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Using satellite imagery to assess plant species richness: The role of multispectral systems

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Abstract

Question: The use of variations in the spectral responses of remotely sensed images was recently proposed as an indicator of plant species richness (Spectral Variation Hypothesis, SVH). In this paper we addressed the issue of the potential use of multispectral sensors by testing the hypothesis that only some of the bands recorded in a remotely sensed image contain information related to the variation in species richness.

Location: Montepulciano Lake, central Italy.

Methods: We assessed how data compression techniques, such as Principal Component Analysis (PCA), influence the relationship between spectral heterogeneity and species richness and evaluated which spectral interval is the most adequate for predicting species richness by means of linear regression analysis.

Results: The original multispectral data set and the first two non-standardized principal components can both be used as predictors of plant species richness ($R^2 \approx 0.48$; $p < 0.001$), confirming that PCA is an effective tool for compressing multispectral data without loss of information. Using single spectral bands, the near infrared band explained 41% of variance in species richness ($p < 0.01$), while the visible wavelengths had much lower prediction powers.

Conclusions: The potential of satellite data for estimating species richness is likely to be due to the near infrared bands, rather than to the visible bands, which share highly redundant information. Since optimal band selection for image processing is a crucial task and it will assume increasing importance with the growing availability of hyperspectral data, in this paper we suggest a 'near infrared way' for assessing species richness directly from remotely sensed data.

Keywords: Environmental heterogeneity; Multispectral images; Principal Component Analysis; Quickbird; Spectral Variation Hypothesis.

Abbreviations: DN = Digital number; NDVI = Normalized Difference Vegetation Index; SVH = Spectral variation hypothesis.

Nomenclature: Pignatti (1982).

Introduction

Species richness is a basic indicator of biodiversity, and it underlies many ecological models and conservation policies (Colwell & Coddington 1994; Yoccoz et al. 2001). In this framework, the use of remotely sensed data for assessing species richness at local scales represents a new challenge in ecology (Carmel & Kadmon 1998; Nagendra & Gadgil 1999). As stated by Innes & Koch (1998), remote sensing has long been underused in biodiversity studies with respect to traditional field based surveys, although it could provide a powerful tool for environmental monitoring and conservation issues (see also Stohlgren et al. 1997; Foody & Cutler 2003).

On the other hand, in response to the calls for more development of remote sensing in biodiversity, estimate methods for predicting plant species richness from remotely sensed data have recently been developed. Some authors have used vegetation indices and regression analysis (e.g. Gould 2000; Oindo & Skidmore 2002; Fairbanks & McGwire 2004; Gillespie 2006), while Foody & Cutler (2003) made use of feedforward neural networks. Others made use of surrogate data, such as vegetation maps (Lauver & Whistler 1993; Griffiths et al. 2000; Luoto et al. 2002). Recently, Palmer et al. (2002) proposed the use of variations in the spectral responses to assess plant species richness from remotely sensed images (Spectral Variation Hypothesis; SVH). SVH states that habitat heterogeneity may be estimated from the spectral heterogeneity of remotely sensed data. Since habitat heterogeneity generally allows more species to coexist, SVH represents a potential tool for predicting local plant species richness. SVH was tested by Palmer et al. (2002) in the Tallgrass Prairie Reserve, Oklahoma, using aerial high resolution panchromatic photographs, and by Rocchini et al. (2004) in the Montepulciano Lake Reserve, Italy, with a multispectral Quickbird satellite image. In both cases, a significant relationship between spectral heterogeneity and species richness was detected. Rocchini et al. (2004) further hypothesized that the number of bands used for quantifying image spectral heterogeneity may affect the accuracy of the relationship between the spectral data and species richness. Nonetheless, to our knowledge, the effects of the size of the (multi)spectral system on the quantification of SVH were never explored.

In theory, the use of high-resolution multispectral sensors, such as Quickbird or Ikonos, should improve the quantification of habitat heterogeneity. For instance, one would expect that, as the number of bands increases, the goodness of evaluations should also increase. However, this is not necessarily the case. The addition of redundant data could increase noise without adding valuable information (Bajcsy & Groves 2004). Processing a large number of bands can thus result in lower accuracy than processing a subset of relevant bands without redundancy. In this view, the employed bands, e.g. their number and their spectral bandwidth, represents a key issue for assessing species richness directly from remote sensing data.

In this paper, we specifically test the hypothesis that a few bands are potentially useful for estimating local species richness out of a multispectral data set. We focus on the fact that some bands are known to be good indicators of vegetation biomass and growth (e.g. Boyd et al. 2002; Wang et al. 2005; Lasaponara 2006), but no information is available about the performance of such bands as indicator of species richness.

Study area

The study area is the Montepulciano Lake Natural Reserve, Tuscany (11°54'51'' E, 43°05'47'' N). This is one of the most important wetland areas of central Italy because of its migratory bird populations and rare aquatic plants. The Reserve (470 ha) is centred around a shallow lake of 100 ha. Wetland area (270 ha) is principally dominated by *Phragmites australis* and *Carex* spp. The remaining area is dominated by cultivated fields, marginal areas and riparian woodlands.

Methods

Field data

Vascular plant species richness was recorded with field sampling, performed during June 2002 within random stratified sampling units. To obtain spatial strata, the study area was overlaid with a square grid of 500 m × 500 m (25 ha) extracted from the kilometric universal transverse mercator (ED50) grid. Within each 500 m × 500 m cell, one square macroplot of 100 m × 100 m (1 ha) was randomly selected, yielding a total of 22 macroplots. Each macroplot was in turn divided into four 50 m × 50 m quadrants. Finally, within each quadrant a square plot of 10 m × 10 m was randomly chosen. Within each 10 m × 10 m plot, all vascular plants were recorded. The vascular plant species richness at the macroplot scale was obtained as the pooled list of species found in the four 10 m × 10 m plots nested within each macroplot.

In order to locate sampling units as accurately as possible, static GPS methodology with differential correction was used.

Remotely sensed data processing

A Quickbird multispectral image (spatial resolution ca. 3 m; spectral resolution from 450 nm to 890 nm: four bands) acquired in June 2002 was radiometrically corrected by a dark object subtraction to reduce atmospheric effects (Chavez 1988, 1996). Such a relative correction involves subtracting a constant digital number (DN) value from the entire image. The theoretical assumption of dark object subtraction is that, due to atmospheric scattering, satellite sensors should record a non zero DN value for dark objects with 0% reflectance. Such a DN value is thus subtracted from each band. Absolute image correction is highly recommended for image mosaicing (Cihlar 2000) or change detection (Oetter et al. 2001; Du et al. 2002) but, as these were not relevant in this study, no other corrections were made. Although atmospheric effects modify actual reflectance values, the spectral differences in satellite images indicate differences in reflectance characteristics of the ground and vegetation cover (Tuomisto et al. 2003), therefore ensuring ecological variability will be detected.

To geometrically correct the image 20 ground control points and a high resolution (i.e. 10 m) digital terrain model were used.

As mentioned above, multispectral remote sensing data often have extensive interband correlation. Therefore, the 'intrinsic dimensionality' of the Quickbird multispectral image (i.e. blue, 450 - 520 nm; green, 520 - 600 nm; red, 630 - 690 nm and near infrared, 760 - 890 nm) was assessed using unstandardized principal component analysis (PCA). In remote sensing applications, PCA is used to find general trends across a scene allowing the extraction of the principal gradients contained within a dataset and discarding minor components with little explanatory value (see e.g. Ricotta et al. 1999). PCA undertakes a linear transformation of a set of numerical variables to create a new variable set with principal components reciprocally uncorrelated and ordered in terms of the amount of variance explained with respect to the original data. With unstandardized PCA, each principal component is a linear combination of the original variables, with coefficients equal to the eigenvectors of the variance/covariance matrix (see e.g. Jensen 1996 or Duda et al. 2001 for details). In our case, the first and second principal components accounted for 58.1% and 41.5% of the total variance respectively. By contrast, the third and fourth components together explained only 0.4% of the variance. Due to this intrinsic bidimensionality, only the first two principal components were retained for analysis.

Analysis

A measure of spectral heterogeneity was computed for each macroplot (1 ha). The mean Euclidean distance from the centroid within the bidimensional PCA scatter plot of the pixels contained in a 33 × 33 pixel window overlapping with each macroplot was calculated (Fig. 1). The rationale behind this measure is the following: each pixel of the image can be viewed as a point in a *n*-dimensional spectral space (where *n* is the number of spectral bands), the centroid of which represents the mass centre of the pixel cloud having as co-ordinates the mean of pixel values (Palmer et al. 2002). Within each sampling unit, higher distances from the centroid correspond to higher spectral heterogeneity (Rocchini et al. 2004).

The same measure of spectral heterogeneity was then computed using the original four-dimensional spectral system and each spectral band separately. This was done (1) to assess how data compression influences the relationship between spectral heterogeneity and species richness and (2) to evaluate the most adequate spectral interval to predict species richness. Linear regression analyses between the measures of spectral heterogeneity of the six spectral data sets and species richness observed in the sampling units were then performed.

Results

The adopted field sampling protocol covered just 0.16% of the nature reserve but captured ca. 50% of the flora listed for the same area by a traditional floristic survey (Angiolini et al. in press). We acknowledge that species richness at macroplot scale was underestimated, since it was measured as the pooled species list from the inner plots. Despite this, the method used for this study adequately captured the variability in species richness at the macroplot level, which ranged from 0 to 56 due to differences in habitat types (water bodies or cultivated lands to mixed areas with many different habitats).

Spectral heterogeneity, measured by using either the original four-dimensional spectral system or the reduced bidimensional PCA space, revealed a significant predictability power of species richness (Fig. 2a, b). In

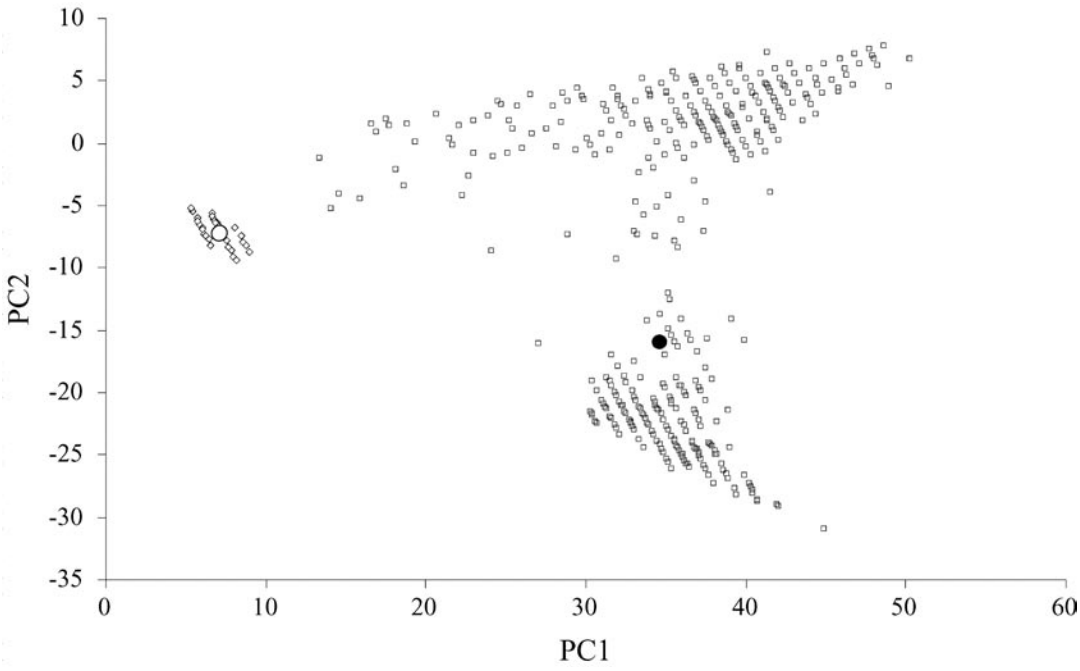

Fig. 1. Example of method for computing spectral heterogeneity for a macroplot. Pixel values within the PCA spectral space of two macroplots of different heterogeneity are shown. ◆ = pixels of an ecologically homogeneous macroplot which falls within the lake and shows a mean distance from centroid, ○ = 0.61; □ = pixels of a macroplot falling within an ecologically heterogeneous condition with marsh, hedgerows and cultivated fields, showing a mean distance from centroid, ● = 10.69.

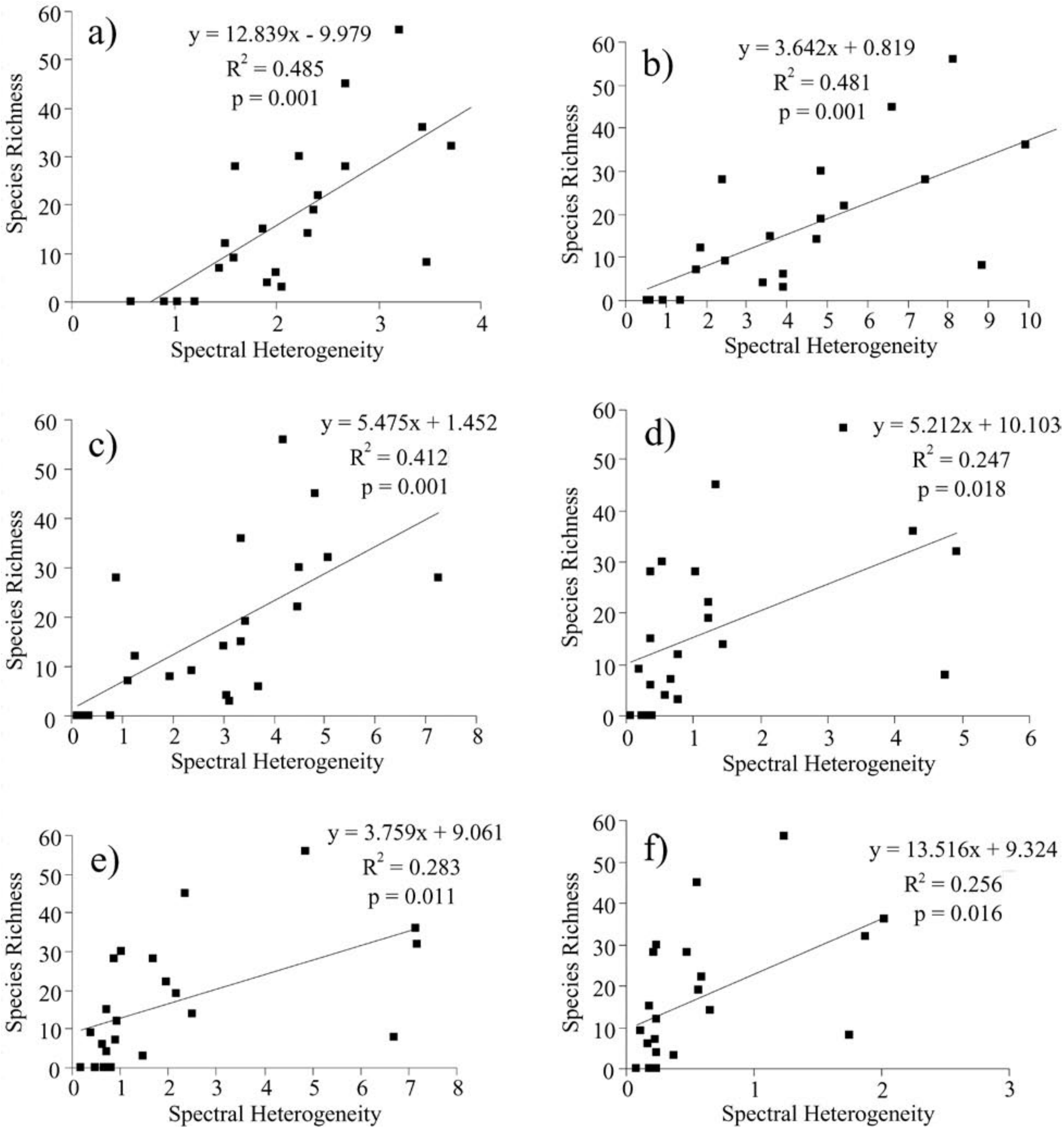

Fig. 2. Regression models between spectral heterogeneity and species richness, using: (**a**) the original four-dimensional spectral data set, (**b**) the first two principal components, (**c**) the near infrared spectral band, (**d**) the red spectral band, (**e**) the green spectral band and (**f**) the blue spectral band

both cases, the coefficient of determination R^2 is slightly higher than 0.48 ($p < 0.001$). With regression models using single spectral bands, the near infrared band explained 41% of variance in species richness ($p < 0.01$, Fig. 2c), while the three tested bands in the visible wavelengths showed a much lower prediction power (Fig. 2d, e, f).

The factor loadings (i.e. correlations) of each spectral band on the first two principal components (Table 1) showed that the near infrared band was highly positively correlated with the first principal component. By contrast, the three visible bands were all equally negatively correlated with the second principal component. This means that one of these three visible bands alone contributes significant information, but little information is added by including more than one of them.

Table 1. Factor loadings (i.e. correlations) of the four Quickbird spectral bands on the first two principal components.

	PC1	*PC2*
Blue (450 -520 nm)	0.42	–0.91
Green (520 - 600 nm)	0.46	–0.90
Red (630 - 690 nm)	0.38	–0.93
Near infrared (760 - 890 nm)	0.94	0.32

Discussion and Conclusions

The present study showed a 'near infrared way' to assess species richness directly from remotely sensed data. That is, the potential of the Quickbird satellite for estimating species richness is due to the near infrared band rather than to three highly redundant visible bands. This result is in good agreement with previous observations showing that near infrared wavelengths have a great potential for discrimination of plants species (e.g. Verbyla 1995; Nagendra 2001). On the other hand, it should be noted that the use of the information contained in the visible bands is useful, when summarized into a PCA, for improving the predictability of local species richness over the use of near infrared alone ($R^2 = 0.48$ vs. $R^2 = 0.41$). Moreover, 41% of the variance explained means that 59% (most) of the variance has not been explained. In fact, univariate models such as that proposed in this paper are obviously expected to reach only a part of the total variance of the system (see Orlóci 1978; Orlóci & Kenkel 1985; Legendre & Legendre 1998). Thus, the development of remotely sensed tools for estimating species richness data at fine spatial scales should aim to sustain, rather than replace, statistical based species inventory fieldwork (Palmer et al. 2002; Rocchini et al. 2005). These remotely sensed tools cannot replace the botanist's subjective (i.e. experience based) 'internal algorithm' for maximizing species listing in a survey. However, this and other studies show the promise of remotely sensed images for providing a spatial definition of biodiversity hotspots for floristic exploration, monitoring activities and management practices (Gillespie 2006).

From a statistical viewpoint, one might argue that, when using non-standardized PCA, the near infrared band will have a large impact, with respect to visible bands, on the relationship between spectral heterogeneity and species richness because the range of its digital numbers is much greater. However, from a biological viewpoint, it is well known that vegetation highly reflects in the near infrared part of the spectrum (Jensen 1996; Lillesand et al. 2004). The high reflectance in the near infrared is linked to scattering processes at the leaf scale, such that different types of vegetation show distinctive variability because of variations in leaf shape and size, water content, overall plant architecture and density of vegetation cover. Thus, the use of non-standardized data compression tools is based on a solid biological background for which the different spectral bands contribute to PCA according to their biological relevance. On the other hand, using standardized PCA (not shown here) we obtained analogous results, supporting the idea that the proposed 'near infrared way' for assessing plant species richness from remotely sensed data is not merely a statistical artefact.

The wetland environment surveyed in this paper represents a relatively simple ecosystem for testing the proposed method, since most of the vegetation was structurally simple and the remotely sensed image recorded almost all the vegetation on the ground.

On the other hand, in forest ecosystems the spatial heterogeneity perceived by the remote sensor is almost exclusively related to the canopy cover (Nagendra 2001). However, the structure of the tree canopies could reveal heterogeneity related to forest structure and diversity, thus providing useful results, especially in ecosystems with a very high degree of fragmentation.

Several authors have used well established parameters based on the infrared:red ratio, using the Normalized Difference Vegetation Index (NDVI) variance as a measure of spectral variability (Gould, 2000; Oindo & Skidmore 2002; Fairbanks & McGwire 2004). However, as recently stressed by Foody & Cutler (2006), the use of such approaches may not always be appropriate. For example, they found a very weak correlation ($r = 0.49$, R^2 equalling ca. 0.24) between species richness and NDVI in a Borneo tropical forest compared to the results of more sophisticated techniques such as neural networks ($r = 0.69$, $R^2 \approx 0.48$). Moreover, Rocchini et al. (2004) found a rather weak relationship between NDVI variance and species richness ($R^2 = 0.30$) with the present dataset. From a biological viewpoint, this may be due to the fact that plant biomass is not necessarily related to species richness (e.g. Weiher 2003). Also, in wetland areas such as the Montepulciano Lake Reserve, the weak correlation between NDVI variance and species richness may be partially caused by the presence of water, which severely affects the spectral response of the vegetation index. Moreover, from a statistical viewpoint, using NDVI would reduce the values' dynamic range by rescaling original data and will inevitably impact any measure of pixel value dispersion.

Remotely sensed data sources, such as Quickbird or Ikonos, with ca. 3 m and 4 m of spatial resolution respectively, permit the identification of transition zones and heterogeneous habitats, avoiding the problem of a lack of detectability of sub-pixel heterogeneity (e.g. mixed pixels, Small 2004; Schiewe 2005). Therefore, the use of multispectral sensors of fine spatial resolution shows promise for improving the detail of studies concerning environmental heterogeneity with respect to panchromatic data (finer spatial resolution, only one band available) and coarse resolution satellites (coarser spatial resolution, many bands available). This is particularly true by considering the recent overcoming of the scale gap, once perceived with coarse spatial resolution satellites, such as Landsat or Spot (Kerr & Ostrovsky 2003).

Optimal band selection necessarily depends on the individual spectral data set and the parameter being estimated (Lawrence & Ripple 1998). Thus, no single band selection method is superior over all problem domains, since different wavelengths are sensitive to different biophysical mechanisms (see even Duda et al. 2001). Optimal band selection for image processing is a crucial task that will assume growing importance with the increasing availability of hyperspectral data (Conese & Maselli 1993). For example, hyperspectral sensors allow the splitting of the near infrared spectrum into many narrowly spaced bands, enabling capture of those spectral interval(s) that better explain species richness variability. The only hyperspectral sensors currently available either use aircraft platforms, such as Mivis, or have low spatial resolution, such as Aster or Modis (Mehner et al. 2004). Nonetheless, we believe that, at least at local scales, hyperspectral sensors of high spatial and temporal resolution represent the potential of remote sensing tools for biodiversity research.

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