Remote sensing data to assess compositional and structural indicators in dry woodland

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ABSTRACT

Integrating field-based and remotely sensed data has proven valuable for assessing on-the-ground diversity of plants across a range of spatial scales. Here we assessed whether remotely sensed data is a good indicator of vegetation composition and structure in dry, *Prosopis flexuosa*-dominated woodlands. Our objectives were (1) to quantify on-the-ground vegetation composition and structure using (A) field-based methods and (B) remotely sensed images and analysis techniques, and (2) to evaluate how well the data extracted from remotely sensed data estimate field-based measures of vegetation composition and structure. We selected 40 individuals of *P. flexuosa* in Ischigualasto Provincial Park (San Juan, Argentina) and its influence zone. Each individual was the center of a plot (1500-m^2) where we recorded richness (compositional indicator) and abundance (structural indicator) of trees, shrubs and other plants (i.e. cacti, grasses and forbs). To assess woodland structure, we evaluated canopy area of each *P. flexuosa* and the proportion of adult *P. flexuosa* trees in a plot. In addition, we used Landsat 8 OLI to calculate SATVI (Soil Adjusted Total Vegetation Index) values from the pixel that corresponds with the center of each sample plot, and then estimated first- and second-order texture measures (in 3 × 3 and 5 × 5 moving window sizes). We fitted generalized linear models with different error distributions. Vegetation richness was significantly and directly related to range and entropy (3 × 3 and 5 × 5 windows). Both trees and shrubs, were related to SATVI values and first- and second-order means (3 × 3 and 5 × 5 windows). Moreover, shrub abundance was inversely related to range and entropy (5 × 5 window); and the "other plants" group was inversely related to first- and second-order means in the same window. Variance of the canopy area was directly related to range (5 × 5 window); however, proportion of adults was not related to remote sensing data. Our findings suggest satellite imagery-derived image texture is a valuable tool for management and conservation, and can indicate areas of high plant species richness and abundance of trees and shrubs and help differentiate areas of different canopy sizes in dry *P. flexuosa*-dominated woodlands of Argentina.

1. Introduction

Woodlands around the world have undergone substantial change in the past decades as a result of expanding human populations and economies (Allen et al., 2010). Changes in the quantity and quality of woodlands worldwide affect important global-scale ecosystem services including biodiversity, climate regulation, carbon storage, and water supplies (Hansen et al., 2013). If maintaining woodland ecological integrity is a goal of conservation, then it is necessary to evaluate the condition of this ecosystem using biodiversity indicators that allow quantifying spatial and temporal changes in vegetation (Lawley et al., 2015). This approach could include monitoring indicators of compositional, structural, and functional biodiversity. Compositional indicators include identity attributes, such as species richness, relative abundance, frequency, and proportions of endemic, exotic, threatened and endangered species. Structural indicators, on the other hand, are measures of the three-dimensional arrangement of vegetation, such as density of different plant forms, canopy cover, vegetation biomass, foliage density and layering, distribution of key physical features and ground components (Noss, 1990). Assessing the performance of indicators and their monitoring is a key aspect of management programs and practices (Pyke et al., 2002; Gaitán et al., 2013).

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Indicators of compositional, structure, and biological diversity can be measured using both field- and remotely-based measurements. These two methods have some differences in their spatial and temporal scales of application, costs, expertise required and, importantly, in the different environmental attributes and indicators each can quantify (Lawley et al., 2015). On the one hand, the need to locate site within homogeneous patches of vegetation probably depends on the research questions and scale of the study. According to Oliver (2002) for woodland and open forest vegetation communities in New South Wales (Australia), indicators of vegetation condition are obtained from field-based assessment, such as alpha diversity of native trees, cover of native and exotic species, cover of organic litter, and recruitment of native tree/shrub saplings, among others. However, shortcomings of this method are inconsistencies between different plot sizes, lack of replication and lack of multiple spatial scales. Field-based approaches are thus costly and time consuming, and difficult to implement in remote areas (see review Lawley et al., 2015). On the other hand, remotely sensed data is increasingly recognized for its applicability to ecological research, which includes quantifying and classifying land features, modeling ecosystem functions such as net primary productivity, mapping land cover change, and is used as a proxy for species richness and biodiversity across multiple spatial scales (see review Bradley et al., 2012). The ability of researchers to accurately measure vegetation characteristics using remotely sensed data varies with the sensor (i.e. spatial, spectral and temporal resolutions), background characteristics, and vegetation attributes of individual species such as size, shape, aggregation, phenology and physical structure such as canopy cover (Lawley et al., 2015).

In vegetation science and landscape ecology, remotely sensed images can be processed and classified using image processing software (Palmer et al., 2002). Classification of landscape into discrete units with specific climate, landforms, soils and vegetation provides a foundation for monitoring, conservation and management. Landscape stratification has been practiced worldwide and classifications are refined or updated as more information and data become available (Mücher et al., 2010). However, classification of an image to obtain discrete land cover classes can result in an important loss of information, such as within-class spatial variability in on-the-ground local attributes (e.g., vegetation cover or density). Moreover, another difficulty could be defining boundaries at transition zones between different land cover types (i.e. ecotones), or could involve an expensive process when an extensive ground-truthing survey is necessary to discriminate between different cover types (St-Louis et al., 2006). An alternative that addresses these drawbacks is the use of raw, unclassified imagery (Nagendra, 2001).

The reflectance of an image could be assessed by using spectral vegetation indices, which allow us to detect green vegetation reflectance and can be calibrated to indicate biomass, vegetation cover, productivity and vegetation types (see review Goirán et al., 2012). The variability in reflectance values among neighboring pixels, caused by horizontal and vertical variability in plants, can be captured by measures of an image texture, which quantify heterogeneity within a defined area of an image as a continuous variable (St-Louis et al., 2006, 2009; Bellis et al., 2008; Wood et al., 2012, 2013; Campos et al., 2015, Campos et al., 2016a,b). Image texture is an image analysis approach that can be applied to remotely sensed images to measure spatial variability in gray tones (e.g., for Digital Aerial Photographs) or reflectance values (from multi-spectral satellite data, Haralick et al., 1973). These indices have been used for characterizing vegetation patterns (Ge et al., 2006) and have been successfully applied to different species and environments to predict occurrence of bird species in grassland (Bellis et al., 2008), desert ecosystem (St-Louis et al., 2006, 2009), grassland, savanna, and woodland (Wood et al., 2012) as well as occurrence of large-sized mammals (*Tragelaphus eurycerus isaaci*, Estes et al., 2008) and small mammals (*Octomys mimax*, Campos et al., 2015). Since remote sensing data represents a powerful tool for deriving quantitative information about diversity, attempts were made to predict

species richness by means of spectral heterogeneity. Species richness is a compositional indicator that has been widely used in research, since it is a direct proxy for α-diversity, i.e. the local diversity of a site (see review Rocchini, 2007). NDVI (Normalized Difference Vegetation Index) texture, as opposed to NDVI only, accounted for 65% of the variability in plant species richness in the Canadian Arctic (Gould, 2000) and predicted up to 43% of the variability in hardwood forest leaf area index (LAI) in Canada (Wulder et al., 1998). Moreover, texture of NDVI was the best predictor of bird species richness among all of the measures from individual Landsat TM bands in the Chihuahuan Desert, New Mexico (St-Louis et al., 2009). Identification and monitoring of sites with high species richness within a landscape can provide a basis for future monitoring and an ecological basis for species management and conservation (Rocchini, 2007).

In our research, we assess whether remote sensing data-derived image texture metrics are a good indicator of vegetation composition and structure at different scales, using as case study the dry woodlands of *Prosopis flexuosa* in the Monte Desert of Argentina, a dominant tree and therefore a key species in this ecosystem (Rossi and Villagra, 2003; Cesca et al., 2012). Our objectives were: (1) to quantify on-the-ground vegetation composition and structure using (A) field-based methods and (B) remotely sensed images and analysis techniques; and (2) to evaluate how well the data acquired from remotely sensed imagery estimates field-based measures of vegetation composition and structure in dry woodlands.

2. Methods

2.1. Study area

The study was conducted in Ischigualasto Provincial Park (Fig. 1), San Juan province, Argentina (29°55′S, 68°05′W) and its zone of influence. The Park has an area of 62,916 ha and is located in a hyper-arid sector of the Monte Desert, which corresponds to the northern section of Monte of hills and closed basins (Monte de Sierras y Bolsones). Average annual precipitation is 100 mm (Labraga and Villalba, 2009). Temperature is characterized by considerable day/night variations and a wide range throughout the year, (Abraham and Martínez, 2000); mean annual temperature is 22 °C, with a maximum of 45 °C and a minimum of −10 °C (Cortez et al., 2005). The study area is dominated by outcrops of sandstones with varying salt content; moreover, there are areas of fine-textured substrata (sands and clays) where water accumulates after a rainfall event (Márquez et al., 2005). The vegetation is xerophytic due to the low rainfall and high temperatures, with heterogeneous cover that ranges from 5 to 80% (Márquez et al., 2005).

2.2. Field survey

Fieldwork was conducted from August to December of 2016. We selected 40 individuals of *P. flexuosa* about 3 m tall (spaced at least 300 m apart, Fig. 2), and each of them was taken as the center of a 1500 m^2 plot (0.15 ha). For the purpose of our study, we wanted to focus on areas most likely to have one or more individuals of *P. flexuosa*. We therefore located our study plots where we could find trees along roads, which are known to be used for movements of the species' main dispersers (medium and large mammals, Campos et al., 2016a,b). Inside each plot, we ran five 30 m-long transects separated by 10 m, and listed all species of plants in 20 subplots (3 × 2 m, separated by 6 m), as well as recorded the number of individuals of each species. Based on this information, we calculated richness (compositional indicator) and abundance (structural indicator) of plants. To obtain a plot-level measure of richness, we recorded the tally of species across all subplots. To account for variations in the vertical structure of vegetation, we classified plant species into three groups (trees, shrubs, and other plants incl. cacti, grasses and forbs) and we summed up the total number of individuals belonging to each of the three groups across all subplots to
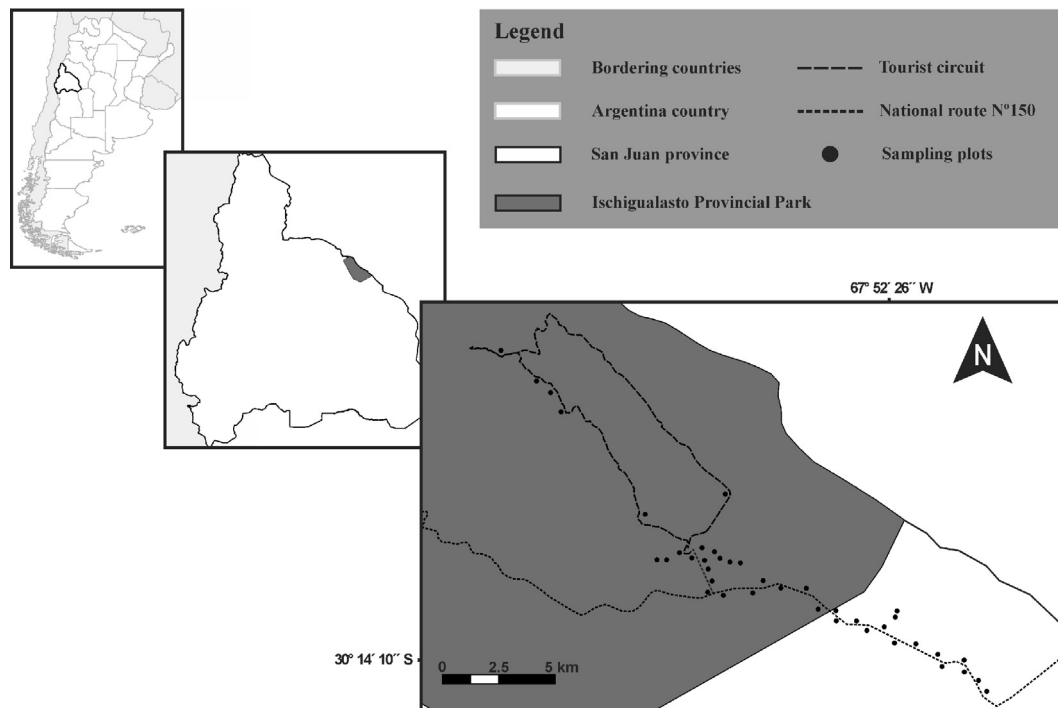
Fig. 1. Map of Ischigualasto Provincial Park and sample plots.

Fig. 2. Dry woodland of *P. flexuosa* in Ischigualasto Provincial Park.

obtain a plot-level measure of group abundances.

To assess woodland structure, for each *P. flexuosa* tree considered in a sub-plot we recorded: basal diameter of each shaft, tree height and canopy dimensions (largest and smallest diameters). The equivalent basal diameter for each *P. flexuosa* tree was calculated using the formula employed by Alvarez et al. (2006), which considers the diameter of each shaft. Because basal diameter, height and canopy area were strongly correlated ($\rho > |0.8|$) we considered only the canopy area of *P. flexuosa* for the analysis. Because we were interested in knowing whether *P. flexuosa* woodland was renewed, we calculated variance of canopy area in each plot and proportion of adult *P. flexuosa* trees in relation to the total number of individuals. We considered an individual with a basal diameter less than 7.5 cm to be a juvenile tree (Alvarez et al., 2006).

2.3. Remote sensing variables

We used a 30-m resolution Landsat 8 Operational Land Imager (OLI)

image (path 232 row 081) acquired on 24 January 2016 (U.S. Geological Survey, Earth Explorer, 2107) for quantifying vegetation composition and structure. The image was rescaled to the Top Of Atmosphere (TOA) reflectance with a correction for the sun angle using coefficients provided in the product metadata file. The image was reported to have less than 1% cloud cover.

Several satellite-derived vegetation indices, especially those obtained from the difference between near-infrared and visible red bands, such as NDVI (Normalized Difference Vegetation Index), are estimators of green and vigorous vegetation, but have shown limited success in measuring senescent and leafless vegetation (Goirán et al., 2012). As in other deserts around the world, the vegetation of the Monte Desert in the arid West of Argentina is organized as a two-phase mosaic composed of a phase of shrub- (i.e. *Larrea* spp.) or tree- (i.e. *Prosopis* spp.) dominated patches alternating with sparsely covered areas (Bisigato et al., 2009). Moreover, most vegetation of the Monte Desert has small leaf area and non-photosynthetic tissues for extended periods (Goirán et al., 2012), thus the most commonly used vegetation indices (e.g., NDVI) are not appropriate for mapping or quantifying the amount of green biomass (Goirán et al., 2012; Campos et al., 2015). Because of this, we calculated SATVI (Soil Adjusted Total Vegetation Index; Marsett et al., 2006), which is sensitive to both green and senescent vegetation, and which includes a parameter that normalizes the effect of bare soil:

$$SATVI = \frac{\rho_{band6} - \rho_{band4}}{\rho_{band6} + \rho_{band4} + L} \times (1 + L) - \frac{\rho_{band7}}{2}$$

where ρ is reflectance values in different bands of the OLI sensor. SATVI considers the shortwave infrared (band 6) and the mid infrared (band 7) reflectance instead of near-infrared used in the calculation of NDVI, the green index widely used in research. Moreover, SATVI has a parameter (L) that minimizes the effects of soil background on the vegetation signal. Huete (1988) recommended three values of L factor: L = 1 for analyzing very low vegetation densities; L = 0.5 for intermediate vegetation densities, and L = 0.25 for higher densities. Since our focus was on areas that were vegetated within dry woodlands of *P. flexuosa*, we used an intermediate L value (i.e. 0.5) in SATVI.

Image texture contains important information about the spatial and

Table 1

Summary statistic for field-based data at plot-level. Shown here are mean (± SE), minimum and maximum values of variables. Variance of canopy area in *P. flexuosa* was logarithmic transformed.

Field-based data	Mean ± SE	Min–Max	Remote sensing data	Mean ± SE	Min–Max
Richness	11.40 ± 0.53	7–22	SATVI	0.06 ± 0.00	−0.04 to 0.11
Abundance of trees	11.00 ± 2.37	0–78	First-order mean at 3 × 3	0.05 ± 0.00	−0.03 to 0.10
Abundance of shrubs	86.72 ± 17.77	16–574	First-order range 3 × 3	0.04 ± 0.00	0.01–0.09
Abundance of cacti	12.05 ± 2.71	0–78	First-order mean at 5 × 5	0.05 ± 0.00	−0.03 to 0.10
Abundance of grasses	57.25 ± 18.22	0–574	First-order range 5 × 5	0.06 ± 0.00	0.03–0.11
Abundance of forbs	11.07 ± 3.46	0–127	Second-order mean at 3 × 3	33.69 ± 0.18	30.22–35.89
Variance of canopy area	7.62 ± 0.29	4.00–10.12	Second-order entropy 3 × 3	1.37 ± 0.08	0.35–2.20
Proportion of adult trees	0.75 ± 0.04	0.33–1.00	Second-order mean at 5 × 5	33.52 ± 0.18	30.32–35.80
			Second-order entropy 5 × 5	1.80 ± 0.07	0.76–2.64

structural arrangement of objects (Haralick et al., 1973). First-order texture measures are based on the number of occurrences of each gray level, or reflectance, value within a given processing window. Second-order texture measures use a gray-level co-occurrence matrix (GLCM) to calculate texture values, which indicates the probability that each pair of pixel values co-occurs in a given direction and distance, and therefore allows taking into account the spatial relationship among neighboring pixels (Hall-Beyer, 2007; Haralick et al., 1973). We used the following texture measures: first-order (mean, range, variance) and second-order (mean, variance, contrast, entropy, and angular second moment; Appendix 1).

The values of the SATVI green index were extracted from the pixel that corresponded to the center of each sample field plot. Moreover, to consider different scales, we calculated first-order texture measures using 3 × 3 (equivalent to 90 m × 90 m, area 0.81 ha) and 5 × 5 (equivalent to 150 m × 150 m, area 2.25 ha) moving window sizes, i.e. the pixel values within a moving window were used to calculate a statistic that was assigned to the central pixel (Hall-Beyer, 2007; Haralick et al., 1973). We did not evaluate a window size larger than 3 × 3 or 5 × 5, because it would be far from the plot level and, as proposed by Anys et al. (1994), if the window size of analysis is too large, it could overlap different features and introduce spatial errors. Second-order texture measures were calculated using the same moving windows. Considering the distance between two neighboring pixels, second-order texture measures were calculated from the GLCM in four directions (0, 45, 90, and 135 degrees) and averaged so as not to infer directionality (Haralick et al., 1973). All texture measures were calculated with the SATVI image because we were interested in capturing spatial heterogeneity in vegetation. All remote sensing variables were calculated using ENVI GIS (ENVI, 2015) and Quantum GIS (2016, Version 2.18.2 "Las Palmas").

2.4. Statistical analysis

To investigate whether spatial variability in on-the-ground compositional and structural indicators were characterized by SATVI and image texture measures (first-order mean, range, variance, and second-order mean, variance, contrast, entropy, and angular second moment) at different moving window sizes (i.e., 3 × 3 and 5 × 5 window sizes), we employed generalized linear models (GLMs). We included field-based data on: a) richness (compositional indicator), b) abundance of plants (i.e. trees, shrubs, other plants), c) variance of canopy size and d) proportion of adult *P. flexuosa* trees in relation to all individuals of *P. flexuosa* in a plot (b, c and d: structural indicators) as dependent variables. We used GLM models with a Poisson error distribution to model species richness and abundance of plants. We used a negative binomial error distribution for those variables showing overdispersion (abundance of trees, shrubs, other plants; Crawley, 2007). We log-transformed variance of canopy size because model residuals from the raw data were not normally distributed (Zar, 1999). We used beta regression models (Cribari-Neto and Zeileis, 2010) for modeling the

proportion of adult *P. flexuosa* in a plot because the data is bounded between 0 and 1. All fixed variables were standardized by z-scores prior to analysis. To identify collinearity between fixed variables at each scale (3 × 3 and 5 × 5 moving windows) and order (first and second), we used Spearman rank correlation, a non-parametric measure of statistical dependence (Zar, 1999). We excluded variables when the r coefficient was > |0.6|; therefore, we used the following subset of texture measures: first-order mean and range in 3 × 3 and 5 × 5 moving windows; second-order mean and entropy in 3 × 3 and 5 × 5 moving windows. For each response variable, we considered scales and different orders of texture measures (i.e. first and second) in different models, due to their strong correlation when considered within the same model. For each full model, a backward elimination procedure was used to remove insignificant variables without losing important information. We calculated a pseudo R² (Zuur et al. 2009), with deviance values of the best models:

$$\frac{null\ deviance - residual\ deviance}{null\ deviance} * 100$$

To check for spatial-autocorrelation among sampling points, we fitted semivariograms with the Pearson residuals of the regression models (Zuur et al., 2009). 95% confidence envelopes based on 99 permutations of the model residual values across all locations were constructed to evaluate departure from the assumption of no spatial autocorrelation (Ribeiro and Diggle, 2016). We found no evidence of spatial autocorrelation in the model residuals. All statistical analyses were conducted in R (R Core Team, 2017) using the following packages: "sp" (Pebesma and Bivand, 2005; Bivand et al., 2013), "geoR" (Ribeiro and Diggle, 2016), "MASS" (Venables and Ripley, 2002) and "betareg" (Cribari-Neto and Zeileis, 2010).

3. Results

Shrubs were the most abundant group, represented by *Atriplex* spp., *Plectrocarpa tetracantha*, *Larrea cuneifolia*, *Lycium* spp., *Suaeda divaricata* and *P. torquata*, in decreasing order (Table 1 and Fig. 3). The group containing cacti, grasses and forbs (i.e. "other plants" group) was second in abundance, followed by trees (*P. flexuosa* and *Geoffroea decorticans*, Table 1 and Fig. 3). In the "other plants" group, grasses were first in abundance, followed by cacti and forbs (Table 1 and Fig. 3). *P. flexuosa* individuals reached heights of up to 8.20 m, with a mean of 2.25 m. Mean canopy size was 49.58 m² and mean basal diameter was 16.56 cm², with a maximum canopy size of 395.84 m² and a basal diameter of 60.00 cm².

Our models explained up to 24% of the variability in species richness (Table 2). At different scales, 3 × 3 and 5 × 5 moving windows, species richness was significantly and directly related to range and entropy (Table 2). The models for abundance of trees, shrubs and the "other plants" group explained up to 15%, 29% and 11% of the variability, respectively (Table 2). Abundance of trees was directly related to SATVI and first- and second-order means in 3 × 3 and 5 × 5 moving windows (Table 2). Abundance of shrubs was directly related to
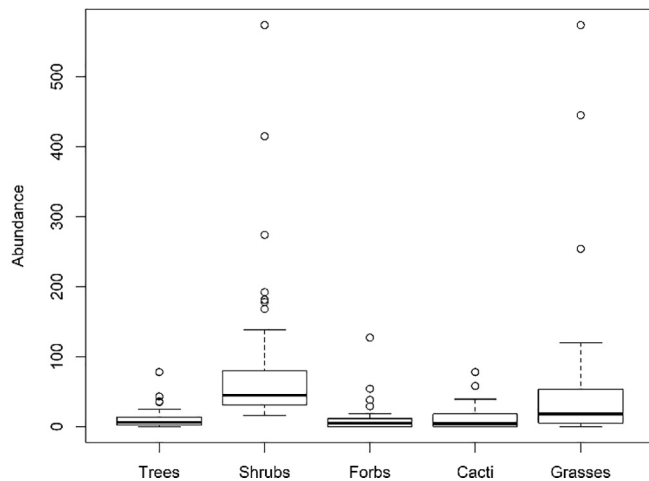
Fig. 3. Box plot for abundance of trees, shrubs and "other plants" group (i.e. cacti, grasses and forbs) in the study area.

SATVI, first-order mean (3 × 3 and 5 × 5), second-order mean (3 × 3); and inversely related to range and entropy in the 5 × 5 moving window (Table 2). The "other plants" group was inversely related to first- and second-order means in the 5 × 5 moving window (Table 2). The variance of canopy area in a plot was directly related to range (5 × 5), this model explained up to 16% of the variability (Table 3). However, the proportion of adult trees was not significantly related to any of the remote sensing data (Table 3).

4. Discussion

Species richness has been measured in many places and over long time periods, because it is a useful tool for detecting diversity hotspots, thus being an indicator of ecological condition or conservation value (see review Rocchini, 2007). When classified images are used to detect species-rich sites through remotely sensed data, loss of information occurs because the classification process by definition uses a wide array of continuous quantitative information to categorize each pixel into a few discrete classes (Palmer et al. 2002) that cannot capture within-class variability (St-Louis et al., 2006). Continuous variables, such as texture measures derived from satellite imagery, are increasingly used to quantify heterogeneity within a defined area (St-Louis et al., 2006, 2009; Bellis et al., 2008; Wood et al., 2012, 2013; Campos et al. 2015, Campos et al., 2016a,b) because variability in reflectance values among neighboring pixels can reflect spatial heterogeneity in plant distribution at a finer scale than image classification, and thus can capture more subtle changes in vegetation characteristics (St-Louis et al., 2009). Texture measures have been developed in different environments to predict habitat for species and to characterize vegetation patterns (Ge et al., 2006). Range and entropy are measures of image heterogeneity, since the first is the difference between the highest and lowest values of SATVI and the second is a measure of disorder in the image. Both texture measures were positively related to species richness, thus, higher spectral variability captured higher on-the-ground species richness. This finding goes hand in hand with that summarized by the Spectral Variation Hypothesis, which proposes a link between spectral heterogeneity and biodiversity only in terms of species richness (Palmer et al., 2002).

The relationship between spectral heterogeneity and species richness is scale dependent because ecological processes operate at different scales (Rocchini et al., 2004). Variability in plant species richness was not captured by pixel-level SATVI values (0.09 ha), however, vegetation heterogeneity captured by image texture measures explained up to 24% and 17% of the variability in species richness using 3 × 3 (0.81 ha) and 5 × 5 (2.25 ha) moving windows, respectively. Although the explained variance was relatively low, these variables had a significant and positive relationship with species richness. Rocchini et al. (2004) found that the measure of spectral heterogeneity was able to predict about 20% of the variance of species richness on a 0.01-ha area (high spatial resolution) and 48% on a 1-ha area (low spatial resolution). However, our results showed that a 2.25-ha area is too low a spatial resolution to represent richness in *Prosopis* woodland, so the explained variability decreases compared to 0.81 ha. When spatial resolution is too low, discriminating by spectral variation becomes difficult (see review Nagendra, 2001).

In our study, abundance of shrubs was higher than that of cacti, grasses, forbs, i.e. the "other plants" group, and trees. Both, the green index itself and the first- and second-order mean texture measures (in 3 × 3 and 5 × 5 moving windows) were related to shrub and tree

Table 2
Results of best models between field-based (richness, abundance of trees, shrubs and other plants -cacti, grasses and forbs-) and remote sensing data (i.e. first- and second-order texture measures of SATVI). Shown here are parameter estimates (± SE), p-values for significance (* = P < 0.05; ** = P < 0.01, *** = P < 0.001) and pseudo R^2 for models.

Field-based data	Order of texture measures	Moving window	Remote sensing data	Estimate ± SE	p-value	pseudo R^2
Richness			SATVI	0.03 ± 0.05	0.57	0.88
	1st order	3 × 3	Mean	0.06 ± 0.05	0.21	13.03
			Range	0.10 ± 0.05	*	
		5 × 5	Range	0.12 ± 0.05	*	17.44
	2nd order	3 × 3	Entropy	0.10 ± 0.05	*	23.68
		5 × 5	Entropy	0.10 ± 0.05	*	12.14
Abundance of trees			SATVI	0.39 ± 0.18	*	10.94
	1st order	3 × 3	Mean	0.49 ± 0.18	**	14.02
		5 × 5	Mean	0.46 ± 0.18	**	11.98
	2nd order	3 × 3	Mean	0.50 ± 0.18	**	14.45
		5 × 5	Mean	0.46 ± 0.18	**	11.80
Abundance of shrubs			SATVI	0.30 ± 0.14	*	11.68
	1st order	3 × 3	Mean	0.33 ± 0.13	*	15.34
		5 × 5	Mean	0.27 ± 0.13	*	25.57
			Range	−0.29 ± 0.13	*	
	2nd order	3 × 3	Mean	0.31 ± 0.14	*	13.19
		5 × 5	Entropy	−0.45 ± 0.12	***	28.62
Abundance of other plants			SATVI	−0.14 ± 0.15	0.38	2.12
	1st order	3 × 3	Mean	−0.25 ± 0.15	0.10	6.97
		5 × 5	Mean	−0.30 ± 0.15	*	9.96
	2nd order	3 × 3	Mean	−0.25 ± 0.15	0.10	11.37
		5 × 5	Mean	−0.30 ± 0.15	*	9.58

Table 3
Results of linear regression between field-based (variance of canopy area in *P. flexuosa* and proportion of adult trees) and remote sensing data. Shown here are parameter estimates (± SE), p-values for significance (* = P < 0.05; ** = P < 0.01; *** = P < 0.001) and pseudo R^2 for models.

Field-based data	Order of texture measures	Moving window	Remote sensing data	Estimate ± SE	p-value	Pseudo R^2
Variance of canopy area in *P. flexuosa*			SATVI	−0.10 ± 0.33	0.76	0.32
	1st order	3 × 3	Range	0.40 ± 0.26	0.14	7.45
		5 × 5	Range	0.62 ± 0.26	*	16.13
	2nd order	3 × 3	Entropy	0.03 ± 0.02	0.15	6.89
		5 × 5	Entropy	0.03 ± 0.02	0.28	3.85
Proportion of adult trees of *P. flexuosa*			SATVI	−0.11 ± 0.18	0.52	1.60
	1st order	3 × 3	Mean	−0.08 ± 0.18	0.66	0.91
		5 × 5	Range	−0.13 ± 0.18	0.49	1.62
	2nd order	3 × 3	Mean	−0.10 ± 0.18	0.60	1.32
		5 × 5	Entropy	0.11 ± 0.18	0.56	1.22

abundance. The satellite sensor would be capturing the most abundant shrub species, which also have lots of vigorous green leaves, i.e. *L. cuneifolia*, followed by *S. divaricata* and *P. torquata*. Moreover, we found an inverse relation between shrub abundance and texture measures of heterogeneity (range and entropy), which shows that, at large scale, shrubs are captured by the satellite sensor as homogeneous patches of vegetation. On the other hand, despite their low abundance, trees were positively related to SATVI and mean texture measure, probably because they have green stems, e.g. *C. praecox* and *G. decorticans*, and a lot of green leaves in summer (January), e.g. *P. flexuosa*. In the Monte Desert, plant patches are dominated by shrubs and/or trees which are associated with soils bearing high nutrient concentrations (i.e. fertility islands) as a consequence of erosion and sedimentation/accumulation processes, therefore they are key structures throughout this ecosystem (see review Bisigato et al., 2009).

Measuring the structural heterogeneity of woodlands allows assessing their condition and dynamics, regeneration patterns, microclimate variation, habitat availability for wildlife and economic aspects (see review Zenner and Hibbs, 2000). Our results show that variance of canopy area was positively related to range in the 5 × 5 moving window, despite the low variability explained by the model. Image range (i.e. the difference between the highest and lowest values of a contiguous set of pixels) is a texture measure of heterogeneity, so its significant and direct relationship with variance of canopy area would make it an indicator of variability in age structure, which could be a proxy for the reproductive status of these *Prosopis* woodlands. Probably, the low variability explained by the model is because juvenile trees are poorly captured by the image due to their morphologic characteristics (i.e. short-statured, simple vertical canopy structure and relatively low canopy cover). The structural heterogeneity of the woodland affects important ecological patterns and processes such as availability of habitat and resources, diversity of organisms, seed regeneration, recruitment and microclimate (see review Valbuena et al., 2012). We consider that further research is needed to assess the structural heterogeneity of the woodland through remote sensing data, which ensures a broader applicability of these measures in desert ecosystems.

In our study area, occurrence of *P. flexuosa* is strongly associated to its main dispersers (medium- and large-sized mammals) which use areas close to roads (manuscript in preparation). Therefore, the sampling plots in our study site were set up near roads. Because of this, future research should consider assessing these proxies for determining the composition and structure of *P. flexuosa* woodland in other areas with different ecological features. Moreover, possibly the environmental heterogeneity of our study area, characterized by highly diverse topography, aspect and drainage, has an influence on texture measures

due to the effect of hills and shadows, even when using a vegetation index (Matsushita et al., 2007).

Conservation strategies require information on the status of woodlands in dryland systems because they are a fundamental determinant of key ecosystem processes. Field-based and remote sensing data are two different methods that allow monitoring the woodland status through ecological indicators. Field-based data provide indispensable information which can be difficult to acquire across broad spatial extents. However, remote sensing offers systematic spatial and temporal data on vegetation attributes, which can be evaluated at broad scale (Nagendra, 2001; Lawley et al., 2015). Our findings will contribute to identifying sites with high species richness, abundance of shrubs and trees, through remotely sensed data. Moreover, measures of texture could be a useful tool for ascertaining whether the woodland is renewed, since they are related to variability in the canopy area of *P. flexuosa*. Future work is needed to assess the applicability of image texture to other ecosystems, using high-resolution spectral or spatial satellite imagery, and satellite imagery obtained from other sensors (e.g. radar image). Furthermore, to develop appropriate methods for predicting biodiversity, scientists need to understand the effects of the main drivers of biodiversity (e.g. latitude, elevation, climate, productivity, human disturbance) and their influence across a range of spatial scales. These causal variables and these effects are still debated (Lavers and Field, 2006). Anyway, as a first step, this work expands our understanding about the relationship between field-based data and remote sensed data, providing evidence that SATVI and texture measures could be used as a proxy for richness, abundance of shrubs and trees, and canopy size in dry woodland of *P. flexuosa*.

Appendix 1

First- and second-order image texture measures: statistic description of behavior, statistic formulae and acronym description. First-order texture measures calculated from the original image values. Second-order image texture measures calculated from a gray-level co-occurrence matrix

(GLCM).

Type of measures	Texture measures	Description	Formula*
1st order measures	Mean	Gray level average in the moving window.	$\sum_{i=0}^{N-1} i*p(i)$
	Range	Difference between maximum and minimum gray level in the moving window.	$\max\{i\}-\min\{i\}$
	Variance	Dispersion of gray level around the mean.	$\sum_{i=0}^{N-1}(i-\mu)^2 p(i)$
2nd order measures	Mean	Gray level average in the GLCM window.	$\sum_{i=1}^{N}\sum_{j=1}^{N} i*p(i,j)$
	Variance	Gray level variance in the GLCM window.	$\sum_{i=1}^{N}\sum_{j=1}^{N}(i-\mu)^2 p(i,j)$
	Contrast	A measure of the amount of local variation in pixel values among neighboring pixels.	$\sum_{n=0}^{N-1} n^2 \left\{\sum_{i=1}^{N}\sum_{j=1}^{N} p(i,j)\right\}_{|i-j|=n}$
	Entropy	Shannon-diversity. High when the pixel values of the GLCM have varying values.	$-\sum_{i=1}^{N}\sum_{j=1}^{N} p(i,j)\log(p(i,j))$
	Angular second moment	High when the GLCM is locally homogenous.	$\sum_{i=1}^{N}\sum_{j=1}^{N}\{p(i,j)\}^2$

*From Haralick et al. (1973).

$p(i)$: the probability of each pixel value.

N: the number of distinct gray levels in the image.

μ: mean of gray level.

$p(i,j)$: is the (i,j) th entry of the normalized GLCM matrix, $= P(i,j)/R$ where R is a normalizing constant.

References

Abraham, M.E., Martínez, F.M., 2000. Argentina. Recursos y problemas ambientales de las zonas áridas. Primera parte: Provincias de Mendoza, San Juan y La Rioja. Tomo I: Caracterización Ambiental. GTZ, IDR (Univ. Granada), IADIZA, SDSyPA, Argentina.

Allen, C.D., Macalady, A.K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A., Breshears, D.D., Hogg, E.H. (Ted) Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.H., Allard, G., Running, S.W., Semerci, A., Cobb, N., 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. For. Ecol. Manage. 259, 660–684.

Alvarez, J.A., Villagra, P., Cony, M.A., Cesca, E.M., Boninsegna, J.A., 2006. Estructura y estado de conservación de los bosques de *Prosopis flexuosa* D.C. (Fabaceae, sub-familia: Mimosoideae) en el noreste de Mendoza (Argentina). Rev. Chil. Hist. Nat. 79, 75–87.

Anys, H., Bannari, A., He, D.C., Morin, D., 1994. Texture analysis for the mapping of urban areas using airborne MEIS-II images. In: Proc. First Int. Airborne Remote Sens. Conference and Exhibition 3, pp. 231–245.

Bellis, L.M., Pidgeon, A.M., Radeloff, V.C., St-Louis, V., Navarro, J.L., Martella, M.B., 2008. Modeling habitat suitability for greater rheas based on satellite image texture. Ecol. Appl. 18, 1956–1966.

Bisigato, A.J., Villagra, P.E., Ares, J.O., Rossi, B.E., 2009. Vegetation heterogeneity in Monte Desert ecosystems: a multi-scale approach linking patterns and processes. J. Arid Environ. 73, 182–191.

Bivand, R.S., Pebesma, E., Gomez-Rubio, V., 2013. Applied Spatial Data Analysis with R, second ed. Springer, NY Available at: <http://www.asdar-book.org/>.

Bradley, B.A., Olsson, A.D., Wang, O., Dickson, B.G., Pelech, L., Sesnie, S.E., Zachmann, L.J., 2012. Species detection vs. habitat suitability: are we biasing habitat suitability models with remotely sensed data? Ecol. Model. 244, 57–64.

Campos, C.M., Campos, V.E., Miguel, F., Cona, M.I., 2016a. Management of protected areas and its effect on an ecosystem function: removal of *Prosopis flexuosa* seeds by mammals in Argentinian drylands. PLoS ONE 11 (9), e0162551. http://dx.doi.org/10.1371/journal.pone.0162551.

Campos, V.E., Gatica, G., Bellis, L., 2015. Remote sensing variables as predictors of habitat suitability of the viscacha rat (*Octomys mimax*), a rock-dwelling mammal living in a desert environment. Mamm. Res. 60, 117–126.

Campos, V.E., Cappa, F.M., Fernández Maldonado, V., Giannoni, S.M., 2016b. Using remotely sensed data to model suitable habitats for tree species in a desert environment. J. Veg. Sci. 27, 200–210.

Cesca, E.M., Passera, C., Villagra, P., Alvarez, J.A., 2012. Effect of *Prosopis flexuosa* on understory species and its importance to pastoral management in woodlands of the Central Monte Desert. Rev. FCA UNCUYO 44, 207–219.

Cortez, E., Borghi, C.E., Giannoni, S.M., 2005. Plan de manejo Parque Provincial Ischigualasto, fase I y II. Ente Autárquico Ischigualasto, Gobierno de San Juan. San Juan, Argentina.

Crawley, M.J., 2007. The R Book. John Wiley and Sons, London, England.

Cribari-Neto, F., Zeileis, A., 2010. Beta Regression in R. J. Stat. Softw. 34, 1–24. Available at: <http://www.jstatsoft.org/v34/i02/>.

ENVI, 2015. Environment for Visualizing Images. Version 5.3. Research Systems, Boulder, Colorado, USA.

Estes, L.D., Okin, G.S., Mwangi, A.G., Shugart, H.H., 2008. Habitat selection by a rare forest antelope: a multi-scale approach combining field data and imagery from three sensors. Remote Sens. Environ. 112, 2033–2050.

Gaitán, J.J., Bran, D., Oliva, G., Ciari, G., Nakamatsuc, V., Salomone, J., Ferrante, D., Buono, G., Massarad, V., Humano, G., Celdrán, D., Opazoc, W., Maestre, F.T., 2013. Evaluating the performance of multiple remote sensing indices to predict the spatial variability of ecosystem structure and functioning in Patagonian steppes. Ecol. Indic. 34, 181–191.

Ge, S., Carruthers, R., Gong, P., Herrera, A., 2006. Texture analysis for mapping *Tamarix parviflora* using aerial photographs along the Cache Creek, California. Environ. Monit. Assess. 114, 65–83.

Goirán, S.B., Aranibar, J.N., Gomez, M.L., 2012. Heterogeneous spatial distribution of traditional livestock settlements and their effects on vegetation cover in arid groundwater coupled ecosystems in the Monte Desert (Argentina). J. Arid Environ. 87, 188–197.

Gould, W., 2000. Remote sensing of vegetation, plant species richness, and regional biodiversity hotspots. Ecol. Appl. 10, 1861–1870.

Hall-Beyer, M., 2007. The GLCM Tutorial Home Page. Current Version 2.10. Available at: <http://www.fp.ucalgary.ca/mhallbey/tutorial.htm>.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 15, 850–853.

Haralick, R.M., Shanmugam, K., Dinstein, I., 1973. Textural features for image classification. IEEE Trans. Syst. Man Cybern. SMC-3, 610–621.

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25, 295–309.

Labraga, J.C., Villalba, R., 2009. Climate in the Monte Desert: past trends, present conditions, and future projections. J. Arid Environ. 73, 154–163.

Lavers, C.P., Field, R., 2006. A resource-based conceptual model of plant diversity that reassesses causality in the productivity–diversity relationship. Global Ecol. Biogeogr. 15, 213–224.

Lawley, V., Lewis, M., Clarke, K., Ostendorf, B., 2015. Site-based and remote sensing methods for monitoring indicators of vegetation condition: an Australian review. Ecol. Indic. 60, 1273–1283.

Márquez, J., Martínez Carretero, E., Dalmasso, A., Pastrán, G., Ortiz, G., 2005. Las áreas protegidas de la provincia de San Juan (Argentina) II. La vegetación del Parque Provincial de Ischigualasto. Multequina. Lat. Am. J. Nat. Resour. 14, 1–27.

Marsett, R.C., Qi, J., Heilman, P., Biedenbender, S.H., Watson, M.C., Amer, S., Weltz, M., Goodrich, D., 2006. Remote sensing for grassland management in the arid southwest. Rangel. Ecol. Manage. 59, 530–540.

Matsushita, B., Yang, W., Chen, J., Onda, Y., Qiu, G., 2007. Sensitivity of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to topographic effects: a case study in high-density cypress forest. Sensor 7, 2636–2651.

Mücher, C.A., Klijn, J.A., Wascher, D.M., Schaminée, J.H.J., 2010. A new European Landscape Classification (LANMAP): a transparent, flexible and user-oriented methodology to distinguish landscapes. Ecol. Indic. 10, 87–103.

Nagendra, H., 2001. Using remote sensing to assess biodiversity. Int. J. Remote Sens. 22, 2377–2400.

Noss, R.F., 1990. Indicators for monitoring biodiversity – a hierarchical approach.

Conserv. Biol. 4, 355–364.

Oliver, I., 2002. An expert panel-based approach to the assessment of vegetation condition within the context of biodiversity conservation: Stage 1. The identification of condition indicators. Ecol. Indic. 2, 223–237.

Palmer, M.W., Earls, P., Hoagland, B.W., White, P.S., Wohlgemuth, T., 2002. Quantitative tools for perfecting species lists. Environmetrics 13, 121–137.

E.J. Pebesma R.S. Bivand 2005 Classes and methods for spatial data in R R News 5 2 <https://cran.r-project.org/doc/Rnews/> Available at:.

Pyke, D.A., Pellant, M., Shaver, P., Herrick, J.E., 2002. Rangeland health attributes and indicators for qualitative assessment. J. Range Manage. 55, 584–597.

Quantum GIS Version 2.18.2 "Las Palmas" Development Team, 2016. QGIS Geographic Information System. Open Source Geospatial Foundation Project. Available at: < http://qgis.osgeo.org/ > (accessed 21.02.17).

R Core Team, 2017. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria Available at: <http://www.R-project.org/>.

Ribeiro, P.J. Jr., Diggle, P.J., 2016. geoR: Analysis of Geostatistical Data. R Package Version 1.7-5.2. Available at: < https://CRAN.R-project.org/package=geoR > .

Rocchini, D., 2007. Effects of spatial and spectral resolution in estimating ecosystem-diversity by satellite imagery. Remote Sens. Environ. 111, 423–434.

Rocchini, D., Chiarucci, A., Loiselle, S.A., 2004. Testing the Spectral Variation Hypothesis by using satellite multispectral images. Acta Oecol. 26, 117–120.

Rossi, B.E., Villagra, P.E., 2003. Effects of *Prosopis flexuosa* on soil properties and the spatial pattern of understorey species in arid Argentina. J. Veg. Sci. 14, 543–550.

St-Louis, V., Pidgeon, A.M., Radeloff, V.C., Hawbaker, T.J., Clayton, M.K., 2006. Image texture in high-resolution remote sensing images as predictor of bird species richness. Remote Sens. Environ. 105, 299–312.

St-Louis, V., Pidgeon, A.M., Clayton, M.K., Locke, B.A., Bash, D., Radeloff, V.C., 2009. Satellite image texture and a vegetation index predict avian biodiversity in the Chihuahuan Desert of New Mexico. Ecography 32, 468–480.

U.S. Geological Survey, Earth Explorer, 2017. Available at: < http://earthexplorer.usgs.gov/ > (accessed 18.01.17).

Valbuena, R., Packalén, P., Martín-Fernández, S., Maltamo, M., 2012. Diversity and equitability ordering profiles applied to study forest structure. For. Ecol. Manage. 276, 185–195.

Venables, W.N., Ripley, B.D., 2002. Modern Applied Statistics with S, fourth ed. Springer, New York.

Wood, E.M., Pidgeon, A.M., Radeloff, V.C., Keules, N.S., 2012. Image texture as a remotely sensed measure of vegetation structure. Remote Sens. Environ. 121, 516–526.

Wood, E.M., Pidgeon, A.M., Radeloff, V.C., Keuler, N.S., 2013. Image texture predicts avian density and species richness. PLoS ONE 8 (5), e63211. http://dx.doi.org/10.1371/journal.pone.0063211.

Wulder, M.A., LeBrew, E.F., Franklin, S.E., Lavigne, M.B., 1998. Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). Remote Sens. Environ. 64, 64–76.

Zar, J.H., 1999. Biostatistical analysis. Prentice-Hall, USA.

Zenner, E.K., Hibbs, D.E., 2000. A new method for modeling the heterogeneity of forest structure. For. Ecol. Manage. 129, 75–87.

Zuur, A., Ieno, E.N., Walker, N., Saveliev, A.A., Smith, G.M., 2009. Mixed Effects Models and Extensions in Ecology with R. Springer, New York, USA.