2000); the mean of the pairwise Euclidean distances from the centroid of sampling plots using multispectral wavebands (Oldeland et al., 2010; Palmer et al., 2002; Rocchini et al., 2004, 2007); simple hyperspectral indices based on within-transect spatial variability (coefficient of variation) (Carter et al., 2005; Lucas & Carter, 2008); or the range of derivative reflectance of different wavelength regions (Carlson et al., 2007). Some of these studies have been carried out at broad scale (large extensions) relating medium ground-sampling areas (<1 ha and >0.1 ha) to medium-high spatial resolution remote sensed data (e.g., Landsat TM, ETM+ and QuickBird), and linking species richness to the different habitat structures that originate large environmental gradients (Gillespie et al., 2009; Gould, 2000; Levin et al., 2007). Other few studies have been carried out at finer scales with no gradients, relating small ground-sampling areas (<0.1 ha) to hyperspectral and high spatial resolution sensors (e.g., AVIRIS, Hymap, QuickBird), and linking species richness to chemical and structural properties of different life-forms and their spatial interactions (Carlson et al., 2007; Carter et al., 2005; Lucas & Carter, 2008; Palmer et al., 2002; Rocchini, 2007; Rocchini et al., 2004, 2007). In all cases, and irrespective of the spatial scale analyzed, a positive relationship between spectral variation and plant species richness has been reported. However, the degree of correlation was scale-dependent (i.e., the larger the plot size, the greater the explained variance). Such strong relationships are the basis for the Spectral Variation Hypothesis (SVH) (Palmer et al., 2002; Rocchini et al., 2004, 2007), which proposes that spectral

heterogeneity of remotely sensed images is related to the spatial heterogeneity of the environment, or of different life-form assemblages, providing a biophysically-based approach for plant species richness estimation (Carlson et al., 2007; Rocchini et al., 2004). Supporting these remotely sensed approaches to predict species richness, ecological studies at very fine scales have shown that the percentage cover of various plant life-forms and their derived spatial structures can potentially influence patterns of species richness (Bruno et al., 2003). According to these findings, areas dominated by herbaceous plants are richer than those composed mainly by woody plants (i.e., shrubs and/or trees) (López-Pintor et al., 2006); whereas areas composed by a mixture of herbs and woody plants provide a greater spatial heterogeneity and hold higher species richness (Agra & Ne'eman, 2009; Grytnes, 2000; Grytnes & Birks, 2003; Holzapfel et al., 2006).

Therefore, as the spatial interactions among various life-forms can exert significant effects on total plant species richness, and the multi-spectral and high spatial resolution of QuickBird data enables the distinction of compositional and spatial vegetation patterns (Coburn & Roberts, 2004), we hypothesize that: 1) reflectance and texture-derived data would serve as proxies of species richness at fine scales, through a strong interaction among them. Spectral texture will be a useful predictive variable of species richness if total plant species richness depends mainly on the mixtures of life-forms (i.e., herbs and woody plants), because spectral texture is able to distinguish spectrally heterogeneous stands (with high species richness) from homogeneous ones (usually with low species richness). However, reflectance in the VIS (Visible: 450–690 nm) and NIR (Near infrared: 760–900 nm) regions will be essential for predicting species richness if the bulk of total species richness is composed by species of a single life-form, like herb plants in Mediterranean environments; because reflectance in VIS and NIR is able to distinguish plant species with different fractions of green vegetation cover (i.e., senescent herb plants, containing high species richness, from evergreen woody plants with low species richness). Moreover, we also expected that: 2) the relationship between species richness and satellite-derived data would be spatially dependent, so that the overall fit would increase with increasing sampling area, because at larger sampling sizes a larger range of different microhabitats is detected by the sensor, and therefore the relationship between species richness and spectral variability will be strengthened. Finally, the role of explanatory variables would be expected to change with the sampling size due to the different grained patterns observed at each scale.

The main objectives of this work are: i) to develop multiscale, spatially explicit, predictive models of total plant species richness by relating QuickBird data with plant species richness collected from field plots of different sizes, in a burned area 1 year after fire. ii) To provide a biophysically-based support to the predictive models of species richness derived from satellite data by relating total plant species richness with species composition (i.e., percentage cover of the different life-forms) found in field plots; and finally, iii) to provide the physical bases to link remotely sensed data to different vegetation patterns and, ultimately, to different species richness by relating life-form percentage cover with satellite data. In all cases, non-parametric, machine learning techniques, including regression trees (RTA) and boosted regression trees (BRT) were applied (Elith et al., 2006).

## 2. Methods

### 2.1. Study area

The study site is located near the village of Anchuras (central Spain; Fig. 1), in an open woodland (abandoned *dehesa*) of *Quercus suber* L. that was affected by a large fire on August 1st 2002. The fire-affected area was 1415 ha, and is at a mean altitude of 500 m. The climate is Mediterranean, with an average total annual rainfall

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