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How are landscape complexity and vegetation structure related across an agricultural frontier in the subtropical Chaco, NW Argentina?

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A B S T R A C T

Human-driven alteration of the Chaco strongly affects ecological patterns and associated processes at all spatial scales. To understand these modifications, sufficient methods for describing and quantifying high levels of landscape complexity caused by human activities in the region are urgently needed. Most methods involve the use of passive remote sensors, which capture complexity in only two dimensions (2D). A common 2D approach has been to calculate landscape metrics, such as Shannon's Landscape Diversity Index. But, it is not clear what aspects of three dimensional (3D) vegetation structure are being captured by these metrics. 3D structure is known to be as important as or more important than 2D structure in determining landscape patterns of biodiversity of many groups of organisms. In addition, studies have used a limited number of coarsely defined land-cover classes to calculate metrics. Our question was: how is vegetation structure related to remote sensing attributes in an agricultural frontier in the subtropical dry Chaco, NW Argentina? A secondary question was to explore the relationships between traditional landscape metrics and the semivariogram, a geostatistical tool used to describe 2D complexity. We described landscape complexity from the panchromatic QuickBird band and measured vegetation structure in 22-1 ha plots across an agricultural frontier in the subtropical dry Chaco, northern Argentina. A total of 2683 individual trees in 51 plant species and 21 families were measured in the field and 25,665 points were recorded to estimate foliage height diversity. Four landscape complexity groups were identified by a two-way cluster analysis using the 2D metrics. Four vegetation variables differed significantly among the 2D complexity groups: the standard deviation of the Enhanced Vegetation Index, the coefficient of variation of density per transect (CV density), mean tree diameter (DBH), and foliage height diversity (FHD). Largest patch index and semivariogram range were negatively related to CV density, mean DBH and FHD, while semivariogram sill, mean shape index, landscape shape index and number of patches were positively related to all three vegetation variables. Landscape metrics were not related to tree species diversity or density as previously shown, probably as a result of structural similarity among the dominant tree species in the Chaco biome.

1. Introduction

Human-driven changes of landscapes are affecting biodiversity patterns and associated ecological processes at all spatial scales (MacDougall et al., 2013). Landscape complexity, broadly defined as the number, arrangement, and scaling relationships of key elements of ecosystem structure (Gustafson, 1998; Lovett et al., 2006), mediates changes in biodiversity patterns and associated processes. The mechanisms of this mediation are variable and include species' movement (Huffaker, 1958), changes in productivity and biomass (Daufresne and Loreau, 2001), and changes in food web structure (Bellisario et al., 2012). To understand the consequences of human-driven changes, methods for describing and quantifying landscape complexity are urgently needed.

Different methods to quantify changes in landscape complexity have been developed in the last decades (Lovett et al., 2006; Wu, 2013). Most of these methods involve the use of passive remote sensors which capture complexity in two dimensions (2D) (Hyde et al., 2006) and the calculation of landscape metrics to quantify 2D complexity, such as Shannon's Landscape Diversity Index (SDI)

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(Gustafson, 1998). These metrics reveal how landscape complexity affects processes occurring at species-, food web-, and ecosystem-scales (Kupfer, 2012), though most studies involving their calculation were interested in examining their behavior through time (Uuemaa et al., 2009) or were limited to a few coarsely defined land-cover classes such as forests. Alternatively, complexity can be described in three dimensions (3D). LIDAR (LIght Detection And Ranging) technology has been used successfully to capture vegetation 3D complexity (Lefsky et al., 2002) but the high costs of this technology still limit its application in most parts of the world (Selkowitz et al., 2012). In the absence of LIDAR and given that anthropogenic and natural disturbances affect habitats sometimes in a subtle manner we need to combine remote sensing and field data in order to identify what aspects of complexity are being modified by human activities (Pisek and Oliphant, 2013). But there are not enough field studies to confidently calibrate the information yielded by most remote sensors (Hall et al., 2011). In addition, studies quantifying 2D landscape complexity do not clearly link pattern to processes (Li and Wu, 2004; Cushman et al., 2008); thus we are not able to clearly interpret metrics. One way of interpreting the link between patterns and processes is examining what aspect of the 3D vegetation is being captured by landscape metrics.

Linking field data of vegetation structure to landscape complexity as determined from satellite images has shown to be complex (Malhi and Román-Cuesta, 2008) likely because vegetation structure depends on many factors such as plant species identities, species distributions, species life history traits, and disturbance history, among others (Whitmore, 1978). The degree to which each factor can be represented in 2D dimensions will determine how well vegetation structure is represented in satellite images (Broadbent et al., 2008). For example, studies have generally focused on plant species richness and they showed variable and sometimes contradictory relationships with landscape metrics. Kumar et al. (2006) showed that plant species richness was positively related to Simpson's landscape diversity, edge density and interspersion and negatively related to mean patch size; Moser et al. (2002) showed that it was positively related to shape complexity, and Burton and Samuelson (2008) showed that it was positively related to forest cover and largest patch index and negatively related to landscape diversity. Fewer studies have related other aspects of vegetation to landscape metrics (e.g. forest succession stage and crown closure were related to Shannon's landscape diversity (Terzioğlu et al., 2009)). Last, a smaller group of studies have examined vegetation characteristics in relation to semivariograms, a geostatistical tool used to describe 2D complexity from satellite images (Curran, 1988; Costantini et al., 2012). Semivariograms have been used mainly to characterize canopy cover (Cohen et al., 1990; Colombo et al., 2004; Johansen and Phinn, 2006) but it is not clear how they complement with traditional metrics. Because most studies focus on only one or two characteristics of vegetation to relate them to landscape metrics or their description of vegetation is frequently coarse, we still do not understand the generalities of the relationship between vegetation structure and remote sensing data. We need to refine the resolution of both, vegetation and remote sensing data in order to find these generalities. This approach will help us scale up the study of biological patterns and processes from plot to landscape.

Our question in this study was: how is vegetation structure related to remote sensing attributes in an agricultural frontier in the subtropical dry Chaco, NW Argentina? A secondary question was to explore the relationships between traditional landscape metrics and the semivariogram. We collected vegetation data at fine scale and QuickBird data in 22 1 ha-plots including forest, riparian forest, and agricultural fields across the agricultural frontier.

2. Methods

2.1. Study area

This study was conducted in the dry Chaco biome within the Tapia-Trancas watershed located in the province of Tucumán, NW Argentina (26°50′S, 65°20′W, Fig. 1). The dry Chaco, one of the three biomes within the Chaco, shows a continental, warm and subtropical climate with mean annual temperature of 20 °C (18–23 °C) and annual rainfall of 450 mm falling between October and March (Bianchi and Yáñez, 1992). It is characterized by subtropical xerophytic vegetation that includes spiny, small trees and shrubs, some cacti, herbs, epiphytes, and vines (Cabrera, 1976; Vervoost et al., 1981). Dominant tree species include *Schinopsis lorentzii* (Anacardiaceae) and *Aspidosperma quebracho-blanco* (Apocynaceae) whereas dominant shrubs include *Acacia aroma*, *Acacia praecox*, *Prosopis alba* and *Cercidium praecox* (Fabaceae) (Digilio and Legname, 1966).

During the last 40 years the Tapia-Trancas watershed has experienced increasing habitat degradation due to agricultural expansion, deforestation, grazing pressure, and fire (Aizen and Feinsinger, 1994; Grau et al., 2005; Aide et al., 2012). This has resulted in a complex mosaic of forest fragments embedded in a matrix of pastures, corn, sorghum, legume, and soybean fields. Large areas of nearly continuous dry Chaco forest can still be found surrounding the agricultural fields and urban areas are relatively small. As any other ecosystem edge, where particularly high species diversity and complex ecological interactions are found (Fagan et al., 1999), agricultural frontiers in the dry Chaco are a priority for conservation (Brown et al., 2005).

2.2. Image pre-processing

To describe landscape complexity we used a high resolution QuickBird image (2.6 m resolution for multispectral bands and 0.55 m resolution for panchromatic band) collected in November 2007, centered on the study site and covering an area of 10 × 10 km. This period of the year was selected because the rainy season had started and tree crowns were full of leaves. Accordingly, during this period the maximum biological activity occurs (e.g., Monmany and Aide, 2009).

QuickBird multispectral images have four bands (blue [450–520 nm], green [520–600 nm], red [630–690 nm], and near infrared [760–900 nm]) that yield information about differences between soil (blue band) and vegetation and information about different attributes of plant communities (green, red, and near infrared). The QuickBird data was subjected to a series of procedures. First, the red and infrared bands in the multispectral image were enhanced using the Gram-Schmidt Spectral Sharpening module in ENVI 4.8 (Exelis Visual Information Solutions, Boulder, Colorado). Through this pan-sharpening a low spatial resolution band (2.8 m in the multispectral image) is merged with a high-resolution band (the 0.55 m panchromatic band) with resampling to the high-resolution pixel size (Exelis Visual Information Solutions, 2004). The result is an image with the best spectral and spatial resolution possible. Second, the image was converted to top-of-atmosphere spectral radiance and then atmospherically corrected to at-surface spectral reflectance using the QUAC tool in ENVI 4.8.

Once corrected, we used the built-in function in ENVI to calculate the Normalized Difference Vegetation Index (NDVI) and we used Band Math to calculate the Enhanced Vegetation Index (EVI), both derived from combining the red (RED) and infrared (NIR) bands according to the following:

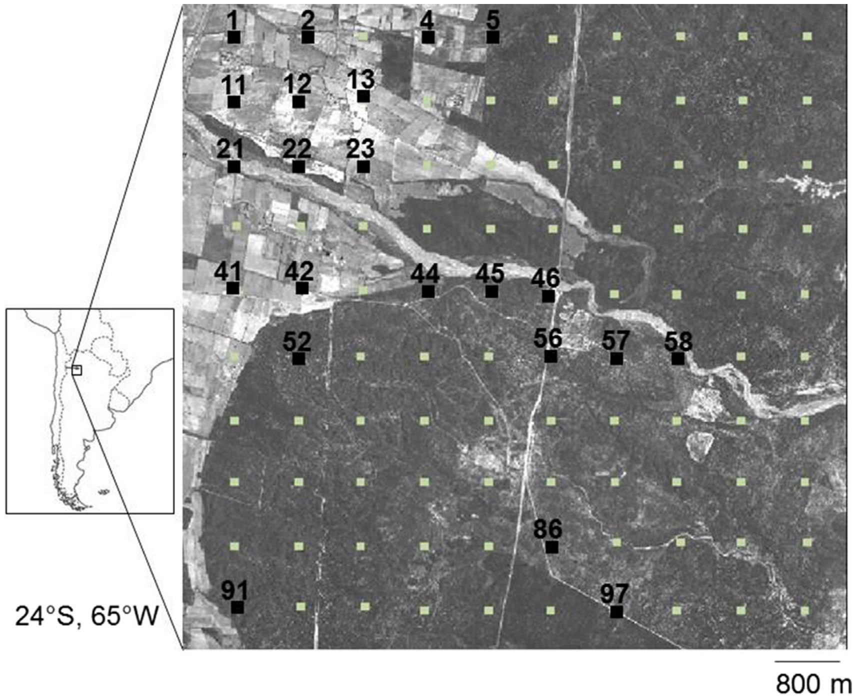

Fig. 1. Study site in NW Argentina. The QuickBird image shows the 10 × 10 km area within which we selected 22 plots (numbered) measuring 1 ha each.

$$NDVI = \left(\frac{NIR - RED}{NIR + RED}\right) \quad (1)$$

$$EVI = G * \frac{NIR - RED}{(NIR + C1 * RED - C2 * BLUE + L)} \quad (2)$$

where G (2.5) is called the gain factor, C1 (6) and C2 (7.5) are empirical parameters, BLUE is the blue band, and L (1) minimizes soil background reflectance variation (Gallardo-Cruz et al., 2012). We calculated the EVI because, as opposed to NDVI, it does not saturate under dense canopy conditions (Gallardo-Cruz et al., 2012).

2.3. Landscape metrics and semivariograms

In ArcMap 10 (ESRI, 2011), a shapefile was created consisting of 100–200 × 200 m plots arranged in a regular grid (Fig. 1). We used this shapefile as a mask to extract the information from the 22 plots sampled in the field (see below) for all subsequent image analyses using the spatial analyst tool. First, in ENVI 4.8 we ran an unsupervised isodata classification of the panchromatic band into seven classes to calculate landscape metrics. This procedure resulted in a finely resolved characterization given the relatively high number of classes within a visually simple landscape. Using the Patch Analyst module (Rempel et al., 2012) in ArcMap 10, we calculated seven landscape-level metrics, related to the proportion area-edge, the shape and aggregation of patches, and the diversity of patch types (*Landscape complexity* variables in Table 1).

Second, we extracted the pixel values from the red, the infrared, and the NDVI band to calculate the semivariogram, γ(h) in each band and plot according to:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N} [Z(x_i) - Z(x_i + h)]^2 \quad (3)$$

where *N(h)* is the number of pairs of observations (Z) made at locations x_i and $(x_i + h)$, separated by a vector h (Cressie, 1993). Thus $\gamma(h)$ measures the degree of similarity between the values of pairs of pixels separated by distance h. The semivariogram parameters range and sill were determined for each plot using the gstat package (Pebesma, 2004) in R (R Development Core Team, 2011). Because the range indicates the distance at which the maximum variance is observed (sill), both parameters are useful to describe heterogeneity (Cohen et al., 1990). Weighted sum of squared differences was used for model fitting (spherical and exponential) and 150 m was the maximum distance for semi-variance calculations.

2.4. Three dimensional vegetation structure

From the large-scale regular grid, 22 1 ha-plots were selected based on accessibility and land cover representation (Fig. 1). Contrasting land covers were found in the study area and we included a similar number of plots in each land cover type to capture the variability in complexity. The plots included agricultural fields mostly represented by alfalfa, corn, and wild herbs; agricultural fields with hedgerows containing large trees; riparian forests surrounding the Choromoro river; and forests with different degrees of disturbance, including highly disturbed areas with bare ground. Within each plot we established ten 2 x 100 m-transects (each 10 m apart) along which vegetation characteristics were measured every 10 m. Between any two points separated by 10 m we established an additional measuring point determined randomly, making the total number of sampled points per transect 20 (starting point was 0 m). Random points were used to “fill in” the spatial variability at scales smaller than a distance of 10 m along the transect. At each sampling point detailed information on vegetation structure was collected from which additional variables were calculated (Table 1). A total of 2683 individuals in 50 woody plant species and 21 families were inventoried (Appendix 1) and for all individuals larger than 5 cm of diameter-at-breast-height (DBH) DBH was measured at 1 m at each side of the transect along the 100 m (Monmany, 2013). To

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Table 1
Names and description of variables measured in the field (related to structure, composition, and spatial arrangement) and in the classified panchromatic band of the QuickBird image. In parentheses, the abbreviations read on Fig. 2.

Variable name	Description
Structural variables	
Mean DBH	Mean diameter-at-breast-height
DBH SD	Standard deviation of DBH
DBH range	Maximum− minimum value of DBH
DBH diversity	Shannon–Weiner's diversity index applied to DBH classes
Basal area	Sum of basal area for the plot
Tress>40 cm DBH	Number of trees larger than 40 cm DBH
Tress>10m	Number of trees higher than 10 m
Foliage height diversity	Shannon–Weiner's diversity index applied to foliage height classes
Composition	
Density	Number of individuals per hectare
Species richness	Total number of species
Species diversity	Shannon–Weiner's diversity index
Spatial arrangement	
Mean density per transect	Mean density per transect within each plot
CV density per transect	Coefficient of variation (SD/mean) of density per transect and within each plot
Cox Index	Variance/mean of density per transect and within each plot
Landscape complexity	
NDVI Sill (Sill)	Semivariogram sill using the NDVI band
NDVI Range (Range)	Semivariogram range using the NDVI band
Largest Patch Index (LPI)	Percent of the total landscape that is made up by the largest patch
Landscape Shape Index (LSI)	Total landscape boundary and all edge within the boundary divided by the square root of the total landscape area and adjusted by a constant. The LSI increases with increasing landscape shape irregularity or increasing amounts of edge within the landscape.
Patch Richness (PR)	Number of different patch types within the landscape's boundary
Shannon's Diversity Index (SDI)	Measure of relative patch diversity
Shannon's Evenness Index (SEI)	Measure of patch distribution and abundance. Equal to zero when the observed patch distribution is low and approaches one when the distribution of patch types becomes more even.
Mean Shape Index (MSI)	Shape complexity. Equal to 1 when all patches are square and it increases with increasing patch shape irregularity.
Total number of patches (NUMP)	Total number of patches in the landscape

determine foliage height diversity a pole was erected up to the canopy (maximum average height in the Chaco is 15 m, Cabrera, 1976). We counted the number of times the pole made contact with a leaf or branch (MacArthur and MacArthur, 1961) within seven vertical layers (0–0.5 m, 0.5–1 m, 1–2 m, 2–4 m, 4–6 m, 6–10 m, and >10 m). To estimate foliage height diversity we calculated the Shannon–Wiener diversity index: $-\sum$ pi ln pi, where pi is the proportion of the total foliage which lies in the *ith* of the chosen horizontal layers (i = 1, 2 … 7, MacArthur and MacArthur, 1961). We recorded 25,665 points for this estimation.

2.5. Data analysis

To determine what aspects of vegetation structure were related to landscape complexity as measured from the satellite image, we ran a series of analyses. First a Two way Cluster Analysis was run in PCORD 5.0 (McCune and Mefford, 1999). Hierarchical clustering is useful to organize a large data set into groups on the basis of a given set of quantitative characteristics; it successively joins the most similar observations and the results are normally displayed as dendrograms (McCune et al., 2002). Two way Cluster analysis has been used to assist in the identification of meaningful landscape and community patterns (e.g. Khan et al., 2011). We analyzed the landscape metrics calculated from the panchromatic band per site in the main matrix (22 sites in the rows and nine landscape metrics in the columns) (*Landscape complexity* in Table 1). The linkage method was Flexible Beta and the distance measure was Sorensen (Bray–Curtis). In PC ORD, the resulting dendrogram was scaled by Wishart's objective function converted to a percentage of information remaining (McCune and Mefford, 1999). The final number of groups was determined combining statistical analysis with dendrogram examination and on-field knowledge of the sites. The statistical significance of the groups was analyzed using Multi-Response Permutation Procedures (MRPP). MRPP is a nonparametric technique for testing the hypothesis of no difference between two or more groups. The *A* statistic (i.e., "chance-corrected within-group agreement") was used in combination with the p-value to determine the significance. If $A = 0$, the groups are no more or less different than expected by chance; if $A = 1$, all sample units are identical within each group. In community ecology $A > 0.3$ is fairly high.

Second, we ran a discriminant function analysis (DFA) to test how the "complexity" groups reflected differences in EVI and vegetation characteristics. DFA is an eigenanalysis technique that requires predefined groups and the discriminant function itself is the linear combination of variables that maximizes the probability of correctly assigning observations to their pre-determined groups (McCune et al., 2002). The matrix analyzed in this step included EVI and a subset of the vegetation characteristics measured in the field. For this subset we selected: mean EVI, the standard deviation of EVI, tree density, tree Shannon's diversity, mean DBH, CV of density per transect, number of trees higher than 10 m, basal area, and foliage height diversity. Data were log-transformed to correct for non-normality. The package MASS in R was used to run the linear discriminant analysis (Venables and Ripley, 2002). Finally, we ran ANOVA and Tukey (pos-hoc comparisons) tests in R to test for differences in the four vegetation characteristics that best explained the complexity groups.

3. Results

3.1. Two-way cluster analysis

The dendrogram of the plots resulting from the Two way Cluster Analysis was trimmed at four groups (Fig. 2). At this level of

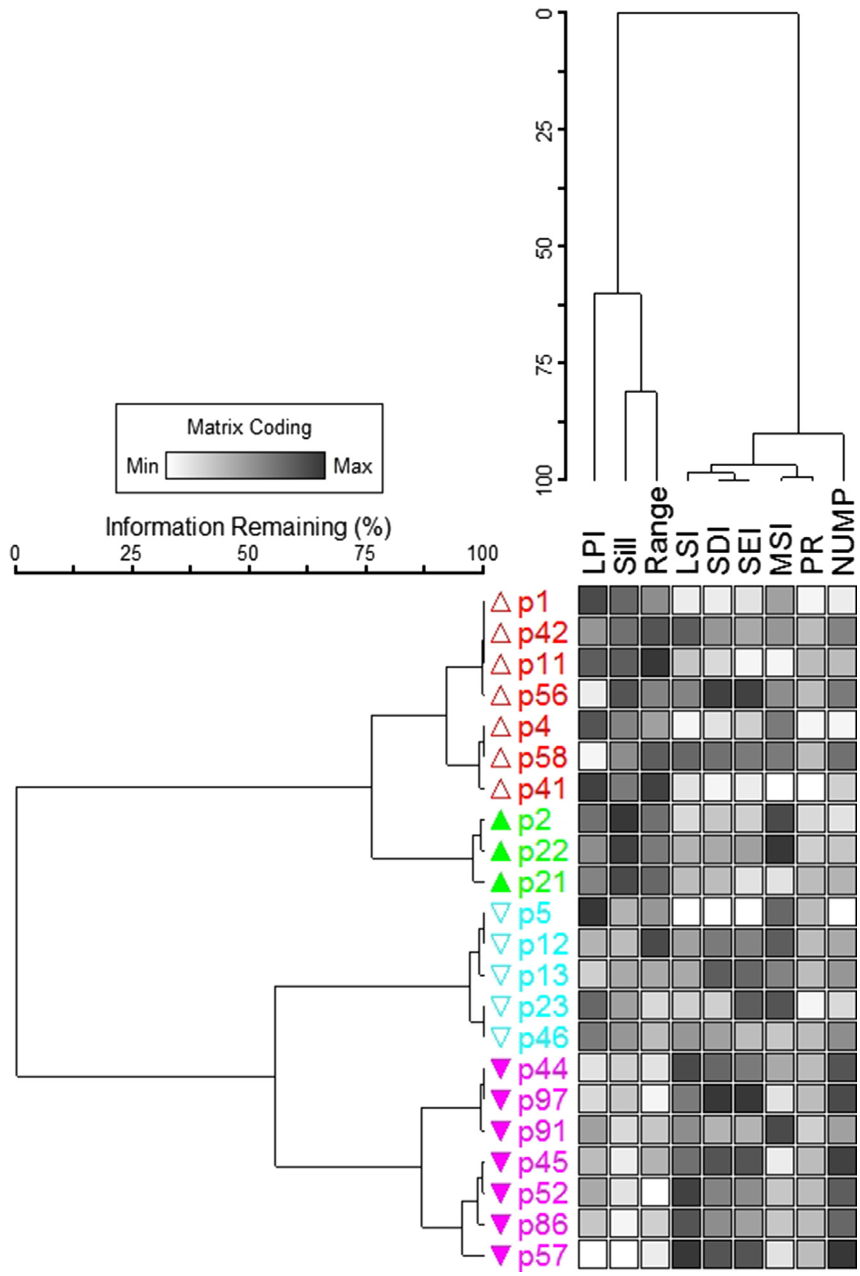

Fig. 2. Two-way cluster dendrogram based on Sorensen distance measure showing the four complexity groups (different colors and symbols) and the landscape metrics. The matrix in gray tones shows the distribution of minimum and maximum values for the metrics. The percentage scales show the amount of information explained by the dendrograms. Plot locations can be seen in Fig. 1. LPI; Largest Patch Index, Sill: NDVI semivariogram sill, Range: NDVI semivariogram sill, LSI: Largest Shape Index, SDI: Shannon's Diversity Index, SEI: Shannon's Evenness Index, PR: Patch Richness, MSI: Mean Shape Index, NUMP: Number of Patches. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

grouping more than 75% of the information was retained and the within-group agreement was fairly high (A = 0.695, p = 4×10^{-8}). In addition, this grouping was representative of the complexity observed in the field. Based on the landscape metrics we distinguished visually two groups of plots; one group included the metric Largest Patch Index (LPI) and the NDVI semivariogram parameters whereas the second included the rest of the metrics (Fig. 2, upper dendrogram). The red, IR and NDVI bands showed very similar values of range and sill. In the two-way cluster analysis, only NDVI was included to facilitate interpretation.

The four final complexity groups were: 1. agricultural plots; 2. riparian/hedgerow plots; 3. bare ground plots; and 4. forest plots (Fig. 2, lower dendrogram). In the agricultural plots 2D complexity was driven mainly by a high percent of the plots covered by large patches (highest Largest Patch Index), which were different from the neighbor patches (highest NDVI range). Landscape Shape Index (LSI), Shannon's Diversity Index (SDI), and Shannon's Evenness Index (SEI) were lowest, though highly variable. Riparian/hedgerow plots, represented by riparian sites and hedgerows dividing properties, showed a high 2D complexity. This complexity was driven by high NDVI variability (highest sill) and high patch shape irregularity (highest Mean Shape Index); Patch Richness (PR) was lowest in these sites. Bare ground plots, represented by agricultural plots and disturbed forest with a high percent of bare soil cover, showed intermediate values of 2D complexity. Landscape Shape Index, Shannon's Diversity Index, Shannon's Evenness Index, Mean Shape

Index, total number of patches (NUMP), semivariogram sill, and semivariogram range were intermediate. At the opposite extreme of agricultural plots, 2D complexity in forests was represented by a high diversity of patch types (highest Shannon's Diversity Index and Shannon's Evenness Index), a high amount of edges among the patches (highest Landscape Shape Index) and the highest number of patches (NUMP). The smallest percent of area covered by large patches (lowest Largest Patch Index), and the most homogeneous plots (lowest NDVI semivariogram parameters) were observed in forests.

3.2. Discriminant function analysis

In order to identify which vegetation structure characteristics were related to remote sensing attributes, we based the discriminant analysis on the groups defined by the two-way cluster analysis. The first discriminant function explained 59.9% of the variance in the data (Wilk's Lambda = 0.025, df1 = 27, df2 = 29.85, F = 2.782, p = 0.004, Table 2A). The variables that contributed most strongly to the formation of the discriminant functions were: the standard deviation of EVI, the coefficient of variation of tree density per transect, mean DBH and foliage height diversity (Table 2B). The standard deviation of EVI was dominant over the other three variables, with more than double the absolute value. When the accuracy of the model was tested, the percent of plots correctly assigned by the model to the groups was low in group 2 (Riparian/hedgerow, 0.33) and higher in the other three groups (0.57–0.71) (Table 2C).

3.3. ANOVA tests

EVI SD, the coefficient of variation of density per transect, mean DBH and Foliage Height Diversity significantly differed among the four complexity groups defined by the two-way cluster analysis (Table 3; Fig. 3). EVI SD was highest but highly variable in the agricultural plots, followed by the riparian/hedgerow and bare ground plots, respectively. EVI SD was lowest and significantly different in the forest plots and the lowest variability was observed in the riparian/hedgerow plots. The CV of density per transect was highest in the riparian/hedgerow plots, followed by the bare ground and forest plots. It was lowest and significantly different in the agricultural plots and the highest variability was observed in the bare ground plots. The lowest variability was observed in the forest plots. Mean DBH was highest in the riparian/hedgerow plots, followed by the bare ground and agricultural plots. Both bare ground and agricultural plots included some forest and many agricultural plots, which resulted in a high mean DBH variability and the lowest values in these two groups. The lowest variability was observed in the forest plots. Foliage Height Diversity was highest in the riparian/hedgerow plots, followed by the forest and agricultural plots. The lowest value and the highest variability of Foliage Height Diversity were found in the agricultural plots. The lowest variability was observed in the forest plots.

Table 2
Results of the discriminant function analysis (DFA) of the landscape metrics measured on the panchromatic and the NDVI bands of the QuickBird image. (A) Relative contributions of each discriminant function to distinguish among the four complexity groups (see also Figs. 2 and 3). (B) Relationship of each variable to the first discriminant axis. (C) Accuracy of the model, percent of plots correctly assigned by the model to the four complexity groups.

A. Relative contributions of discriminant functions		
Axis	Eigenvalue	Proportion explained
LD1	4.918	0.5991
LD2	2.235	0.2723
LD3		0.1286

B. Loadings on first axis	
Variable	Raw coefficient of linear discriminants
EVI SD	−21.201172
CV density per transect	8.341639
Mean DBH	−7.202831
Foliage height diversity	5.280039
Basal area	3.444887
Species diversity	2.632250
Tress > 10 m	−2.431245
Density	1.347714
Mean EVI	1.059494

C. Percent of correct placement	
Group	Percent correct
1	0.5714
2	0.3333
3	0.6000
4	0.7143

Table 3
A. ANOVA table and mean values for the four most important variables in the discriminant Function Analysis among the four complexity groups (see also Fig. 3). 1: Agricultural plots, 2: Riparian/hedgerow plots, 3: Bare ground plots, and 4: Forest plots.

A. ANOVA results				
Variable	df	SS	F	p
EVI SD	3	0.0342	10.251	0.0004
CV density per transect	3	0.1370	3.1419	0.0508
Mean DBH	3	2.3712	4.9514	0.0112
Foliage height diversity	3	0.2234	5.3252	0.0084

B. Mean values				
Variable	1	2	3	4
EVI SD	0.54	0.72	0.38	0.32
CV density per transect	0.14	1.06	0.66	0.44
Mean DBH (cm)	2.80	13.16	6.07	8.95
Foliage height diversity	0.55	1.43	1.10	1.46

3.4. Linking vegetation structure to remote sensing attributes

The field vegetation measurements corresponded to the remote sensing attributes in different ways. First, in the agricultural plots vegetation variables showed the lowest values because the major part of the plots did not have trees; low 3D complexity was represented by the lowest values of CV density per transect, mean DBH, and Foliage Height Diversity. In two dimensions this was translated into the lowest values of Landscape Shape Index (low total amount of edges among the patches), Shannon's Diversity Index and Shannon's Evenness Index. No field data matched the highest values of Largest Patch Index and NDVI range observed in the agricultural plots, but a high variability of vegetation structural characteristics such as canopy type, plant physiognomy, and canopy architecture (high standard deviation of EVI) added information to the description of 2D. Second, in the riparian/hedgerow plots the highest values of vegetation variables and the highest values of some 2D metrics were observed. The highest values of CV density per transect, mean DBH, and Foliage Height Diversity were translated into the highest values of NDVI variability (sill) and highest patch shape irregularity (Mean Shape Index). Third, in the bare ground plots both field measurements and satellite data showed intermediate values. Fourth, in the forest vegetation measurements did not show the highest values but the smallest variation of CV density per transect, mean DBH, and Foliage Height Diversity was observed in these plots. The highest diversity of patch

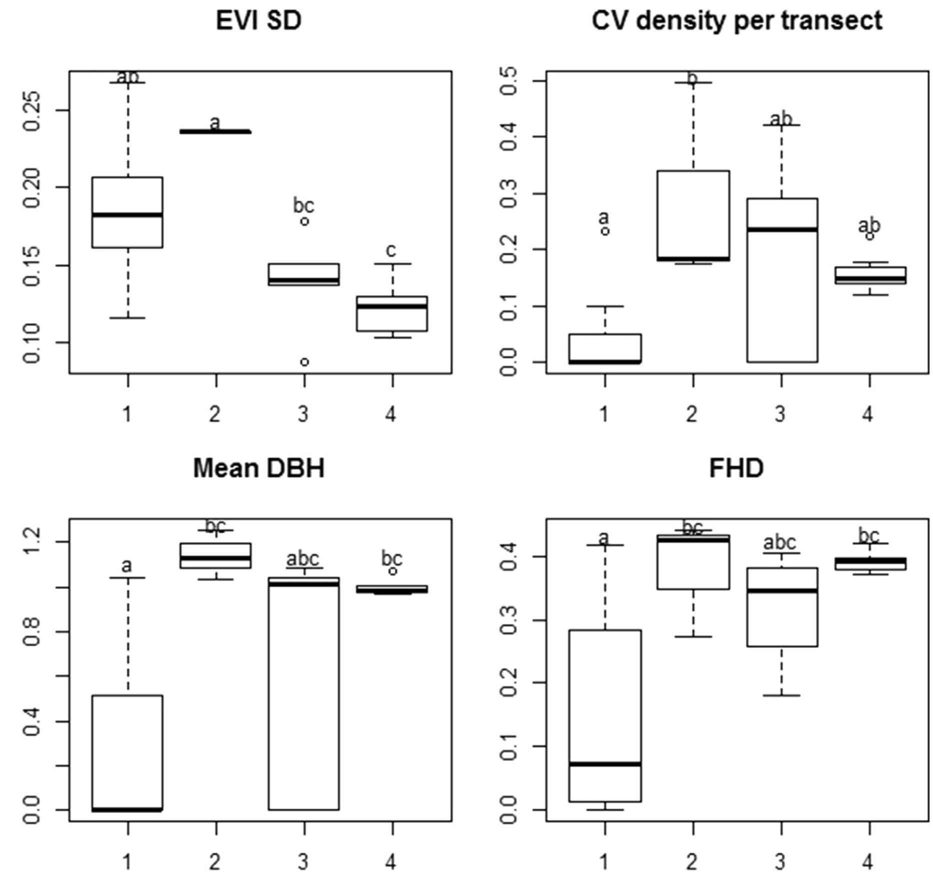

Fig. 3. Box-and-whisker plots of the four most important variables identified by the discriminant Function Analysis among the four complexity groups: Standard Deviation of Enhanced Vegetation Index (EVI SD), Coefficient of Variation (CV) of density per transect, mean Diameter-at-Breast Height (DBH), and Foliage Height Diversity (FHD). The box shows the lower and upper quartiles, the black line within the box is the median, and the whiskers are the minimum and maximum values, respectively. The *y*-axis is in a logarithmic scale. 1: agricultural plots, 2: riparian/hedgerow plots, 3: bare ground plots, and 4: forest plots. Significant differences resulting from Tukey's poshoc comparisons are represented by the letter above each box.

types (Shannon's Diversity Index and Shannon's Evenness Index), highest amount of edges among the patches (Landscape Shape Index) and highest number of patches (NUMP) did not correspond to the highest values of vegetation variables. Instead, the homogeneity observed in three dimensions was translated into the smallest percent of area covered by large patches (lowest Largest Patch Index), the lowest NDVI semivariogram parameters, and the lowest standard deviation of EVI calculated from the satellite data.

4. Discussion

We were able to interpret landscape metrics calculated from a QuickBird image by examining their relationship with field data collected in the subtropical Chaco. The two-way cluster analysis separated the metrics into two groups and the plots into four groups based on data calculated from the image. The metrics included landscape composition (the number and amount of different habitat types; e.g. Shannon's Diversity Index), landscape configuration (the spatial arrangement of those habitat types; e.g. Mean Shape Index), and landscape heterogeneity (e.g. semivariogram sill) variables. A combination of satellite bands was related to vegetation structure and vegetation characteristics that better explained the grouping included structural and spatial arrangement variables such as mean DBH and the CV of density per transect, respectively.

Combining 2D and 3D measures of complexity we obtained a complete spatial description of the plots. In contrast to previous studies (Moser et al., 2002; Kumar et al., 2006; Burton and Samuelson, 2008), we examined a list of vegetation characteristics, one of which was plant species diversity and we did not find plant species diversity or density to be related to landscape metrics. This may be a particularity of the Chaco forests, where one plant family is dominat (i.e. Fabaceae) and the plants in general show very similar structural characteristics to struggle against drought. Species diversity may not be well represented by metrics in the Chaco because differences among species may be subtle and not well captured by the QuickBird image there. We suggest that species diversity may not be a useful vegetation variable to link to landscape metrics in ecosystems physically similar to Chaco. Instead, the coefficient of variation of density per transect, mean DBH, and Foliage Height Diversity are better surrogates of vegetation structure to be linked to remote sensing data.

The low three dimensional complexity observed in the agricultural plots was related to a low compositional complexity (i.e. low values of Shannon's Diversity Index and Shannon's Evenness Index). Previous studies do not report a comparison between vegetation and compositional vs configurational complexity; we suggest that vegetation structure at a micro-scale (e.g. considering herbs height) should be explored in relation to landscape metrics in order to understand configurational complexity and correctly calibrate remote sensing data. Riparian/hedgerow plots showed a high three dimensional that corresponded to a high configurational complexity. This result has been previously found in riparian environments of wetter regions of the world (Johansen and Phinn,

2006) suggesting that the pattern is strong and putting riparian forests at a focal position to calibrate data from remote sensing. In forests, the smallest variation of three dimensional complexity corresponded mainly to a high compositional complexity, the lowest semivariogram parameters and lowest standard deviation of EVI. These results agree with previous studies relating variables other than plant diversity to metrics, in that compositional complexity as determined from remote sensing depended on the variability in vegetation data (e.g. forest succession stage and crown closure) (Terzioğlu et al., 2009).

Two dimensional complexity was best described in the agricultural plots by the combination of three satellite bands: high values of the panchromatic Largest Patch Index, high values of NDVI semivariogram range and high values of the standard deviation of EVI. All three bands showed different aspects of 2D complexity, thus we recommend combining bands when vegetation-satellite data are explored. In addition, an interesting outcome of the two-way dendrogram was that Largest Patch Index, a configurational metric, and NDVI semivariogram range gave information similar enough as to be grouped together and apart from the rest of the metrics. This is the first study reporting the similarity between a traditional landscape metric and the semivariogram and we recommend to include semivariograms in combination with other metrics in future studies calibrating the information from remote sensing.

The relationship between landscape complexity as measured from the image and vegetation structure as measured in the field may be influenced by different factors. First, it has been acknowledged that the scale (i.e. grain and extent) at which each was measured can largely influence the results (Uuemaa et al., 2009; Gallardo-Cruz et al., 2012). In our case, we assured that scale had a minimum effect by using the highest spatial resolution possible in the image (both the panchromatic and the pansharpened bands had a 0.6 m pixel size) and the highest resolution possible in the field (measured all plants within 10–2 m × 100 m transects per plot). In addition, we used the largest extent logistically possible to measure in the field (i.e. 1 ha). Still downscaling and upscaling landscape metrics in relation to vegetation remain a challenge as has been pointed out in other studies (Mander et al., 2005).

Second, the spectral information used to calculate metrics can alter the relationship between the image and field data (Wen et al., 2012). In our study the semivariogram calculated on the individual bands red and near infrared were almost identical to those calculated from the NDVI. Similar results have been previously attributed to highly fractal vegetation (Wen et al., 2012). In addition in our study the complexity addressed by the EVI band corresponded in most cases with that addressed by the NDVI band while the panchromatic band represented other aspects of complexity. NDVI and EVI are usually used in combination given the complementary information they yield with respect to vegetation (Huete et al., 2002) and our results reinforce this recommendation.

Third, different metrics used to describe landscape complexity can relate in different manners to vegetation complexity (Cushman et al., 2008). To address this issue, in our study we followed a conservative approach selecting the metrics by three criteria: 1- metrics only at the landscape level, 2- metrics that showed the least inter-correlation possible, and 3- metrics that have shown to be less sensitive to classifications. Metrics calculated at the landscape level have previously been shown to explain variation better than metrics at the class level (Cushman et al., 2008). Therefore and in the search for simplicity, we limited the calculations to this level. In addition, it has been repeatedly pointed that many metrics are highly intercorrelated (Uuemaa et al., 2009). We tried to minimize this problem including metrics that relate to different aspects of compositional and configurational complexity. For example, both Largest Patch Index and Largest Shape Index belong to the configurational complexity metrics but have been shown to be independent from one another (Cushman et al., 2008). In fact, our results showed the same pattern. Last, we used metrics that show low sensitivity to image classifications such as Shannon's Diversity Index and Shannon's Evenness Index (Altamirano et al., 2012).

4.1. Study implications and conclusions

This study integrated high resolution field data with high resolution image data to understand complexity. This is the first study that combines semivariograms with traditional landscape metrics to understand how they complement each other at the moment of describing complexity. Our approach, though costly in terms of human effort, contributes to the open question of how satellite imagery can be calibrated to understand what aspect of vegetation they are representing (Pisek and Oliphant, 2013). Because LIDAR data is generally not available in many regions of the world (Selkowitz et al., 2012) we need to extract the most information possible from satellite images and validating with field data is of upmost importance.

We have shown how two-way dendrograms give useful information on the inter-relationships among landscape metrics (e.g. Largest Patch Index and semivariogram parameters) and given that metrics provide information on texture, heterogeneity and graininess of landscapes (Cushman et al., 2008), a theoretical challenge emerging from this study is to understand how these metrics are related to texture calculated from the image, among other image descriptions (e.g. Gallardo-Cruz et al., 2012).

Our study has implications for the subtropical dry Chaco, an understudied region of the world which is currently a threatened ecosystem. We have shown that riparian/hedgerow plots provide highly complex habitats. In the face of the projected land cover changes (Aide et al., 2012) one question is how these forests, which are product of natural (riparian) and human (hedgerows) actions are being used by other species in the Chaco. Because highly complex habitats are expected to harbor a high number of species and this has been confirmed by our own data and other studies (Bianchi et al., 2006; Monmany, 2013), we conclude that these sites are of special conservation importance for the biodiversity and ecological processes in subtropical Chaco. In addition, we have shown that highly disturbed forests with a high percent of bare ground formed a unique complexity group and it is important to understand what the implications for biodiversity are. We made an objective, non-functional description of landscape complexity but a question remains open related to how these metrics are related to vegetation characteristics when a functional description is used instead (Fahrig et al., 2011). Last, an open question is how the relationship between metrics and field data changes across different ecosystems.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jaridenv.2015.05.014.

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