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Forest structural diversity characterization in Mediterranean pines of central Spain with QuickBird-2 imagery and canonical correlation analysis

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Abstract. Variation in forest structure provides information on vegetation complexity and provides insights on biodiversity. Characterizing forest structural diversity with remotely sensed data supports reporting, monitoring, and policy development. We explored the relationship between forest structural diversity in Mediterranean pines of the Spanish Central Range and variables derived from imagery captured with a commercial high spatial resolution satellite (QuickBird-2; with pixels sided 2.4 m multispectral and 0.68 m panchromatic). To combine multiple aspects of tree conditions at a stand level, "structural diversity" was characterized at the plot level ($N = 1022$) as a linear combination of the median of absolute differences of individual trees' bole diameter, height, and crown diameter measured on the field from the local median equivalents. Spectral reflectance variations in the visible and near-infrared, as well as image co-occurrence texture metrics from the panchromatic imagery at various window sizes were generated. All relationships to image-derived values were assessed against circular 0.3 ha areas corresponding with the field measured plots. Canonical correlation analysis aided in identification of combinations of reflectance and texture metrics most highly related with forest structural diversity ($R = 0.89$). Reflectance diversity was found to be more important than co-occurrence texture features in describing forest structural diversity when forest structure was limited ($R = 0.47$ vs. $R = 0.39$), whereas texture was more informative to the model when the forest structural diversity was high ($R = 0.88$ vs. $R = 0.63$), relating more complex forest conditions. Our results, although empirically defined by the local conditions and image acquisition characteristics, demonstrated the potential in high spatial resolution imagery for description of forest structural diversity in forests of the Mediterranean environment, especially important for Spain where a national high spatial resolution image data base has been collected.

Résumé. La variation de la structure forestière fournit de l'information sur la complexité de la végétation et apporte un éclairage quant à la biodiversité. La caractérisation de la diversité de la structure forestière à l'aide des données de télédétection est un outil utile pour la communication des données, le suivi et le développement de politiques. On a exploré la relation entre, d'une part, la diversité de la structure forestière dans les pins méditerranéens dans la cordillère centrale de l'Espagne et, d'autre part, les variables dérivées des images acquises par un satellite commercial à haute résolution spatiale (QuickBird-2 avec un espacement de pixels de 2,4 m en mode multispectral et de 0,68 m en mode panchromatique). Pour combiner les multiples aspects des conditions des arbres au niveau du peuplement, la "diversité structurale" a été caractérisée au niveau de la parcelle ($N = 1022$) comme étant une combinaison linéaire de la médiane des différences absolues du diamètre des troncs, de la hauteur et du diamètre de la couronne des arbres individuels mesurés sur le terrain à partir des équivalents de la médiane locale. On a ainsi généré des variations de la réflectance spectrale dans le visible et le proche infrarouge de même que des mesures de cooccurrence de la texture à partir des images panchromatiques pour diverses dimensions de fenêtre. Toutes les relations par rapport aux valeurs dérivées des images ont été évaluées en fonction de parcelles circulaires de 0,3 ha de superficie correspondant aux parcelles mesurées sur le terrain. Une analyse de corrélation canonique a permis d'identifier les combinaisons de mesures de réflectance et de texture les plus reliées à la diversité de la structure forestière ($R = 0{,}89$). On a pu observer que la diversité de la réflectance était plus importante que les caractéristiques de cooccurrence de la texture pour décrire la diversité structurale de la forêt lorsque la structure de la forêt était limitée ($R = 0{,}47$ vs. $R = 0{,}39$), alors que la texture procurait plus d'information pour le modèle lorsque la diversité structurale de la forêt était élevée ($R = 0{,}88$ vs. $R = 0{,}63$), montrant des conditions forestières plus complexes. Nos résultats, bien qu'empiriquement définis par les conditions locales et les caractéristiques d'acquisition

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d'image, démontrent le potentiel des images à haute résolution spatiale pour la description de la diversité structurale de la forêt dans les forêts en milieu méditerranéen, ce qui est particulièrement important dans le cas de l'Espagne où une base de données nationale d'images à haute résolution a été élaborée.
[Traduit par la Rédaction]

Introduction

Forest structural diversity is important for sustainable management (Río et al., 2003) and for conservation of biodiversity (Gil-Tena et al., 2010). Structurally complex forests are found to better contribute to recreational uses compared with plantations (Rydberg and Falck, 2000), and they provide a wider range of habitat conditions as well (Sullivan et al., 2001). The complexity in the arrangement of forest elements is also associated with the resilience to change, that is, the ability to adapt and respond to disturbances and perturbations (Rozdilsky and Stone, 2001; Elmqvist et al., 2003; García-López and Allué, 2011).

The structure of forest stands can be characterized by the size, age, and species distribution in vegetation layers, frequently focusing on the tree component (Poage and Tappeiner, 2005). Measures of forest structure often include vertically distributed features (e.g., dominant height, number, and distribution of strata) and horizontal features (e.g., crown size, gaps) (Spies and Franklin, 1991; Wulder et al., 2004), as well as species richness (Maltamo et al., 2005). The number and variation of relative abundance of different attributes across forest stands defines the forest complexity (McElhinny et al., 2005). When species richness is low, tree size variables such as height, diameter, and crown dimension may become the most important factors affecting structural diversity (Neumann and Starlinger, 2001) and a key aspect to assess stand biodiversity (Pommerineng, 2006).

A variety of indices have been developed to quantify tree size diversity (e.g., Shannon index, Gini coefficient, Simpson index) (McElhinny et al., 2005), requiring measurement of certain parameters on the ground for evaluation (Lexerod and Eid, 2006). Measures describing tree size diversity within stands are important to assess economical, ecological and social values of the forest (Lexerod and Eid, 2006). For an accurate description of stand structure a combination of various measures or resultant indices is often required (Rouvinen and Kuuluvainen, 2005). Furthermore, mapping and monitoring tree size diversity over large areas, and with a given temporal repetition for local and international reporting purposes, requires affordable methods from both economic and application perspectives. The synoptic view, extensive coverage, and the consistency and frequency of data acquisition, make remote sensing uniquely well suited as a source of information for the periodic assessment of forest structural diversity. Remote sensing provides data collected in a consistent and systematic fashion representing large areas at a known period in time (Wulder et al., 2004). The remotely sensed data can be integrated with ground data to extend and inform about local measures to represent wide areas in a consistent, practical, and repeatable manner. The goal of this research is to assess the potential of high spatial resolution imagery to characterize forest structural diversity in Mediterranean pines of the Spanish Central Range with the following objectives: (*i*) to determine and quantify the relationships between "forest structural diversity" measured at the plot level and data captured by a satellite-borne sensor in the form of visible and near-infrared (NIR) spectral reflectance as well as spatial combinations of panchromatic reflectance values, as related by texture metrics; (*ii*) to identify the relative relevance of reflectance measures versus texture metrics in characterizing the forest structural diversity; and (*iii*) to assess how the spectral diversity – structural diversity relationship varies under different conditions of forest density, i.e., determine if different relations occur in open versus closed forest conditions.

Background

Remote sensing has been widely used to characterize forest structure (St-Onge and Cavayas, 1995; Cho et al., 2009; Wolter et al., 2009) and forest structural complexity (Coops and Catling, 1997; Ozdemir et al., 2008; Pasher and King, 2010) with data acquired from a variety of sensor types representing a range of scales of information. Cohen et al. (1995) applied the Tasseled Cap Transformation components from medium spatial resolution Landsat imagery (30 m pixel size) to map four structurally different coniferous classes in Oregon, with an overall accuracy of 82%. White et al. (2010) characterized forest canopy structural diversity in coastal temperate forests of Canada with hyperspectral data from Hyperion EO-1 and canonical correlation analysis. They found that age and height diversity are the structural attributes most strongly related to spectral diversity and concluded that in addition to species, structural diversity should be considered for assessment of biodiversity in coastal environments. Miura and Jones (2010) demonstrated that LiDAR (Light Detection and Ranging) is particularly valuable for description of vertical structure. They developed a protocol for characterization of the structure of a dry Eucalypt forest landscape using different laser pulse return properties from a waveform LiDAR system. The classification scheme consisted of eight structural categories and allowed the quantification of gaps in different layers. Hyde et al. (2006) tested the synergy of various types of sensors for estimation of structural parameters at the stand and at the landscape level in a range of forests environments in California. They concluded that LiDAR with Landsat Enhanced Thematic Mapper Plus (ETM+) was the best combination of sensors producing the most accurate regression models between forest structural parameters and remotely sensed metrics. The synoptic view and the range of techniques available for analysis of data make remote sensing valuable for assisting the assessment of forest structure conditions (Cohen and Goward, 2004).

The availability of high spatial resolution imagery has enabled the development and application of image analysis techniques such as "crown isolation" (Gougeon and Leckie, 2006; Hirata, 2008), "shadow analysis" (Greenberg et al., 2005; Leboeuf et al., 2007), "texture analysis" (Franklin et al., 2001; Kayitakire et al., 2006) or "geostatistical" approaches (Song, 2007; Feng et al., 2010) that individually, or combined, facilitate the study of forest structure and structure complexity at local spatial scales. Panchromatic imagery, with finer spatial resolution (< 1 m pixel size) than multispectral (MS) imagery is well suited for accurate identification of individual tree characteristics (Colombo et al., 2003), enabling the analysis of spatial relations through image texture measures (Ouma et al., 2006; Song et al., 2010). Combining the spatial detail of panchromatic imagery and the unique spectral information conferred by MS imagery leverages complementary information (Lu et al., 2002) that can be employed separately or with a pan-sharpening approach (Ozdemir 2008; Pu et al., 2011). It has been frequently noted that as crown closure increases the capacity to characterize forest structural attributes decreases (Falkowski et al., 2009), with leaf area index (LAI) as an example where an asymptote in LAI is typically reached (e.g., LAI approx. 3–3.5, crown closure 60%). Based upon this understanding of the limitation of optical imagery and related analysis techniques, we posit that forest openness (e.g., open, semi-open, or closed) may indicate which technique is most appropriate for a particular site and that some techniques might be transferable between sensors and sites (Song et al., 2010).

In Mediterranean environments the study of forest structure and complexity has received heightened attention during recent years. Pascual et al. (2008) used LiDAR data and a two-stage object-based methodology to characterize the structure of *Pinus sylvestris* L. stands in forests of central Spain. Five structure types were defined based on height and density parameters. The median and standard deviation of height were the most valuable variables for definition of structure types. The approach applied was proposed for operational application in the inventory procedure and forest management plans. Vázquez de la Cueva (2008) explored the existence of relations between forest structural attributes at the plot level (e.g., height, density, basal area, and crown canopy closure) and spectral information derived from Landsat ETM+ (30 m pixel size) imagery combined with topographic data. The study considered three types of forest in central Spain and applied a multivariate canonical ordination method (redundancy analysis). There was a strong influence of vegetation type on the results but the low percentage of variance explained by the statistical analysis precluded derivation of practical empirical models. Merino de Miguel et al. (2010) explored the existence of relations between dasometric parameters and textural variables in *Pinus pinaster* Ait. stands in central Spain. The research applied geostatistical tools such as the variogram, calculated with orthophotography and IKONOS-2 imagery of original and degraded spatial resolution and found the strongest correlations when the variogram was calculated for spatial resolutions of 1 m and 2 m.

Lamonaca et al. (2008) explored forest structural complexity of a beech forest in Italy with a multilevel classification of QuickBird imagery. Applying field-based diversity indices of tree size, spacing, and species assemblage, they quantified structural heterogeneity amongst forest regions delineated by segmentation and evaluated the relationships between spatial heterogeneity in forest structure and segmented polygons. Their results supported the premise that a mixture of macro and micro structural heterogeneity is present within the beech forests investigated. Ozdemir et al. (2008) examined the potential of ASTER imagery (15 m pixel size) to estimate tree size diversity over forested landscapes in Turkey. With an object-oriented approach they related texture measures with diversity indices, finding the Gini coefficient more related with image parameters than the Shannon index. To the best of our knowledge there has not been any exploration of the capacity of high spatial resolution (< 5 m pixel size) imagery to characterize forest structural diversity in Mediterranean forests at the plot level.

Methods

Forest parameters measured in the field, analogous to those made in support of forest management inventories, were used to derive the structural diversity attributes. The spectral and spatial measures were generated from QuickBird-2 multispectral and panchromatic imagery. The relationship between the measures of forest structural diversity at the plot level and reflectance-texture diversity were then explored using Canonical Correlation Analysis (CCA) and the outputs were interpreted based on the correlations between the diversity measures and the canonical variates (**Figure 1**).

Study area

The study focused on two pine forests in the Central Range of Spain (**Figure 2**): Pinar de Valsaín (hereafter Valsaín) and Valle de Iruelas (hereafter Iruelas), with distinctive structural parameters derived from natural circumstances (e.g., species composition, site condition, disturbances) and human induced factors (e.g., silvicultural treatments and production use) (**Table 1**).

Valsaín is a 7627 ha forest of *Pinus sylvestris* L. on the north facing slopes of Sierra de Guadarrama (Segovia). It is a multifunctional forest, dedicated to timber production, recreational opportunities, and protection, with an established management plan since 1889. The silvicultural system

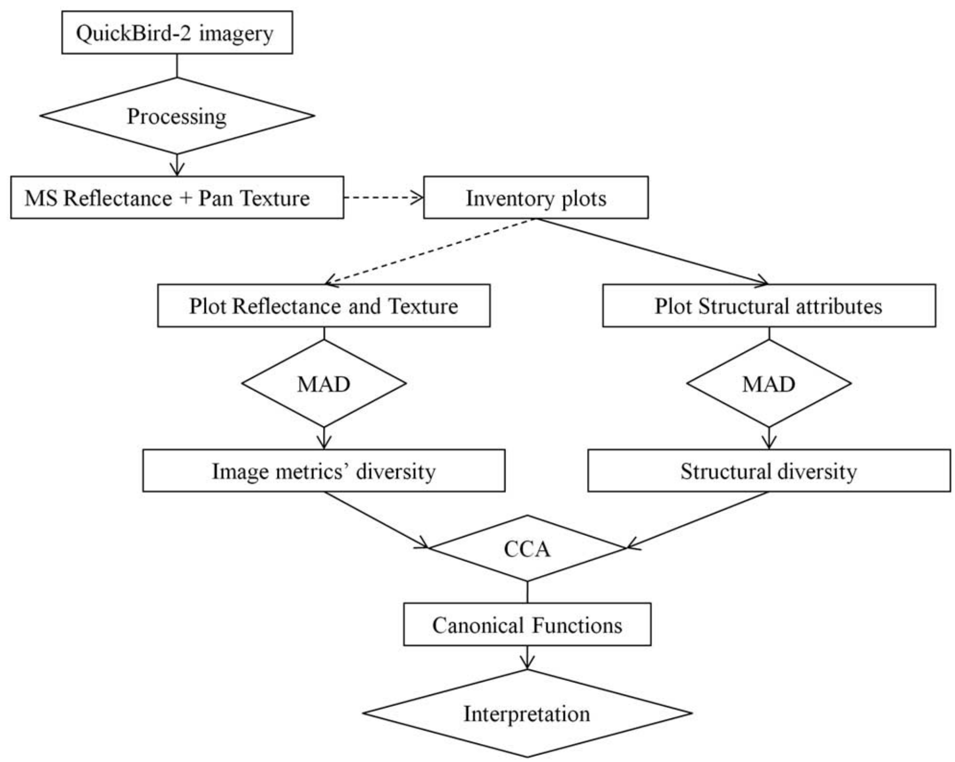

Figure 1. Schematic methodology followed in the study. The relationship between forest structural diversity evaluated with data collected on the ground at the plot level and remotely sensed data measures of diversity is evaluated with CCA.

applied evolved from an initial uniform shelterwood system in permanent blocks (rotation of 120 years and regeneration period of 20 years) to a selective cuttings system until 1988, when a flexible management system was established to allow for revisions to the established plan with reference to the overall production objectives. Management actions and recreational activities such as trail walking, which have gained importance in recent decades and occur mainly at lower elevations, have had an impact on the forest structure (Montes et al., 2004).

Iruelas is a 5483 ha forest of *P. pinaster* Ait., *P. sylvestris* L., and *P. nigra* Arn. in Sierra de Gredos (Ávila). It is also a multifunctional forest producing wood, resin, and pastures and providing recreation opportunities such as trail walking, camping, and bird watching. Although the first management plan was approved in 1886, historical circumstances prevented an implementation directly following specification. The production of resin during the twentieth century favoured old growth development; a rich history of fires has also conditioned the forest structure.

Forest structure diversity parameters

Forest structure is difficult to characterize using a single variable (Lefsky et al., 2005) and requires information relating both vertical and horizontal distribution of vegetation elements. Horizontal structure largely concerns the spatial distribution and density of trees (St-Onge and Cavayas, 1995) and is frequently described through the diameter at breast height (DBH) or some derived statistics; vertical structure refers to tree height distribution requiring some height related parameter for description (Tappeiner II et al., 2007).

Plot-based forest inventories are periodically conducted for management in both study sites. Following local management inventory practices circular plots of 11 m radius, on average, are established over a regular grid with GPS providing precise location, with attributes such as DBH, height, crown diameter, and number of trees being measured for all or a representative sample of trees in each plot. The distribution of structural parameters of individual trees follows an inverse J-shaped curve in Valsaín and Iruelas at a global level, as typically occurs in sustainably managed Mediterranean forests.

We derived "structure diversity attributes" from field measured mensurational data (**Table 1**); the Median Absolute Deviation (MAD) (Equation (1)) of the DBH (D_{MAD}), height (H_{MAD}) and crown diameter (C_{MAD}) was calculated at the plot level for a total of 1022 plots (461 in Valsaín and 561 in Iruelas). MAD variables were normalized with a Box–Cox algorithm (Box and Cox, 1982). The "MAD metrics" are always positive and their values are directly related with structural diversity, i.e., plots with higher values of D_{MAD}, H_{MAD}, and C_{MAD} are structurally more diverse

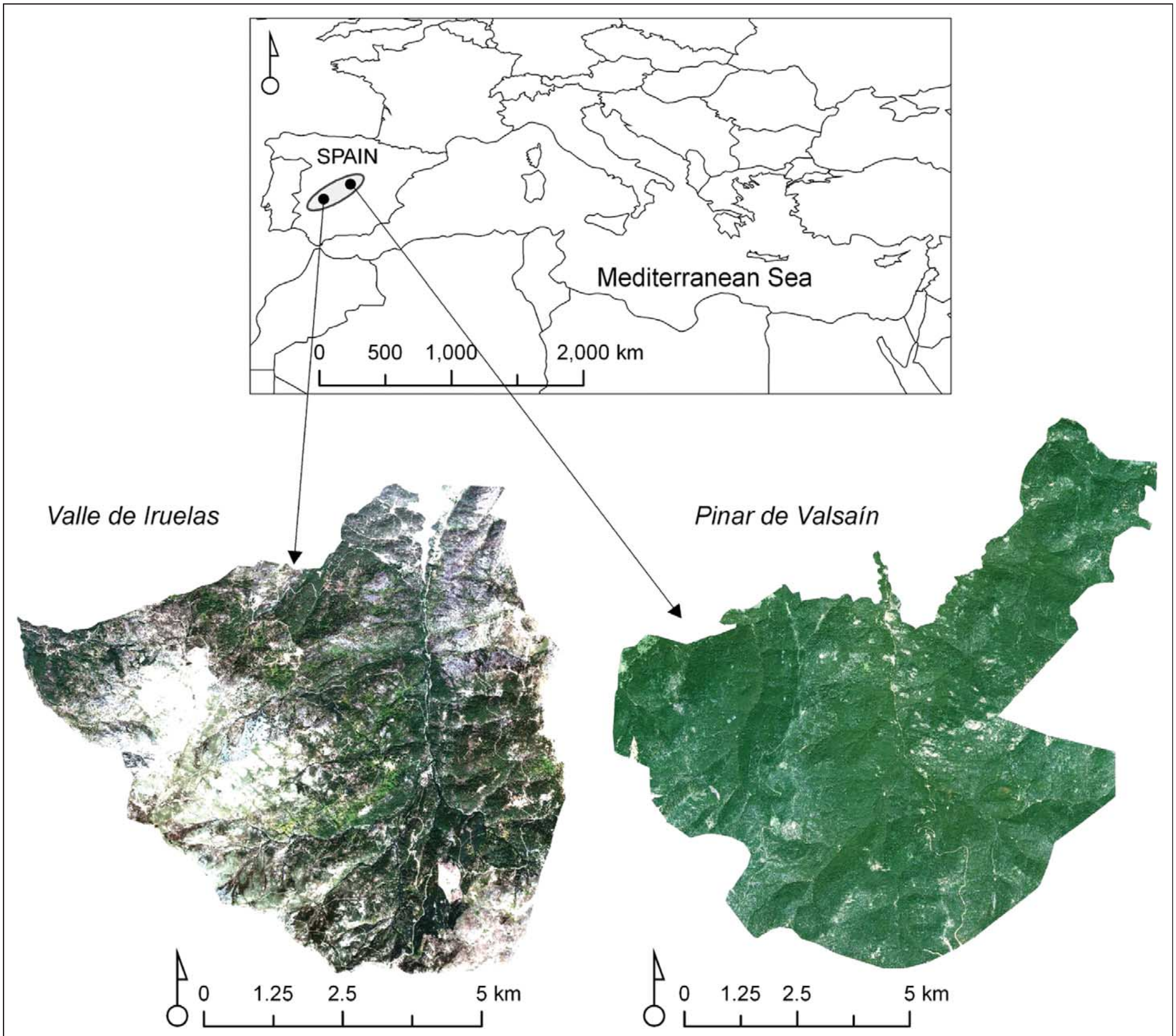

Figure 2. Location of study sites in the Central Range of Spain. Valle de Iruelas is located in Ávila province; Pinar de Valsaín in Segovia province.

Table 1. Descriptive parameters of forest structural attributes measured on the ground.

	Valsaín				Iruelas				Combined			
	DBH	H	C	N	DBH	H	C	N	DBH	H	C	N
Mean	23.30	15.20	4.46	445.78	30.5	13.81	4.61	451.32	30.58	15.97	4.63	448.92
Standard error	0.09	0.03	0.01	13.42	0.11	0.32	0.01	16.07	0.11	0.23	0.01	10.79
Median	25	13.7	4.26	398.67	26.2	13.3	4.17	324.67	26.25	14.7	4.18	365.44
Standard deviation	14.56	6.09	1.75	289.25	15.13	5.57	1.69	395.27	15.24	6.68	1.70	353.04
Sample variance	212.01	37.15	3.09	83667	229.19	31.13	2.87	156243	232.51	44.64	2.90	124641
Range	122	44.2	13.30	1893	204.6	30.5	18.98	2532	209.6	44.5	19.30	2532
Minimum	10	5.8	0.92	33.22	15.0	4.5	2.71	32.46	10	4.5	0.92	32.46
Maximum	132	50	14.23	1926	219.6	35	21.69	2564	219.6	50	21.69	2564.0

Note: DBH, diameter at breast height (1.30 m); H, height; C, crown diameter; N, number of trees per ha.

(and therefore more complex) than plots with lower values. A zero value is possible, while unlikely, if all trees measured in a plot have exactly the same dimension. As a density attribute, the number of trees per ha (N) would be expected to be significant in the characterization of forest structure diversity at the stand level, but at the scale of analysis (plot level) there is no internal variation of this variable. We included the number of trees per ha (N) as an absolute value (no plot MAD could be calculated) in the initial stages of analysis, but found no significance in the models.

$$\mathrm{MAD} = \mathrm{median}_i(\mathrm{abs}\ (X_i - \mathrm{median}_j(X_j))) \quad (1)$$

where X_i is the attribute (i.e., DBH, height, crown diameter) of the ith element in each plot and X_j is the attribute of the jth element of the complete sample.

High spatial resolution imagery

Imagery acquired by the QuickBird-2 satellite covering the study sites was used. QuickBird-2 collects data in various regions of the electromagnetic spectrum, with three bands in the visible and one in the NIR (with 2.4 m $\times$ 2.4 m pixels); an additional panchromatic band provides data with finer spatial resolution (with 0.68 m $\times$ 0.68 m pixels; **Table 2**). QuickBird-2, launched 18 October 2001, is a commercial satellite and is unique among other satellites in this class as it has the largest image footprint and most on-board storage capacity.

Processing of imagery involved: atmospheric correction of the multispectral images with the COST model (Chavez, 1996) using water bodies as dark objects and the atmosphere-scattered path radiance L_λ^p estimated with a relative spectral scattering DOS model (λ^{-4}) under very clear atmospheric conditions (Chavez, 1988). Separate orthorectification of the multispectral (MS) and panchromatic (Pan) bands with a digital elevation model derived from a contour vector map 1:10 000 (www.sitcyl.jcyl.es) (Root Mean Square Error of 0.69–0.72 m for the MS bands and 0.66–0.81 m for the Pan bands); and registration to aerial photography of 0.25 m pixel size (www.sitcyl.jcyl.es), with the full suite of characteristics in **Table 2**.

Table 2. Characteristics of the satellite imagery used in the study.

QuickBird-2 imagery		
Spatial resolution	Multispectral	2.4 m
	Panchromatic	0.68 m
Bands	Blue	0.45–0.52 μm
	Green	0.52–0.60 μm
	Red	0.63–0.69 μm
	NIR	0.76–0.90 μm
	Pan	0.45–0.90 μm
	Valsaín	**Iruelas**
Date	19 May 2004	05 August 2005
Sun elevation (°)	58.4	72.0

Image metrics: reflectance and texture diversity

Image texture is a valuable criterion for visual interpretation, contains information about spatial and structural arrangement of objects (Tso and Mather, 2001), and provides context that may improve estimates of forest structural parameters (Wulder et al., 1998). Image texture is a means to interpret the spatial relationships between digital numbers (Haralick et al., 1973) and to understand how the variability in these values can inform on what is being portrayed by the imagery. Single pixel measures often inform on a portion of an object, with additional content offered when considering neighbouring pixels. Texture measures provide information regarding the simplicity or complexity of neighbourhoods of pixels. For characterization of forest structure, high resolution imagery texture provides spatial information about density, distribution, and spatial arrangement of trees (Ouma et al., 2006) and is also related to the three-dimensional organization of tree crowns (St-Onge and Cavayas, 1995; Bruniquel-Pinel and Gastellu-Etchegorry, 1998). Greater variance in digital numbers often implies a more complex forest environment, whereas simple forest structure is associated with less image variance (Cohen et al., 1990). In short, a relationship exists between image spatial structure and the forest structure in the scene (Wulder et al., 1998). One approach for characterizing the spatial inter-relationships between image digital numbers is the grey-level co-occurrence matrix (GLCM) and associated indices that can be used to describe the matrix (Haralick and Bryant, 1976). The GLCM is a tabulation of how often different combinations of pixel grey levels occur in an image (Hall-Beyer, 2007) at a specific distance and orientation. For evaluation of image texture we applied the approach of Haralick (Haralick and Bryant, 1976), a method using statistical measures based on the GLCM values (Caridade et al., 2008) that is also known as a second order approach.

Exploratory research over a range of measurement contexts (i.e., plot, stand) indicated that second order texture metrics "homogeneity", "contrast", and "entropy" appeared as most appropriate of the GLCM texture metrics for distinguishing forest stands of varying structure (differing height, age, number of trees per hectare, and DBH) for the Mediterranean pine forests present. Homogeneity and contrast are measures of the amount of local variation in the image (Haralick et al., 1973) and are by definition highly correlated (Equations (2–3)). Entropy is a measure of orderliness (Hall-Beyer, 2007) (Equation (4)) or lack of image structure.

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (2)$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \quad (3)$$

$$\text{Entropy} = \sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j}) \quad (4)$$

where $P_{i,j}$ is the (i, j)th entry of the normalized GLCM matrix, N is the number of rows and columns in the image.

Texture metrics evaluated at three different window sizes were calculated over the panchromatic channel of the QuickBird-2 imagery. For evaluation of texture metrics we aimed to apply window sizes corresponding to the mean dimension of the scene objects (Kayitakire et al., 2006), that is, a distance equivalent to individual crown diameters or groups of trees' canopy size, in each of the sites (**Table 3**). For this purpose we followed the semivariogram approach (Johansen et al., 2007; Nijland et al., 2009) whereby the "range" value of the semivariogram identifies the size of the scene objects and therefore determines the window size to use (Franklin et al., 1996). As expected, the uneven structure in Iruelas indicated a need for larger and different window sizes than in Valsaín, where the species and silvicultural system applied have made the forest stands more homogeneous (**Figure 3**). These findings are included at this stage of the communication as the window sizes produced are used to guide subsequent analyses.

Table 3. Texture metrics evaluated in the study sites.

Window	Metric	Valsaín	Iruelas
Small	Homogeneity Contrast Entropy	7 × 7	7 × 7
Medium	Homogeneity Contrast Entropy	9 × 9	13 × 13
Large	Homogeneity Contrast Entropy	13 × 13	23 × 23

To quantify the variation of the image metrics at the plot level we used the MAD which, unlike the standard deviation, is resistant to outliers (Chung et al., 2008); half the values are closer to the median than the MAD and half are further away. For each reflectance band (three in the visible and one in the NIR) the MAD of pixel values was calculated for each 0.3 ha circular area (approx. 616 pixels) and the absolute difference with each equivalent global MAD (calculated using all plots at each site) was evaluated. A similar process was followed with co-occurrence texture metrics over the panchromatic image (approx. 6640 pixels per 0.3 ha circular area).

Canonical correlation analysis

While complex, quantifying structural diversity may be approached through the application of multivariate statistical analysis (McElhinny et al., 2005). The statistical analysis

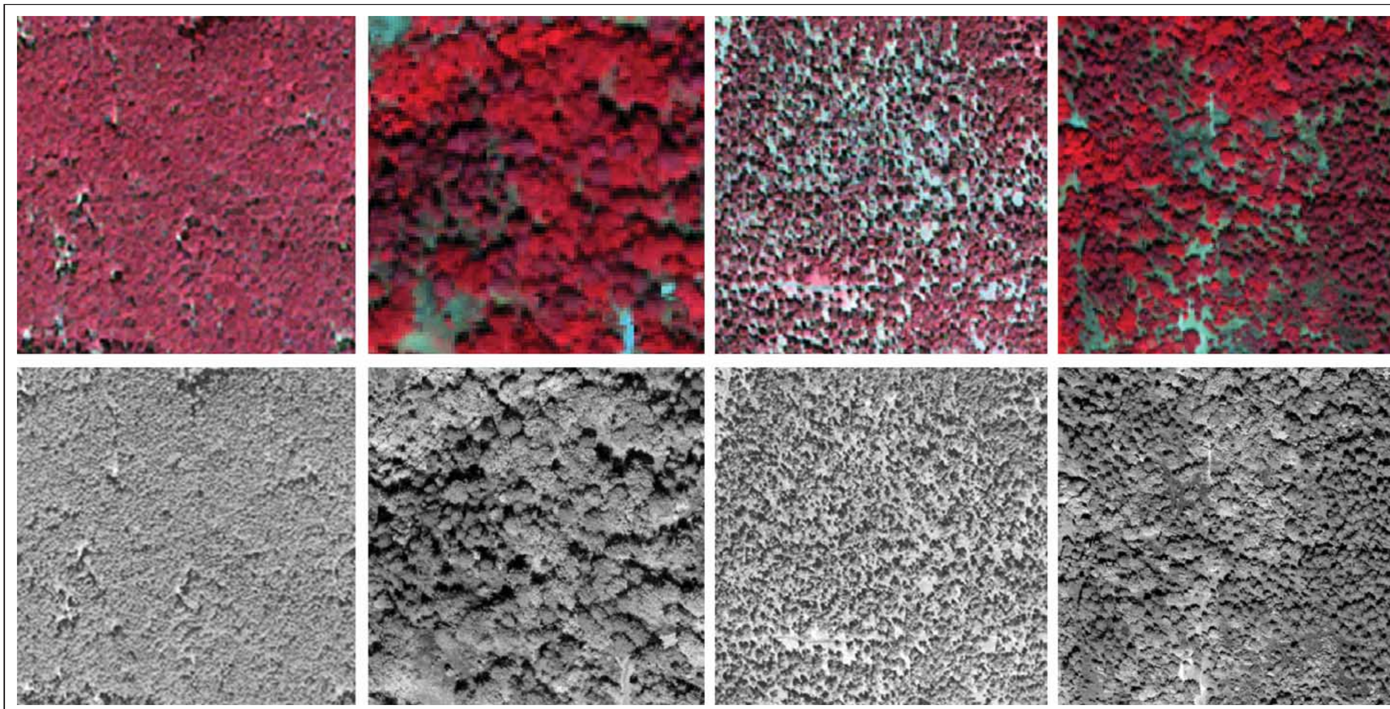

Figure 3. Examples of areas with different forest structure and visual texture (top line: multispectral visualization (Red: NIR, Green: red, Blue: green); bottom line: panchromatic visualization).

required in this study will demonstrate if there is a relation, and how strong it is, between the forest structural diversity measured at the plot level as captured by the inventory attributes and the spectral diversity measured by the reflectance of the MS satellite-borne high spatial resolution sensor and texture co-occurrence metrics evaluated with various window sizes. We chose the CCA statistical approach as it facilitates the study of interrelationships among sets of multiple dependent and independent variables (Hair et al., 2010). CCA places few restrictions on the data: normality, that was tested with the Jarque-Bera test, and absence of outliers that was checked through the Grubbs test (Grubbs, 1950). The ratio of sample size to number of variables was in our case well over the recommended value of ten. In **Table 4** we summarize the variables included in the statistical analysis.

CCA enables generation of two outcomes of interest: the "canonical variates" representing the optimal linear combinations of dependent and independent variables and the "canonical correlation" representing the strength of the relationship between them. All variables are linearly combined by group (dependent and independent) into "variates"; the dependence role is interchangeable and used to facilitate interpretation.

A number of orthogonal (independent) "canonical functions" are derived, maximizing the correlation between linear composites. Each variable partial correlation with the respective canonical function is represented by its coefficient or "canonical weight", which enables understanding of the function composition. However, frequent instability of these coefficients advice the alternative use of "canonical loadings" after a process of variables standardization (Hair et al., 2010). Therefore, canonical loadings measure the simple linear correlation between an original observed variable in the dependent or independent set and the set's canonical variate, intended to indicate the variance that the variable shares with its canonical variate. Variables that are highly correlated with a canonical variate have more in common with the variate and should therefore be given more importance in the variate's interpretation. Additionally, a measure of "redundancy" may be calculated that informs on the amount of variance in a set of input variables (dependent or independent) that is explained by the other canonical variate. To determine which of the canonical functions to interpret, a combined criterion based on the statistical significance, the practical significance of the canonical correlation and the redundancy measures for each variate should be applied (Hair et al., 2010). "Canonical cross-loadings" measure the simple linear correlation between the original observed variables and the opposite set's canonical variate, i.e., they represent the relation between one variable and the linear combination of variables on the other side. These coefficients are useful to determine which independent variables are explicative of the dependent set combination and, in our case, which spectral or textural metrics would better explain the forest structural diversity.

Results

The CCA yielded two results of interest: the canonical variates, which represented the optimal linear combinations of dependent (forest structural diversity) and independent (image reflectance–texture diversity) variables and the canonical correlation, representing the relationship between variates. We describe and interpret some outcomes of the analysis which were relevant to our study objectives.

Canonical correlations and relative importance of reflectance and texture metrics

The number of canonical functions CCA yields is limited by the lower number of variables in either the dependent or

Table 4. Dependent and independent variables used as input into the canonical correlation analysis.

Dependent variables	Independent variables
	Reflectance
	MAD of:
	Blue
	Green
	Red
	Near infrared
	Texture
MAD (Median Absolute Deviation) of:	MAD of:
Diameter (D_{MAD})	Homogeneity small window
Height (H_{MAD})	Homogeneity medium window
Crown diameter (C_{MAD})	Homogeneity large window
	Contrast small window
	Contrast medium window
	Contrast large window
	Entropy small window
	Entropy medium window
	Entropy large window

independent variate (Hair et al., 2010); in our case the maximum number of functions was three, as this was the number of original dependent variables considered (D_{MAD}, H_{MAD}, C_{MAD}). Our interest focused on determining if there is a relation and how strong it is between variates. Therefore, only the strongest relation in each case scenario was retained for further analysis and discussion, even if more than one function was statistically significant (**Table 5**). The statistical significance was tested with the χ^2 test.

In both Valsaín and Iruelas there was a moderate relation between the dependent (forest structural diversity) and the independent (reflectance–texture diversity) variates, with similar values of correlation in both cases (0.50 in Valsaín and 0.51 in Iruelas). To test the strength of the relationship between forest structural diversity and the reflectance and texture variables' groups individually, we ran the analysis independently with either set treated as independent. This analysis showed that when including all variables in the independent group there was a stronger relation than including just one type of image variables (reflectance or texture), which demonstrated the information associated with spectral and textural signatures is complementary (Lu et al., 2002; Colombo et al., 2003; Ouma et al., 2006). Although they exhibited a relatively weak relationship, the reflectance variables alone were more related in both sites with structural diversity than the texture variables alone (**Table 5**).

In a combined scenario, considering all plots from Valsaín and Iruelas together, with "expectation" median values evaluated together, we found a strong relation between variates, with an *R* of 0.89 (**Table 5**). This scenario illustrates a more heterogeneous forest where the range of forest parameters is considerably higher than either the individual sites (**Table 1**). In this case, texture diversity measures were more able to explain forest structural diversity (*R* of 0.88 vs. *R* of 0.63). Possibly the limited explanatory power of texture variables in the individual sites was in part due to the limited range of ground variables and consequent limited variation in image texture outcomes.

Table 5. Canonical correlations of the first canonical function in different scenarios (all statistically significant).

Site	Independent group	*R* (canonical correlation)
Valsaín	Diversity (reflectance and texture)	0.505
	Diversity reflectance	0.474
	Diversity texture	0.389
Iruelas	Diversity (reflectance and texture)	0.512
	Diversity reflectance	0.460
	Diversity texture	0.360
Combined	Diversity (reflectance and texture)	0.890
	Diversity reflectance	0.634
	Diversity texture	0.882

Most significant variables

Canonical cross loadings were interpreted to assess how the individual independent variables (measures of reflectance and texture diversity) related linearly with the forest structural diversity or dependent variate. This procedure enabled identification of those image metrics most contributing in the characterization of structural diversity for the combined case scenario (Valsaín and Iruelas plots analyzed together).

Contrast and homogeneity evaluated at different window sizes were the variables most strongly correlated with forest structural diversity (**Figure 4**). This result supported the intuitive notion that visual changes in the image are related with variability of tree sizes on the ground, as this variability produced internal shadowing effects within the stand. As contrast and homogeneity are by definition strongly correlated metrics, similar cross-loading values were expected, and the opposite sign that occurred at medium window sizes remains unexplained. Variations in the reflectance bands were positively correlated with structural diversity, with the three visible bands found more strongly correlated than the NIR band. The character of entropy is variable and not completely clear, being negatively correlated with structural diversity when measured at the small window size (that is, 7 pixels $\times$ 7 pixels, or 4.2 m $\times$ 4.2 m) and weakly correlated when measured at the other window sizes. It should be noted that at the smaller window sizes, single tree crowns may be represented, resulting in texture measures with a high local variance (with noncrown conditions represented in neighboring locations). These findings support the use of larger windows relating stand conditions, rather than individual trees (objects). Varying behaviour of GLCM metrics at different window sizes was previously reported (Moskal, 1999) and detailed examination would be required for complete understanding in local circumstances.

The linear correlation between the original variables (D_{MAD}, C_{MAD}, H_{MAD}) and the forest structure diversity variate is measured by the canonical loadings. These coefficients showed diameter variability (D_{MAD}) was the most relevant parameter (loading 0.63) in building the forest structure diversity variate, followed by crown diameter variability (C_{MAD}, loading 0.15), and leaving height variability (H_{MAD} loading 0.10) in third position. The importance of diameter variability for characterization of forest structural complexity was an expected result, as diameter is a common variable used for description of forest structure and its variation is frequently used for computation of diversity indices such as Simpson or Shannon (McElhinny et al., 2005).

Validation of the CCA in the combined case scenario

To ensure that the results of the CCA were not specific to the sample data, the method was validated over a subsample of 500 plots, proportionally and randomly selected from

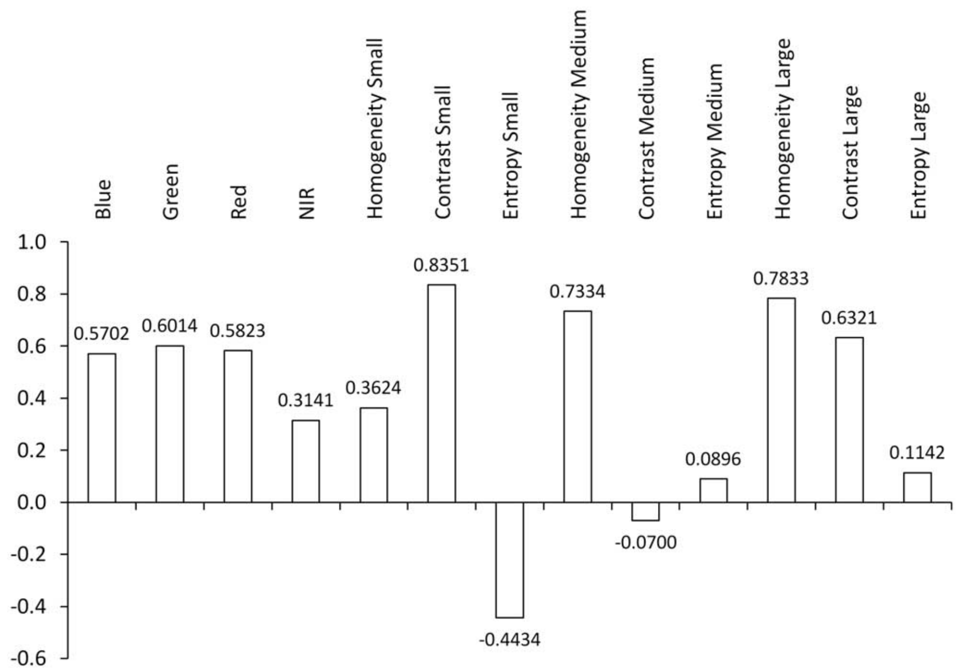

Figure 4. Cross loadings in the combined scenario. Homogeneity and contrast at various window sizes were the variables with highest explicative capacity; visible reflectance was more relevant to the model than NIR data.

both sites (226 plots from Valsaín and 274 plots from Iruelas). The validity of the CCA was assessed by conducting a sensitivity analysis in which the stability of the redundancy index and the overall canonical correlations was assessed applying the same procedure after removing individual independent variables from the analysis (Hair et al., 2010) (**Figure 5**). The similarity of the values of the redundancy index and canonical correlation for all tested situations indicated the stability of the CCA results; cross-loadings were also found to be relatively stable.

Optical sensors have limited capacity to identify canopy height and differences (Hudak et al., 2002), often relying on the existence of image shadows or the calculation of gap fraction to partially accomplish this task (see Mora et al. (2010) for a summary of height estimation from optical imagery). To test the relevance of H_{MAD} in the model, it was removed from the analysis and results were checked: the canonical correlation decreased markedly and the redundancy index was lower than all other situations, demonstrating the significance of H_{MAD} contribution to the structural dependent variate in this model. As expected more notable reductions in redundancy index were found when D_{MAD} or C_{MAD} were removed from the analysis.

Discussion and conclusion

Forest structural diversity defined in terms of field inventory measures at the plot level has been related to values of reflectance and texture diversity as captured by a fine spatial resolution satellite-borne optical sensor in Mediterranean pine forests of the Central Range in Spain. Results showed a strong relationship between both sets of diversity features (field derived and image derived) when considered at the plot level and with an appropriate range of variation, indicating the potential of remote sensing and image processing as an approach for characterization of forest structural diversity over wide areas.

Quantifying structural diversity on the ground is difficult and costly, and its importance for biodiversity and production (Lexerod and Leid, 2006) makes exploring remote sensing as an optional means for this purpose. Remote sensing is not seen to fully supplant the need for field measures, but to spatially and temporally augment such measures. The data acquisition regularity offered by satellites and the consistency over space and time enables repetitive estimations and monitoring. In this study we included field measured variables (DBH, height, and crown diameter) in structure diversity characterization for ease of measurement (McElhinny et al., 2005) and, as identified by Río et al. (2003), among the most important aspects of forest structure. Furthermore, the scale of analysis is also an important factor when measuring or characterizing diversity (Lähde et al., 1999). The availability of field data determined the scale of our analysis, enabled by accessibility to high spatial resolution imagery. The detailed plot-level measures available made for a logical informational link between the field and image-based data sources with both of a comparable scale. We worked with circular spatial units of 0.3 ha, analogous to the inventory plots established and measured on the ground. At this scale of analysis (alpha diversity) the

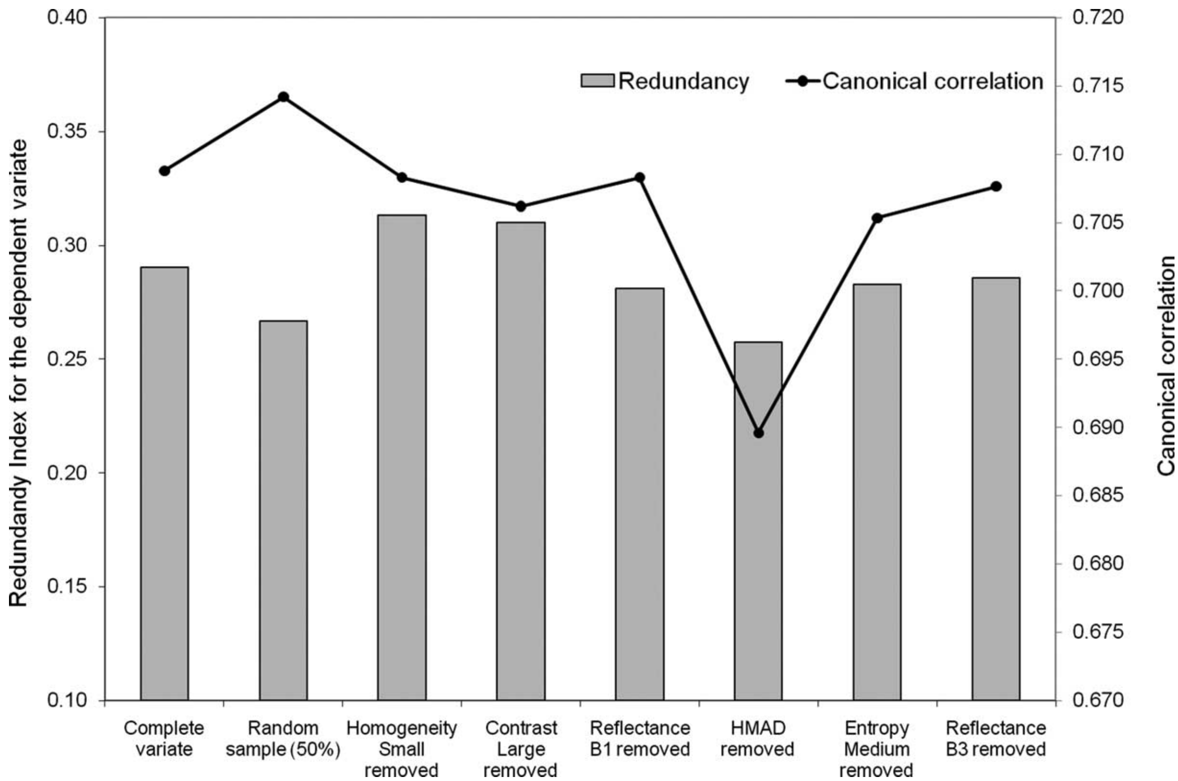

Figure 5. Sensitivity analysis of CCA results. The stability of the results is indicated by minor changes in the redundancy index and canonical correlations when individual variables were removed from the dependent variate.

study showed there is potential for characterization of structural diversity from the space. Lamonaca et al. (2008) reached similar conclusions in a study that applied an object oriented approach for characterization of the structure diversity in Mediterranean environments at the stand level. Pasher and King (2010) modelled and mapped forest structural diversity in temperate hardwood forests of Quebec (Canada) with airborne derived data, highlighting the convenience of satellite derived data for mapping of larger areas.

Interestingly, among our findings was the consideration of the scenarios with various crown closure conditions pooled together, that is, the data from open and dense forest sites analyzed jointly. In this case the relation between the variability in image-derived variables and forest structural diversity was stronger (higher canonical correlation) than considering either individual scenario alone. Previous works with remotely sensed data in the study area (Merino et al., 2010; Vázquez de la Cueva, 2008) found significant relations between image and field variables but poor explanatory power of statistical models. Further work is recommended to determine if the limited success relating structural measures with optical sensors' data is due to the limited local variation in structural parameters.

Diameter and basal area are the attributes most frequently used in studies of structural diversity (Solomon and Gove, 1999; Varga et al., 2005; Motz et al., 2010) and forest structure per se (Goodburn and Lorimer, 1998; Rouvinen and Kuuluvainen, 2005; Rubin et al., 2006). We found these to be the attributes indicating variation in forest structure at the plot level that had the highest relevance in the canonical variates in all scenarios. Height showed slight importance in the canonical relations between field-measured and image-detected diversity but was still relevant to the model, as shown in the sensitivity analysis. Height variation is difficult to detect with optical sensors (Mora et al., 2010), which are better suited for mapping horizontal structure (Hyde et al., 2006). Although shadows and gap fraction are sometimes useful (Shettigara and Sumerling, 1998; Leboeuf et al., 2007), the images we used, captured with high elevation angles (>60 degrees), did not include significant shadows. Including LiDAR measured heights in the modelling process may improve the study results, as fusion of high spatial resolution and LiDAR data is an approach yielding good results (St-Onge et al., 2008; Ke et al., 2010; Chen and Hay, 2011).

In scenarios of relatively low structural diversity, when we considered each of the study sites individually, the variation in reflectance of the visible and NIR was more explicative of the structural diversity than variations in other texture measures evaluated with finer spatial resolution panchromatic data. Similarly, Rocchini et al. (2010) highlighted the relevance of spectral resolution versus spatial resolution for evaluation of species diversity, supported by a series of studies in different environments that buttress this idea.

The information associated with spectral and textural signatures is complementary (Lu et al., 2002) in estimation of forest parameters (Lu and Batistella, 2005). Wulder et al. (1998) observed an improvement of correlation between LAI and image variables including texture in northern deciduous and mixed wood forest in Canada using aerial imagery. Chubey et al. (2006) studied structural parameters of forests in Alberta, Canada, with Ikonos-2 imagery, obtaining successful results when including reflectance and texture variables. Other studies used textural parameters only (Franklin et al., 2001; Couteron et al., 2005; Kayitakire et al., 2006) for estimation of forest structure, which was shown to be particularly useful in complex structures such as tropical forests (Lu and Batistella, 2005). Image texture is influenced by several biophysical parameters including crown diameter, distance between trees, tree positioning, LAI, and tree height. The importance of the window size for evaluation of texture measures has been stressed (Ferro and Warner, 2002; Kayitakire et al., 2006) and the variogram approach is recommended as an appropriate method to guide window size selection (Franklin et al., 1996). We found a common variogram range value in both study sites (open and closed canopy conditions) which is coincident with the median value of crown diameter. The absence of shadows in the imagery allowed the identification of individual trees as dominant textural objects on the ground (Kayitakire et al., 2006). The limited use of texture parameters, previously indicated as due to a lack of software tools (Bruniquel-Pinel and Gastellu-Etchegorry, 1998), is progressively being overcome, but other considerations remain, such as viewing and illumination configurations, spectral domain, and spatial resolution. However, image texture analysis has demonstrated utility for characterizing habitat structure (St-Louis et al., 2006) and identifying areas of high diversity with conservation priority.

Mediterranean forests are notorious for their complex topography (Salvador and Pons, 1998) which often results in high spatial heterogeneity (Neumann and Starlinger, 2001). If field information is contrasted with image data, the accurate spatial location of field plots and a high quality geometric processing (e.g., low RMSE) of the remotely sensed data are particularly important to develop strong empirical models. As demonstrated in this study, high spatial resolution imagery from optical sensors integrated with field measures of forest structure provided a useful approach to investigate and characterize forest structural diversity in Mediterranean pine forests, particularly in Spain where a national high spatial resolution image data base has been initiated, with an annual revisit proposed. Details on the nature of the database and access criteria through Spanish Plan Nacional de Teledetección remain to be determined and communicated.

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