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Using remotely sensed data to model suitable habitats for tree species in a desert environment

Valeria E. Campos, Flavio M. Cappa, Fernández Maldonado Viviana & Stella M. Giannoni

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Brightness index; Conservation; Desert environment; Global Digital Elevation Model; Habitat generalist; Habitat specialist; Plant habitat suitability; Remote sensing data; Texture measures; Woodlands

Nomenclature
Kiesling (1994, 2003) for plants

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Campos, V.E. (corresponding author, vcampos@unsj-cuim.edu.ar)[1,2],
Cappa, F.M. (flaviocappa@unsj-cuim.edu.ar)[1,2],
Viviana, F.M. (vivifernandezm@unsj-cuim.edu.ar)[1,2],
Giannoni, S.M. (sgiannoni@unsj-cuim.edu.ar)[1,2,3]

[1]Interacciones Biológicas del Desierto (INTERBIODES), Av. I. de la Roza 590 (O), J5402DCS Rivadavia, San Juan, Argentina;
[2]CIGEOBIO, UNSJ CONICET, Universidad Nacional de San Juan- CUIM, Av. I. de la Roza 590 (O), J5402DCS Rivadavia, San Juan, Argentina;
[3]Departamento de Biología, Facultad Ciencias Exactas, Físicas y Naturales (Universidad Nacional de San Juan), Av. I. de la Roza 590 (O), J5402DCS Rivadavia, San Juan, Argentina

Abstract

Questions: Can the species–environment relationship be understood using current remote sensing techniques? Can the derived indicators of remotely sensed data serve as a proxy for variables that affect habitat suitability of plant species? Which remote sensing predictors are best associated with woody species occurrence in a desert environment? How well do models with derived indicators of remotely sensed data predict the occurrence of these species? What are the potential distributions of *Ramorinoa girolae*, *Prosopis* spp. and *Bulnesia retama* in the study area?

Location: Ischigualasto Provincial Park, San Juan province, Argentina.

Methods: We selected random field points from a Landsat 8 OLI to determine presence/absence of trees species. We calculated Brightness index (BI) using the same image and used this index to calculate texture measures on a 3 × 3 moving window size. We used the following subset of texture measures: (1) first-order: range, (2) second-order: mean, variance, contrast, entropy, second moment and correlation. We also calculated Topographic Wetness Index (TWI), slope angle and slope aspect from Global Digital Elevation Model.

Results and Conclusion: Second-order mean of BI had an important effect on the occurrence of target trees species. TWI was an important variable for *Prosopis* spp. and *B. retama*, whereas slope angle was important for *R. girolae* and *B. retama*. In addition, the occurrence of *R. girolae* was affected by second-order variance of BI and slope aspect; and the presence of *B. retama* was affected by second-order contrast of BI. All the variables that had important effects on the occurrence of tree species provide environmental information about their different habitat requirements; therefore, our findings indicate that the remote sensing data are reliable to derive indicators of tree species presence in our study area.

Introduction

Habitat suitability models are being increasingly used to assess the impact of future land use or climate changes (Austin et al. 1996; Buckland et al. 1996; Peterson et al. 2002; Thuiller 2003). Remotely sensed data can directly measure or serve as a proxy for variables that affect habitat suitability of species, and are therefore widely recognized for their applicability to ecological research. These data can even improve the overall accuracy of prediction models (see review of Bradley et al. 2012). Remotely sensed measures of vegetation productivity, such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), have been extensively used as predictors of habitat characteristics associated with animal distribution and abundance (Pettorelli et al. 2005, 2011). Moreover, applications for plant habitat modelling are on the rise; indeed, a number of recent studies have applied vegetation proxies or land-cover data to models of habitats for plant species (see review of Bradley et al. 2012). Classification of vegetation in predictive modelling studies is usually not desirable, especially for plant species where circularity would be introduced when using plant communities as predictors. Problems with introduced bias are less likely to occur if the remotely sensed variables do not measure vegetation directly but consider habitat characteristics of the species (Sellars & Jolls 2007; Cord et al. 2010; Bradley et al. 2012).

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The ecological traits of the target species can influence the accuracy of predictions. Brotons et al. (2004) observed difficulties in obtaining accurate estimates for generalist species, regardless of the modelling approach used, because of the high number of factors determining their distributions (Osborne & Suárez-Seoane 2002; Suárez-Seoane et al. 2008). In contrast, models for specialist species show better performance given by the narrow ecological niches of specialists (McPherson et al. 2004; Tsoar et al. 2007; Morán-Ordóñez et al. 2012). Understanding and relating the species–environment relationship to current and evolving remote sensing techniques are relevant steps for the understanding of the complexity of realized ecological niche of species (Zimmermann et al. 2007).

Spatial heterogeneity in a wide range of abiotic features (elevation, aspect, soil type, rainfall patterns, snow accumulation) leads to a non-random plant distribution in the landscapes (Searle et al. 2010). In the Monte Desert of Argentina, as suggested for other desert zones, distribution of plant species seems to result from the existence of a dual gradient – edaphic factors and distance from watercourses – producing significant differences in floristic composition (Acebes et al. 2010). In this region, woody plants produce changes in microclimate (temperature, evaporation, light intensity) and soil properties under their canopy through nutrient accumulation. These conditions favour the establishment of plant species, increase total biodiversity of the system thereby facilitating biological interactions, and reduce the eroding effects of wind and water (Villagra 2000; Rossi & Villagra 2003; Cesca et al. 2012; Campos et al. 2013).

Delineating suitable habitats based on physical habitat variables may contribute to the conservation of suitable habitat areas and the identification of potential habitat for species restoration or reintroduction. Accordingly, our main goal was to evaluate the applicability of remotely sensed information for modelling habitat suitability for woody species with different habitat requirements in a desert environment. We proposed to determine (1) the remotely sensed data that are best associated with the occurrence of tree species in the study area; and (2) the potential of these variables for predicting suitable habitats for these species.

Methods

Study area

The study was conducted in Ischigualasto Provincial Park (IPP), San Juan province, Argentina (29°55′ S, 68°05′ W; Fig. 1). The park extends over an area of 62 916 ha and is located in a hyper-arid sector of the Monte Desert, which corresponds to the centre of the Monte of hills and closed basins (Monte de Sierras y Bolsones). Average annual precipitation is 100 mm (Labraga & Villalba 2009). Temperature is characterized by considerable day/night variations and a wide range throughout the year, with absolute maximum and minimum values of 46.2 and 12.8 °C in summer, and 39.4 and 9.9 °C in winter, respectively (Campos 2012). The study area is dominated

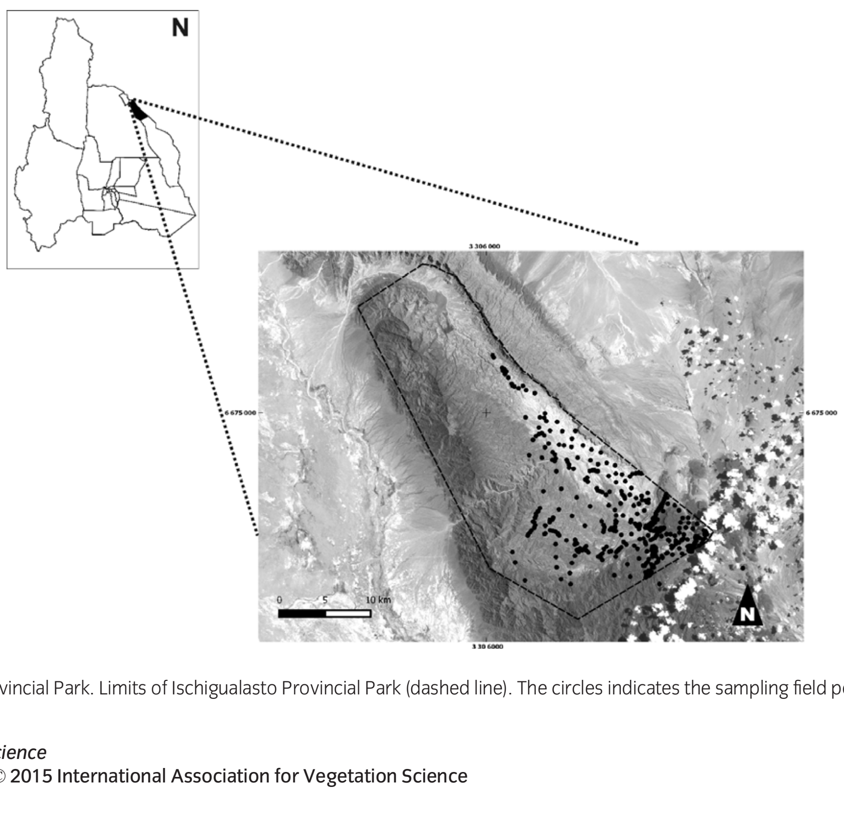

Fig. 1. Ischigualasto Provincial Park. Limits of Ischigualasto Provincial Park (dashed line). The circles indicates the sampling field points.

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by rocky 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, and has a heterogeneous distribution ranging from 5% to 80% (Márquez et al. 2005).

Target species

The Monte Desert is home to key woody species due to the ecosystem services they provide: *Ramorinoa girolae* (Speg. 1924), *Prosopis flexuosa* (Burkart 1976), *P. chilensis* (Burkart 1976) and *Bulnesia retama* (Gillies ex Hook. & Arn. 1874). These selected target species are dominant in the woody vegetation due to their ability to tolerate drought, extreme temperatures and adverse edaphic conditions. *R. girolae* is associated with rocky hillsides (Hadad et al. 2014) and was categorized as vulnerable due to its restricted geographic distribution, slow growth and poor fire resistance (Demaio et al. 2002). *Prosopis* species occur along riverbanks (*P. chilensis* and *P. flexuosa*) or areas with groundwater; therefore, water is available to them throughout the year, as occurs with *P. flexuosa*. According to their requirements, both species could be considered habitat specialists, and therefore would have a narrow ecological niche. Moreover, *B. retama* occurs in a wide variety of soils, from shallow stony to sandy and clay, with some degree of salinity (Dalmasso & Llera 1996); hence, it can be considered a habitat generalist with a wide ecological niche. Predictive models are most useful when the habitat variables of interest can be derived *a priori* (Wiser et al. 1998); therefore, we chose environmental habitat variables relevant to these trees, i.e. soil heterogeneity, slope angle, slope aspect and soil surface moisture.

Field survey

Fieldwork was conducted in Nov 2013. We based sampling design on a Landsat 8 OLI image (30-m resolution) of the study area (path 232, row 081) acquired on 16 Nov 2013 (http://earthexplorer.usgs.gov/). This image was stored in the Quantum GIS program (v 2.4.0 Chugiak, http://qgis.osgeo.org/), which allowed us to select 733 random field points in a logistically accessible area of IPP. This area has different substrata, such as hard and stony soil, fine substratum (sands and clays), as well as diverse topographic features. Moreover, this area harbours the six vegetation communities reported in Acebes et al. (2010). We determined presence/absence of tree species in a 15-m radius area around each field point. The total sampled area was 2189.28 ha.

Remote sensing variables

The Landsat 8 OLI image (30-m resolution) of the study area was rescaled to the Top Of Atmosphere (TOA) reflectance with a correction for the sun angle using coefficients provided in the product metadata file (MTL file). This image has cloud cover of 0.02%.

Tasseled Cap Transformation (TTC; Kauth & Thomas 1976; Crist & Cicone 1984) combines original bands of the image to create new bands in order to enhance some features of interest. The first Tasseled Cap index (Brightness Index, BI) provides data on soil signature; the second index (Greenness Index, GI) reflects vegetation characteristics and the third index (Wetness Index, WI) captures information on the interaction of soil and vegetation. BI was found to be useful to determine substratum heterogeneity in a desert because it is a measure of reflectance on the image (Martinelli 2009; Gatica 2010). We used BI to assess the type of substratum in the study area as it provides information about reflectance particularly generated by the soil.

Image texture is a remote sensing approach of spatial variability of grey level (i.e. grey shadow of pixels); hence, it contains important information about the spatial and structural arrangement of objects on an image (Haralick et al. 1973; Mihran & Jain 1998). First-order texture measures are based on the number of occurrences of each grey level within a given processing window. Second-order texture measures use a grey level spatial dependence matrix (i.e. grey level co-occurrence matrix) to calculate texture values (Haralick et al. 1973), which indicate the probability that each pair of pixel values co-occurs in a given direction and distance (Haralick et al. 1973; Mihran & Jain 1998). Some first-order texture measures are strongly correlated with second-order measures (i.e. mean, variance and entropy; Wood et al. 2012); therefore, we selected second-order measures because they considered the spatial relationships of pixels. We used the following subset of texture measures: first-order (range) and second-order (mean, variance, contrast, entropy, second moment and correlation). We calculated first-order texture measures on BI image, using a 3×3 moving window size, i.e. the pixel values within a moving window were used to calculate a statistic that was assigned to the central pixel (Haralick et al. 1973). We applied a 3×3 window size because this size has the advantage of capturing heterogeneity of pixel values over small extents (8100 m^2; Wood et al. 2012). Second-order texture measures were calculated on BI image using the same moving window, but the pixel values were first translated into a grey level co-occurrence matrix, which allowed us to consider the relationship among neighbouring pixels (Haralick et al. 1973). Second-order texture measures were calculated in four directions, i.e. from the GLCM

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computed at 0° (horizontal neighbours), 45° (diagonally right), 90° (vertically), 135° (diagonally left) and averaged (Haralick et al. 1973). Slope angle and slope aspect were modelled on the basis of a GDEM (ASTER Global DEM 30 m-resolution, with accuracy of 21.31 m at 95% confidence, http://gdex.cr.usgs.gov/gdex/) of the study area. A secondary terrain attribute was also computed from the GDEM as an indicator of soil moisture, i.e. the Topographic Wetness Index (TWI), which quantifies the role of topography in redistributing water in the landscape (Beven & Kirkby 1979). All environmental variables were finally stored as separate layers in the GIS and were extracted for each sampling field point. We used Quantum GIS, SAGA GIS (v 2.1.2, http://www.saga-gis.org/en/index.html) and ENVI GIS (ENVI 2004, Research Systems, Boulder, CO, US) to calculate and obtain the predictor data.

Model building

We parameterized generalized linear models (GLMs) with remotely sensed independent variables and with presence points (1) vs absence points (0) for each tree species as response variables (binomially distributed). We used information-theoretic (I-T) methods described by Burnham & Anderson (2002) to model the data, based on the second-order Akaike information criterion (AIC), which is defined as -2 L + 2 K (L is the maximum log-likelihood of the model and K is the number of parameters in the model; Akaike 1973). The I-T method provides a formal and robust approach that develops a set of hypotheses *a priori* and ranks those hypotheses by quantifying data-based evidence (multimodel inference; Burnham & Anderson 2002; Burnham et al. 2011). Models were compared with ΔAIC, which is the difference between the lowest AIC value (i.e. the best of suitable models) and AIC from all the other models. We considered Akaike weight of a model (w_i), which determines the relative likelihood that the specific model is the best of the suite of all models; then we ranked the models according to their weight value and obtained quantitative measures of the strength of evidence for each one (Burnham & Anderson 2002; Burnham et al. 2011). The w_i for a model is exp(-0.5*ΔAIC score for that model) divided by the sum of these values across all models (Burnham & Anderson 2002). We evaluated the support for predictor variables by summing w_i across all models that contained the parameter being considered (parameter likelihood; Burnham & Anderson 2002). Parameter estimates were calculated using model-averaged parameter estimates based on w_i from all candidate models. To supplement parameter-likelihood evidence of important effects, we calculated 95% confidence interval limits (CL) of parameter estimates.

To obtain presence/absence data for model building for each species, first we selected field points of presence for the species separated by at least 100 m between individuals. Then, to obtain the absence data, we selected field points separated by at least 100 m between them and with presence points of this species. Sometimes presence and absence points were separated by <100 m, so we preferred to keep presence points. We did not evaluate habitat suitability for co-existence of species; therefore, absence points for target species were considered specifically for each species, regardless of the presence of some of the other target species (one or two) or of neither of them, e.g. absence points for *R. girolae* were points where *R. girolae* was absent but with probable presence of either *Prosopis* spp. or *B. retama*, both of them or neither of the species. After selecting sampling points, we kept 118 presence and 472 absence points for *R. girolae*, 156 presence and 308 absence points for *Prosopis* spp., and 128 presence and 444 absence points for *B. retama*. Finally, presence/absence data for each tree species was split into two subsets: training data set (70%), which was used for calibrating the models, and the testing data set (30%), which was then used to evaluate the quality of model predictions with the area under the receiver operating characteristic curve (AUC). Model performance has a useful amount of discrimination with an AUC value >0.5 (Elith et al. 2006).

To identify collinearity between independent variables we used Spearman rank correlation, a non-parametric measure of statistical dependence (Zar 1999). It is important to identify the high collinearity because this can result in coefficient estimates that are difficult to interpret as independent effects and/or have high SE (see review of Zuur et al. 2009). We excluded variables when the coefficient r was $>|0.8|$. Then, we assessed the variance inflation factor (VIFs) for any remaining collinearity on the full models from different sets and excluded variables with VIFs >5, which indicate collinearity between predictors (Heiberger & Holland 2004). To check for spatial autocorrelation among sampling points, we fitted semivariograms with the Pearson residuals of the models containing all explanatory variables (Zuur et al. 2009). We did not find evidence of spatial dependence affecting the models.

All statistical analyses were performed using R (2014, http://www.R-project.org/). We assessed the VIFs using 'HH' package (Heiberger & Robbins 2014). The pattern of spatial autocorrelation was evaluated using the 'sp' (Pebesma & Bivand 2005; Bivand et al. 2008) and 'geoR' (Ribeiro & Diggle 2001; Diggle & Ribeiro 2007) packages. The models were selected with 'MuMIn' package (Barton 2013, R package v 1.9.5. http://CRAN.R-project.org/package=MuMIn). The spatial dependence in the final model was evaluated using 'ROCR' (Sing et al. 2005) package for R.

We constructed habitat suitability maps of the best model of tree species (Figs 2–4), using ENVI GIS and Quantum GIS. The equations of the best models predict the occurrence of tree species categorized into four probability classes.

Results

After performing the correlation analysis, we eliminated variables that were strongly correlated with one another ($r > |0.8|$; i.e. first-order range, second-order entropy, second moment and correlation; Appendices S1-S3); thus, we retained second-order mean, variance, contrast, and variables from GDEM (i.e. slope angle, slope aspect and TWI) for further analysis.

The best model explaining occurrence of *R. girolae* included contrast, mean, variance, slope angle and slope aspect (Table 1). This model had a good performance (AUC 0.70). The probability of occurrence of *R. girolae* was higher with increasing variance and slope angle, but decreased with increasing mean and slope aspect (Table 2). For *Prosopis* spp., w_i of the first and second models was 0.12 (Table 3); however, the best model was the first one because it included the lowest number of parameters, i.e. it was the most parsimonious (Burnham et al. 2011). This model included mean and TWI; the probability of occurrence of *Prosopis* spp. was higher with increasing values of these variables (Table 4). The best model had a good performance (AUC 0.71). The best model for the occurrence of *B. retama* included contrast, mean, TWI and slope angle (Table 5). The probability of occurrence of this species was inversely related to all the variables included in this model (Table 6). This model had a good performance of 0.76.

Discussion

Habitat features have a large influence on plant distribution; remote sensing data provide information about habitat variables at high spatial and temporal resolution and can be quantified across broad extents (Bradley et al. 2012). In this study the high quality of the predictions provided by the selected model indicates that remote sensing data are reliable to derive indicators of tree species presence in our study area. The second-order mean of BI had an important effect on the occurrence of trees species. TWI was an important variable for *Prosopis* spp. and *B. retama*, whereas slope angle was important for *R. girolae* and *B. retama*. Moreover, the occurrence of *R. girolae* was affected by second-order variance of BI and slope aspect, and the occurrence of *B. retama* was affected by second-order contrast of BI. All these variables that had an important effect on the occurrence of trees species provide environmental information about different habitat requirements.

Second-order mean was included in the best model for *R. girolae*; this measure represents the average distribution of grey level (Haralick et al. 1973). The mean texture of BI

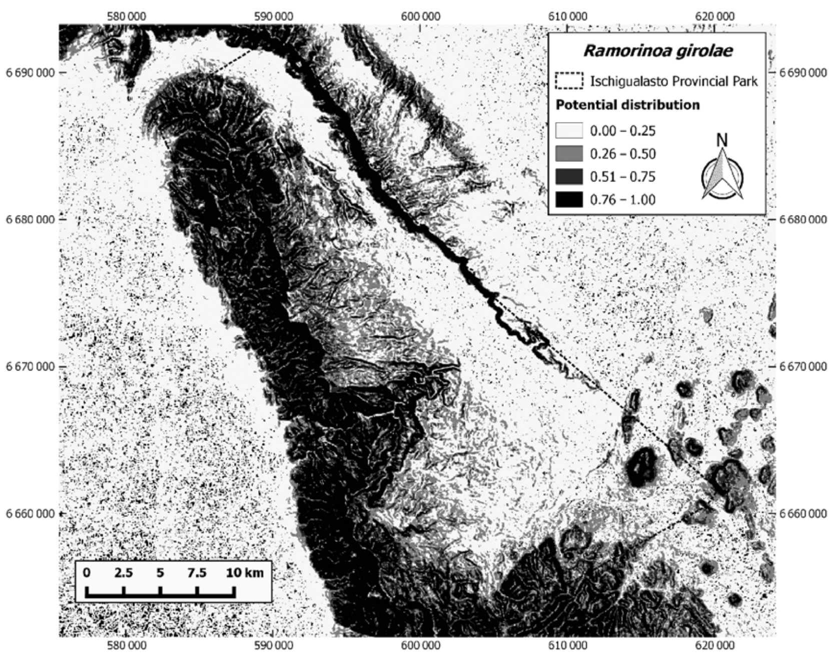

Fig. 2. Potential distribution of *R. girolae*. Probability area for occurrence of *R. girolae* categorized into four probability classes according to the best model.

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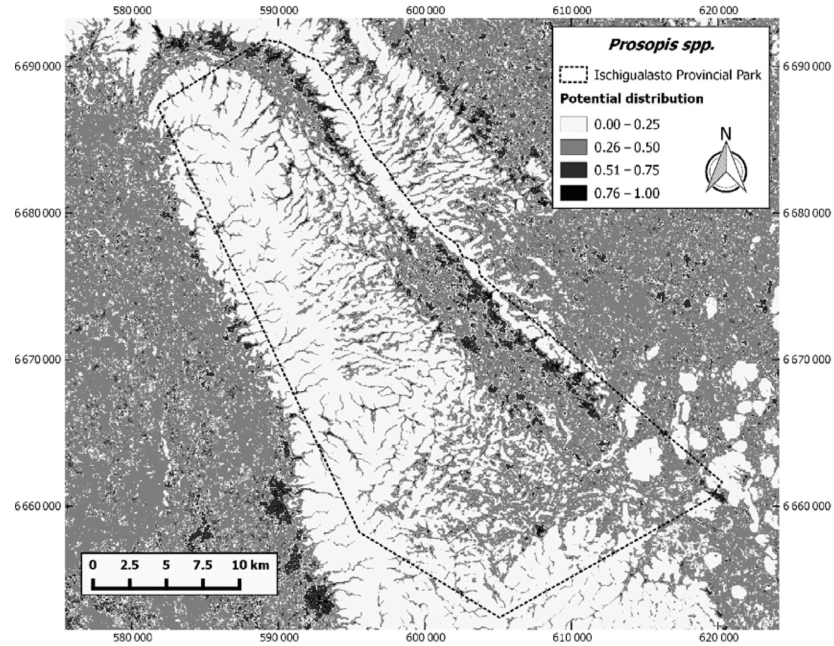

Fig. 3. Potential distribution of *Prosopis* spp. Probability area for occurrence of *Prosopis* spp. categorized into four probability classes according to the best model.

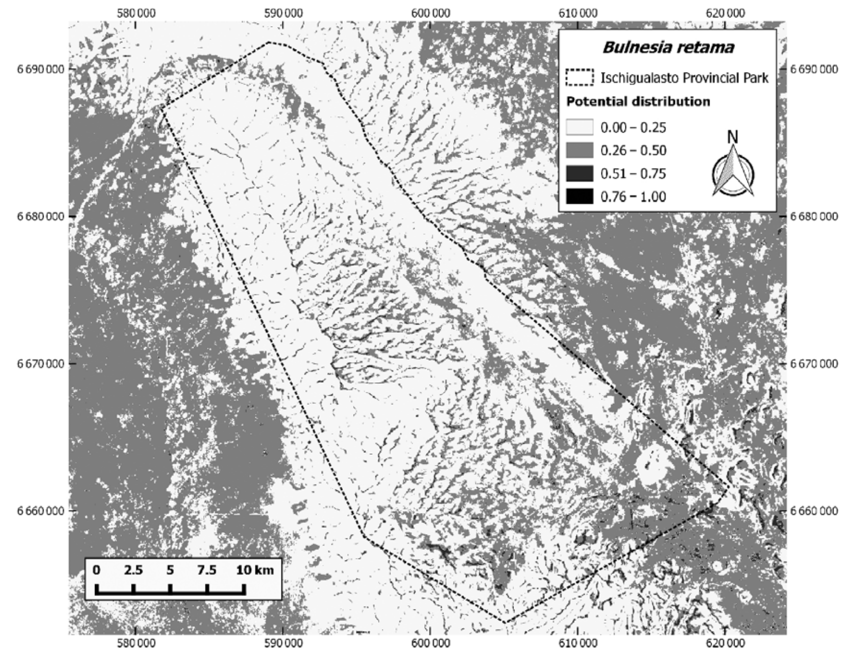

Fig. 4. Potential distribution of *B. retama*. Probability area for occurrence of *B. retama* categorized into four probability classes according to the best model.

was lower on occurrence points than on absence points because low mean values indicate less bright areas, such as the rocky substratum (Campos et al. 2015), where this species occurs. Variance was also included in the best model; this measure is ecologically relevant since it captures textural heterogeneity (Wood et al. 2012). Previous studies found that variance or entropy applied on vegetation index captured the variation of foliage height diversity

Table 1. Summarized results of selection of models explaining the occurrence of *R. girolae* in relation to the second-order texture measures (calculated from Brightness Index in a 3 × 3 moving window), and variables from GDEM. *k* is the number of estimated parameters. Models with Δ_i < 2; univariate models and the null model are shown and listed in decreasing order of importance.

Model	*k*	AIC	Δ_i	w_i
CONT + MN + VAR + SLO + ASP	6	367.74	0.00	0.20
CONT + MN + TWI + VAR + SLO + ASP	7	368.49	0.75	0.14
MN + ASP + SLO + VAR	5	368.65	0.91	0.12
CONT + MN + TWI + VAR + ASP	6	368.86	1.12	0.11
MN + TWI + VAR + SLO + ASP	6	369.58	1.84	0.08
VAR	2	395.53	27.79	<0.00
SLO	2	396.02	28.28	<0.00
TWI	2	398.26	30.51	<0.00
CONT	2	400.41	32.67	<0.00
MN	2	402.31	34.57	<0.00
ASP	2	408.80	41.06	<0.00
Null	1	510.85	56.72	<0.00

Second-order texture measure: MN, mean; VAR, variance; CONT, contrast. GDEM: ASP, slope aspect; SLO, slope angle; TWI, topographic wetness index.

Table 2. Parameter likelihoods, estimates (±SE) and 95% confidence interval limits (CL) for explanatory variables describing the occurrence of *R. girolae*: considering the second-order texture measures (calculated from Brightness Index in a 3 × 3 moving window), and variables from GDEM. Explanatory variables with CL excluding zero are in bold.

Explanatory Variable	Parameter Likelihood	Parameter Estimate ± SE	CL	
			Lower	Upper
Intercept		**4.94 ± 3.31**	**−1.67**	**11.56**
MN	**1.00**	**−0.18 ± 0.05**	**−0.28**	**−0.08**
VAR	**0.92**	**0.18 ± 0.09**	**0.01**	**0.35**
ASP	**0.77**	**−0.00 ± 0.00**	**−0.01**	**−1.22e-04**
SLO	**0.73**	**0.18 ± 0.08**	**0.01**	**0.24**
CONT	0.67	0.10 ± 0.05	−0.01	0.21
TWI	0.57	−0.31 ± 0.19	−0.70	0.06

Second-order texture measure: MN, mean; VAR, variance; CONT, contrast. GDEM: ASP, slope aspect; SLO, slope angle; TWI, topographic wetness index.

Table 3. Summarized results of selection of models explaining the occurrence of *Prosopis* spp. in relation to the second-order texture measures (calculated from Brightness Index in a 3 × 3 moving window), and variables from GDEM. *k* is the number of estimated parameters. Models with Δ_i < 2, univariate models and the null model are shown and listed in decreasing order of importance.

Model	*k*	AIC	Δ_i	w_i
MN + TWI	3	403.04	0.00	0.12
MN + TWI + SLO	4	403.13	0.10	0.12
CONT + MN + TWI + SLO	5	403.86	0.82	0.08
CONT + MN + TWI	4	403.97	0.93	0.08
MN + TWI + SLO + ASP	4	404.26	1.22	0.07
MN + TWI + SLO + VAR	5	404.33	1.30	0.07
MN + TWI + VAR	4	404.34	1.31	0.06
MN + TWI + ASP	4	404.37	1.33	0.06
CONT + MN + TWI + SLO + ASP	6	404.84	1.80	0.05
TWI	2	407.22	4.19	0.02
SLO	2	420.57	17.54	<0.00
MN	2	420.84	17.81	<0.00
Null	1	423.15	20.11	<0.00
VAR	2	424.37	21.34	<0.00
CONT	2	424.58	21.54	<0.00
ASP	2	424.78	21.74	<0.00

Second-order texture measure: MN, mean; VAR, variance; CONT, contrast. GDEM: ASP, slope aspect; SLO, slope angle; TWI, topographic wetness index.

Table 4. Parameter likelihoods, estimates (± SE) and 95% confidence interval limits (CL) for explanatory variables describing the occurrence of *Prosopis* spp.: considering: the second-order texture measures (calculated from Brightness Index in a 3 × 3 moving window), and variables from GDEM. Explanatory variables with CL excluding zero are in bold.

Explanatory Variable	Parameter Likelihood	Parameter Estimate ± SE	CL	
			Lower	Upper
Intercept		**−10.97 ± 2.79**	**−16.54**	**−5.40**
TWI	**1.00**	**0.61 ± 0.17**	**0.28**	**0.95**
MN	**0.92**	**0.10 ± 0.04**	**0.03**	**0.18**
SLO	0.50	0.10 ± 0.07	−0.03	0.24
CONT	0.37	−0.04 ± 0.05	−0.13	0.05
ASP	0.36	−0.00 ± 0.00	−3.36e-03	1.26e-03
VAR	0.32	−0.04 ± 0.08	−0.19	0.11

Second-order texture measure: MN, mean; VAR, variance; CONT, contrast. GDEM: ASP, slope aspect; SLO, slope angle; TWI, topographic wetness index.

and horizontal vegetation structure within savannas (Wood et al. 2012). Variables obtained from GDEM, such as slope angle and slope aspect, were relevant to the occurrence of *R. girolae*. Our results are consistent with findings reported by Hadad et al. (2014), who indicated that this species principally occupies the middle area of rocky hillsides, i.e. areas with a steep slope.

Phreatic aquifers can make an important contribution to the water balance of desert ecosystems, with this flux depending strongly on topography and species composition (Jobbágy et al. 2011). *P. flexuosa* occurrence does not depend on watercourses because it is a facultative phreatophyte species (Jobbágy et al. 2011) that can reach groundwater (Roig 1985). On the other hand, *P. chilensis* is strongly linked to water presence; therefore, it is the dominant species along margins of dry watercourses, which occasionally contain water after heavy rains (Acebes et al. 2010). TWI, an indicator of soil moisture, was positively related to the occurrence of *Prosopis* spp. This index combines local upslope contributing area and

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Table 5. Summarized results of selection of models explaining the occurrence of *B. retama* in relation to the second-order texture measures (calculated from Brightness Index in a 3 × 3 moving window), and variables from GDEM. *k* is the number of estimated parameters. Models with $\Delta_i < 2$, univariate models and the null model are shown and listed in decreasing order of importance.

Model	k	AIC	Δ_i	w_i
CONT + MN + TWI + SLO	5	414.75	0.00	0.32
CONT + MN + TWI + SLO + ASP	6	415.20	0.45	0.25
CONT + MN + TWI + SLO + VAR	6	416.68	1.93	0.12
CONT	2	424.63	9.88	<0.00
VAR	2	431.20	16.45	<0.00
MN	2	433.41	18.66	<0.00
SLO	2	438.22	23.47	<0.00
Null	1	438.73	23.98	<0.00
TWI	2	439.51	24.76	<0.00
ASP	2	440.54	25.79	<0.00

Second-order texture measure: MN, mean; VAR, variance; CONT, contrast. GDEM: ASP, slope aspect; SLO, slope angle; TWI, topographic wetness index.

Table 6. Parameter likelihoods, estimates (± SE) and 95% confidence interval limits (CL) for explanatory variables describing the occurrence of *B. retama*: considering the second-order texture measures (calculated from Brightness Index in a 3 × 3 moving window), and variables from GDEM. Explanatory variables with CL excluding zero are in bold.

Explanatory Variable	Parameter Likelihood	Parameter Estimate ± SE	CL	
			Lower	Upper
Intercept		**8.33 ± 3.09**	**1.97**	**14.69**
CONT	**0.97**	**−0.32 ± 0.11**	**−0.56**	**−0.08**
TWI	**0.96**	**−0.53 ± 0.18**	**−0.88**	**−0.17**
SLO	**0.96**	**−0.30 ± 0.11**	**−0.51**	**−0.09**
MN	**0.86**	**−0.09 ± 0.04**	**−0.18**	**−0.01**
ASP	0.44	0.00 ± 0.00	−8.90e-04	3.80e-03
VAR	0.30	−0.06 ± 0.15	−0.36	0.24

Second-order texture measure: MN, mean; VAR, variance; CONT, contrast. GDEM: ASP, slope aspect; SLO, slope angle; TWI, topographic wetness index.

slope, and has been useful for predicting the spatial distribution of vascular plant species richness in the Swedish boreal forest (Zinko 2004). Another important variable was the second-order mean of BI, with higher values of suitable habitat indicating brighter areas, such as the sandy substratum of watercourses.

Bulnesia retama is a generalist species that inhabits a wide variety of soils; its abundance in IPP is highest in creosote bush scrub, a plant community that occurs on hard, stony and heterogeneous soils (Acebes et al. 2010). Furthermore, it occurs in lower abundance in a saltbush community on fine sandy-silty and disaggregated soils. Both communities are on flat areas with gentle and mild slopes (Bisigato et al. 2009). Our results showed that second-order mean, contrast and slope angle are good continuous spatial measurements of habitat quality for *B. retama* because they were able to detect important features of the landscape for this species. Moreover, TWI was negatively related to the occurrence of *B. retama*, probably because this species has little dependence on groundwater, indicating occasional or opportunistic phreatophitic activity (Jobbágy et al. 2011).

Habitat is defined in Kearney (2006) as the physical characteristics of the place where an organism either actually or potentially lives; thus, a habitat suitability model projects suitable habitat for that organism. Here, we modelled the potential habitat of tree species and, to avoid bias, as suggested by Bradley et al. (2012), we excluded proxies, i.e. green indices or land-cover data that could indicate their current distribution. We discriminated between suitable and unsuitable habitats across IPP by using distribution (presence/absence) of species and remote sensing data. Thus, we were able to predict areas of high probability of occurrence for our target tree species. Generalist species, which select habitats that differed little from the available environmental conditions, are modelled with less accurately than selective species (Hepinstall et al. 2002; Stockwell & Peterson 2002; Brotons et al. 2004; McPherson et al. 2004; Segurado & Araújo 2004; Tsoar et al. 2007). However, our models predicted the distribution of tree species with high accuracy. Probably we need to consider different scales to evaluate the distribution of *B. retama*, which at a fine scale, i.e. in IPP, is abundant on harder and coarser soils but at coarse scale, i.e. Monte Desert, it occurs in a wide variety of soils.

Continuous spatial measurements of habitat quality can be difficult to acquire across broad spatial extents (St-Louis et al. 2006, 2009; Bellis et al. 2008; Wood et al. 2012, 2013). Our findings will contribute to the identification of suitable habitats for these tree species using remotely sensed data. Predictive models that include the variables used in the present work may be useful for managers to identify patterns of occurrence of these species and therefore direct the efforts of new sampling sites and give priority to areas for conservation and restoration.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Spearman rank correlation coefficients of first- and second-order texture measures calculated from Brightness Index (BI) in a 3 × 3 moving window and variables from GDEM for *R. girolae*.

Appendix S2. Spearman rank correlation coefficients of first- and second-order texture measures calculated from Brightness Index (BI) in a 3 × 3 moving window and variables from GDEM for *Prosopis* spp.

Appendix S3. Spearman rank correlation coefficients of first- and second-order texture measures calculated from Brightness Index (BI) in a 3 × 3 moving window and variables from GDEM for *B. retama*.

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