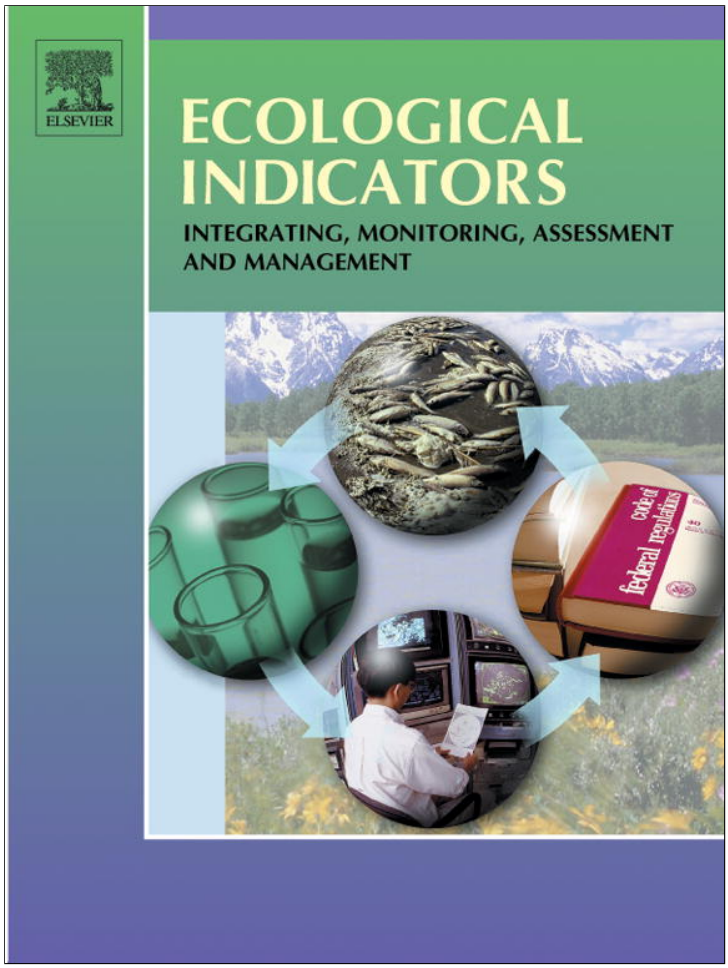

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Original article

Evaluating the performance of multiple remote sensing indices to predict the spatial variability of ecosystem structure and functioning in Patagonian steppes

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ABSTRACT

Assessing the spatial variability of ecosystem structure and functioning is an important step towards developing monitoring systems to detect changes in ecosystem attributes that could be linked to desertification processes in drylands. Methods based on ground-collected soil and plant indicators are being increasingly used for this aim, but they have limitations regarding the extent of the area that can be measured using them. Approaches based on remote sensing data can successfully assess large areas, but it is largely unknown how the different indices that can be derived from such data relate to ground-based indicators of ecosystem health. We tested whether we can predict ecosystem structure and functioning, as measured with a field methodology based on indicators of ecosystem functioning (the landscape function analysis, LFA), over a large area using spectral vegetation indices (VIs), and evaluated which VIs are the best predictors of these ecosystem attributes. For doing this, we assessed the relationship between vegetation attributes (cover and species richness), LFA indices (stability, infiltration and nutrient cycling) and nine VIs obtained from satellite images of the MODIS sensor in 194 sites located across the Patagonian steppe. We found that NDVI was the VI best predictor of ecosystem attributes. This VI showed a significant positive linear relationship with both vegetation basal cover ($R^2 = 0.39$) and plant species richness ($R^2 = 0.31$). NDVI was also significantly and linearly related to the infiltration and nutrient cycling indices ($R^2 = 0.36$ and 0.49, respectively), but the relationship with the stability index was weak ($R^2 = 0.13$). Our results indicate that VIs obtained from MODIS, and NDVI in particular, are a suitable tool for estimate the spatial variability of functional and structural ecosystem attributes in the Patagonian steppe at the regional scale.

1. Introduction

Drylands cover about 41% of Earth's land surface, and are home to more than 38% of the total global population (Millennium Ecosystem Assessment, 2005). Because of climatic restrictions, only 25% of the world's drylands are devoted to agriculture, but they are of paramount importance for grazing, as 65% of the drylands are used for grazing of managed livestock on native vegetation (Millennium Ecosystem Assessment, 2005). These areas also support 78% of the global grazing area (Asner et al., 2004), and over 50% of the world's livestock (Puigdefábregas, 1998).

The establishment and adjustment of land management practices in drylands requires routine monitoring of land functionality (Pyke et al., 2002). This is particularly important for areas that are subject to uses that can promote desertification, such as grazing (Asner et al., 2004). Measuring ecosystem functionality in situ requires assessing variables such as the retention of water and nutrients on landscapes (Valentin et al., 1999), the plant

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productivity (McNaughton et al., 1989) and soil properties related to nutrient cycling (Maestre et al., 2012). These measurements are very time-consuming and costly, and require technical equipment and expertise that may not be always available, particularly in developing countries. Therefore, methods based on easy-to-measure indicators are being increasingly used when monitoring drylands (de Soyza et al., 1997; Herrick et al., 2002; Pyke et al., 2002). A number of methodologies have been developed in the last decades for this aim, which are based on measures of structural attributes of vegetation and soil surface characteristics related to ecosystem functioning (National Research Council, 1994; Herrick et al., 2005; Tongway and Hindley, 2004). One of these methods that have attracted most attention to date is the landscape function analysis (LFA) methodology, developed in Australia by David Tongway and co-workers (Tongway, 1995; Tongway and Hindley, 2004). The LFA uses easily observable vegetation structure attributes and soil surface indicators to assess ecosystem functionality. These indicators are combined in three indices (stability, infiltration and nutrient cycling), which assess the degree to which resources tend to be retained, used and cycled within the system. Several studies have shown significant relationships between the LFA indices and quantitative measurements of these functions in multiple ecosystems and countries, including Australia (Holm et al., 2002), Iran (Ata Rezaei et al., 2006), South Africa (Parker et al., 2009), Spain (Maestre and Puche, 2009; Mayor and Bautista, 2012), and Tunisia (Derbel et al., 2009). The LFA methodology has been selected to develop the MARAS system (Spanish acronym for "Environmental Monitoring for Arid and Semi-Arid Regions"), a large-scale network of long-term monitoring sites across Patagonia (Argentina) aiming to detect early changes in ecosystem structure and function that could indicate the onset of desertification processes (Oliva et al., 2011). The first MARAS permanent sites were set up in 2008, and until now about 200 MARAS have been established. The effort and time required to collect field data for the MARAS system is costly, and this limits the number of sites that can be routinely measured.

Scaling up or extrapolating measurements from small plots to larger, more representative landscapes is an important objective of the MARAS system, as well as of similar initiatives such as Western Australian Rangelands Monitoring System (Pringle et al., 2006) or Land Degradation Assessment in Drylands (Nachtergaele and Licona-Manzur, 2009). Remote sensing tools are extremely important to achieve this objective (Ludwig et al., 2007; Reynolds et al., 2007). Field-based surveys facilitate the interpretation and extrapolation of satellite images by providing data to calibrate empirical models relating ecosystem functionality with remote sensing data (Wessman, 1994).

Vegetation indices (VIs), based on satellite observations, are mathematical transformations of reflectance measurements in different spectral bands, especially the visible (usually red) and near-infrared bands, that are widely used to obtain information about land surface characteristics (Jackson and Huete, 1991). Over the years, a great number of VIs of varying complexity have been proposed, each with advantages and limitations (Bannari et al., 1995). The most commonly used VI is the Normalized Difference Vegetation Index (NDVI, Rouse et al., 1973). Different proportions between vegetation cover and background soil may affect the relationship between NDVI and vegetation attributes in sparsely vegetated areas such as drylands (Huete and Jackson, 1988). NDVI is also sensitive to attenuation and scattering by atmospheric gases and aerosol particles (Carlson and Ripley, 1997). Thus, several alternative VIs have been developed to account for factors such as the background soil (e.g. the Soil-Adjusted Vegetation Index – SAVI –, Huete, 1988), or the atmosphere (e.g. the Atmospherically Resistant Vegetation Index – ARVI –, Kaufman and Tanre, 1992). A wide range of satellite sensors has been used to construct VIs. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor represents a suitable compromise between spatial and temporal resolution, as it provides free-cost products with atmospherically corrected and georeferenced surface reflectances at spatial resolutions down to 250 m, and with temporal frequencies ranging from 1 to 16 days (Justice et al., 1998). Thus, the use of MODIS images to calibrate field-obtained indicators of ecosystem structure and functioning is highly attractive, particularly when economical and/or technical constraints preclude the use of images with higher spatial resolution.

Recent studies have shown that NDVI can satisfactorily predict LFA indices in restored mines in Australia (Ong et al., 2009) and semi-arid grasslands in Spain (García-Gómez and Maestre, 2011). However, and to the best of our knowledge, no previous study has attempted to evaluate the ability of VIs other than NDVI to predict LFA indices, or other surrogates of ecosystem functionality. We aimed to do so by evaluating the relationships between LFA indices, key features of perennial vegetation (basal cover and richness) and several VIs obtained from the sensor MODIS over a large area (800,000 km^2) in the Patagonian steppe. The objectives of this study were to: (i) test whether we can predict the spatial variability in ecosystem structure (species richness and plant cover) and functioning (LFA indices), over a large area using VIs obtained from MODIS data and (ii) evaluate which VIs are the best predictors of these ecosystem attributes.

2. Materials and methods

2.1. Study area

The study area is located in the arid and dry sub-humid sector of Patagonia, in southern Argentina (Fig. 1). This sector represents approximately 90% of the Patagonian area (except for a strip along the Andes mountains in the west with humid climate and forest vegetation). Mean annual precipitation and temperature ranging between 150 mm and 600 mm, and between 5 °C and 16 °C. The landscape consists of a system of hills and plateaus of flattened surfaces. The vegetation is dominated by shrubby steppes dominated by low-stature shrubs such as *Mulinum spinosum* Cav., *Senecio filaginoides* DC., *Senecio bracteolatus* Hook. & Arn. and *Junellia tridens* (Lag.) Moldenke intermingled with tussock grasses of the genus *Stipa*, *Poa* and *Festuca* (Patagonia phytogeographic province, Fig. 1) and by tall shrublands dominated by *Larrea divaricata* Cav., *Larrea cuneifolia* Cav. and *Larrea nitida* Cav (Monte phytogeographic province, Fig. 1). The vegetation has been overgrazed by introduced livestock since the beginning of the XXth century (León and Aguiar, 1985), leading to a strong desertification throughout the study area. According to the FAO desertification assessment methodology (FAO, 1984) del Valle et al. (1998) estimated that 35.4%, 23.5% and 8.5% of Patagonian steppes showed medium-severe, severe and very severe desertification processes, respectively.

2.2. Field sampling

This study was conducted in 194 sites located across the study area. Sites were located within ranches with a livestock management representative of the region (holding paddocks, laneways or other special use areas were avoided), and between 0.5 km and 1.5 km from permanent water bodies. Since the area sampled in the ground is smaller than the MODIS pixel size (see bellow), we located the sites in apparently homogeneous areas to ensure that the sampled area is representative of the surroundings MODIS pixels (Appendix I). We assessed the structural and functional status of each site by using a modified version of the LFA methodology (Tongway and Hindley, 2004). Assessments were conducted between 2008 and 2012 and were made during the growing season

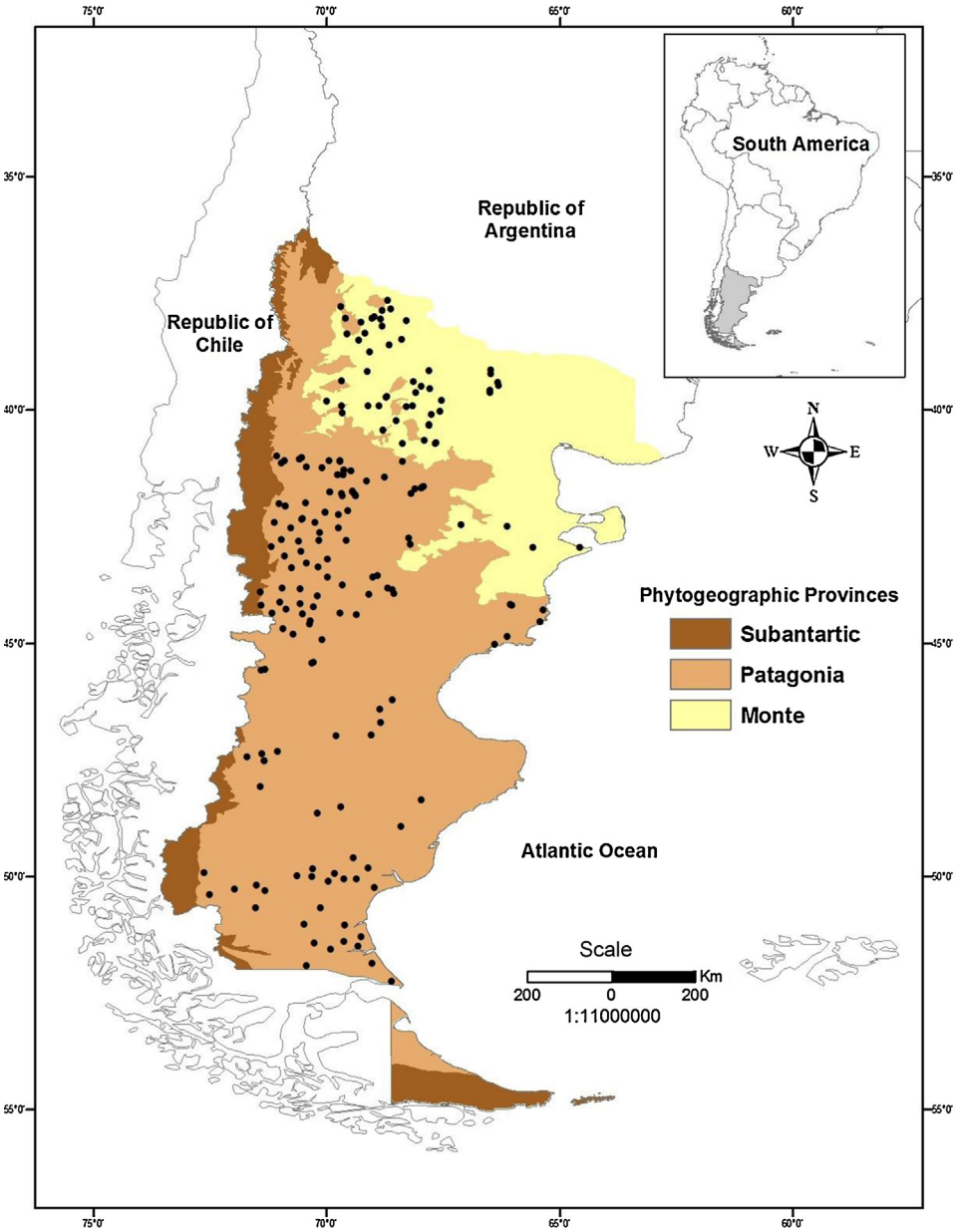

Fig. 1. Location of the study area and of the sampling sites (black dots), and boundaries of the major phytogeographical provinces. See León et al. (1998) for a detailed description of the vegetation found at these provinces.

(September to February). Within each site, we located three 50 m-long transect oriented in the main resource flow direction (slope or wind direction). On two of the transects, we conducted vegetation surveys according to the point-intercept method (Muller-Dombois and Ellenberg, 1974). In each transect, we recorded the type of interception (plant species, bare soil or litter) every 20 cm (500 records per site). The number of perennial plant species present in these transects was used as our surrogate of species richness. In the remaining transect, we collected a continuous record of vegetated and bare soil patches. In each vegetated patch we measured its width at right angles to the transect line. From this transect we obtained the following vegetation attributes: basal cover of vegetated patches (BC), number of vegetated patches per 10 m of transect (NP10m), mean vegetated patch length (VPL) and width (VPW), and mean bare soil patch length (BSL). However, we only used BC in subsequent analyses because it was correlated with the other variables ($r_{NP10m} = 0.49$, $p < 0.001$; $r_{VPL} = 0.49$, $p < 0.001$; $r_{VPW} = 0.20$, $p < 0.001$; and $r_{BSL} = -0.67$, $p < 0.001$, $n = 194$). In the first 10 bare soil patches larger than 40 cm length located along this transect, we evaluated 11 indicators of the soil surface status: total soil cover, aerial canopy cover of perennial grasses and shrub, litter cover and degree of decomposition, cover of biological soil crusts, crust brokenness, erosion type and severity, deposited materials, soil surface roughness, surface resistance to disturbance, test of soil aggregates stability and soil texture (Oliva et al., 2011). These data were combined to obtain three LFA indices: stability, infiltration and nutrient cycling. Details on how these indicators are combined to obtain the LFA indices are given elsewhere (Tongway and Hindley, 2004), and thus will not be repeated here.

2.3. Remote sensing data

Data for each site were acquired from MODIS Land Subsets (2010). We used the MOD13Q1 product, which provides 23 data per year (every 16 days) with an approximated pixel size of

Table 1
Summary of the characteristics of the vegetation index used. NIR, MIR, *R* and *B* are the reflectance value of the near infrared, medium infrared, red and blue bands, respectively, obtained from the MOD13Q1 product.

Index acronym	Algorithm	Description and use	References
NDVI: Normalized Difference Vegetation Index	NIR − *R*/NIR + *R*	This index is one of the oldest, most well known, and most frequently used indices. The combination of its normalized difference formulation and use of the highest absorption and reflectance regions of chlorophyll make it robust over a wide range of conditions. It can, however, saturate in dense vegetation conditions when LAI becomes high.	Rouse et al. (1973)
RVI: Ratio Vegetation Index	NIR/*R*	It is one of most simple indices. RVI is the ratio of the highest reflectance; absorption bands of chlorophyll makes it both easy to understand and effective over a wide range of conditions.	Jordan (1969)
DVI: Difference Vegetation Index	NIR − *R*	This index is less affected by soil background than the NDVI, especially at low leaf area index. However, it does not give proper information when the reflected wavelengths are being affected by topography, atmosphere or shadows.	Tucker (1979)
NDWI: Normalized Difference Water Index	NIR − MIR/NIR + MIR	It is sensitive to changes in liquid water content of vegetation canopies, but it is less sensitive to atmospheric effects than NDVI. Similarly to NDVI, it does not remove completely the background soil reflectance effects.	Gao (1996)
SAVI: Soil Adjusted Vegetation Index	NIR − *R*/(NIR + *R* + *L*) × (1 + *L*)	SAVI minimizes soil brightness-induced variations. *L* is a correction factor which ranges from 0 for very high vegetation cover to 1 for very low vegetation cover. The most typically used value is 0.5, which is for intermediate vegetation cover.	Huete (1988)
MSAVI2: Modified Soil Adjusted Vegetation Index	$[2 \times \mathrm{NIR} + 1 - ((2 \times \mathrm{NIR} + 1)^2 - 8 \times (\mathrm{NIR} - R))^{(1/2)}]/2$	It is a modification of the NDVI to account for areas which have a low (i.e. <40%) vegetation cover. MSAVI2 is particularly important for areas which have different soil brightness coefficients. MSAVI2 eliminates the need for the user specification of *L*.	Qi et al. (1994)
ARVI: Atmospherically Resistant Vegetation Index	NIR − (2 × *R* − *B*)/NIR + (2 × *R* − *B*)	ARVI is an enhancement to the NDVI that is relatively resistant to atmospheric factors (for example, aerosol). It uses the reflectance in blue to correct the red reflectance for atmospheric scattering. It is most useful in regions of high atmospheric aerosol content.	Kaufman and Tanre (1992)
EVI: Enhanced Vegetation Index	2.5 × NIR − *R*/(NIR + *C*1 × *R* − *C*2 × *B* + *L*)	It is an enhancement on the NDVI to better account for soil background and atmospheric aerosol effects. The coefficients adopted in the MODIS-EVI algorithm are; *L* = 1, *C*1 = 6, *C*2 = 7.5.	Huete et al. (2002)
EVI2: Two band EVI	2.5 × (NIR − *R*)/(NIR + 2.4 × *R* + 1)	EVI requires a blue band and is sensitive to variations in blue band reflectance, which limits consistency of this index across different sensors. EVI2 does not require the blue band reflectance, and has been developed by taking advantage of the autocorrelative properties of surface reflectance spectra between the red and blue wavelengths.	Jiang et al. (2008)

250 m × 250 m. These data are geometrically and atmospherically corrected, and include an index of data quality (reliability, which range from 0 – good quality data – to 4 – raw data or absent for different reasons) based on the environmental conditions in which the data was recorded (Justice et al., 1998). For each field site, we used 12 MOD13Q1 images obtained during the full growing season (September to February) of the year in which the site was surveyed. We obtained the following data: pixel reliability, reflectance in visible blue (*B* = 459–479 nm) and red (*R* = 620–670 nm) and near (NIR = 841–876) and mid-infrared (MIR = 2105–2155 nm) portions of the electromagnetic spectrum. Data were extracted for the pixel containing the field site. Additionally, and for 65 randomly selected sites, we extracted data from a 3 × 3 matrix of pixels to test whether the sampled area is homogeneous and representative of a larger area. When pixel reliability was higher than 1, reflectance data were replaced by the mean of closest dates with pixel reliability 0 or 1 to avoid using poor quality data. This was necessary in less than 5% of sites. Reflectance data for 12 dates were then averaged, and used to calculate nine of the most cited VIs in the literature (e.g. Silleos et al., 2006) and whose calculation is possible from MODIS data (Table 1).

2.4. Statistical analyses

We used linear regressions to assess the relationships between the field data (LFA indices and vegetation attributes) and the VIs. To assess the performance of the regression models conducted, we used a cross-validation procedure. For doing so, we randomly selected 154 plots (79.4% of our dataset) to generate each predictive model; the remaining 40 plots (20.6%) were set aside for validation purposes. We repeated this process 300 times to estimate the average and standard deviation of the model parameters and their validations. By contrasting predicted versus observed values we calculated the following metrics (Cohen et al., 2003): root-mean-square error (RMSE), coefficient of variation of RMSE, overall bias, and variance ratio. Statistical analyses were performed with SPSS for Windows, version 17.0 (SPSS Inc., Chicago, IL, USA).

3. Results

The study area shows strong environmental contrasts, something that is reflected in the high variability of the structural attributes of vegetation: basal cover of vegetated patches varied

between 4.5% and 98.5%, and perennial plant species richness varied between 2 and 36 species. High variability was also found for the three LFA indices, as the stability, infiltration and nutrient cycling indices varied between 17.9% and 68.2%, 25.5% and 68.5% and 11.1% and 59.2%, respectively (Appendix II).

We found a close relationship between the VIs calculated for the pixel where the field sampling site was located and VIs calculated from a 3 × 3 matrix of pixels centered on each site location (Appendix III). This suggests that the sampling sites were located in areas sufficiently homogeneous to avoid any scale mismatch between the field and the MODIS data.

Overall, the regressions fitted to the structural and functional variables analyzed showed that NDVI, followed by ARVI and RVI, yielded the highest coefficients of determination (R^2) and the lowest RMSE and, therefore, was the best predictor of these ecosystem attributes (Tables 2–6). SAVI, MSAVI2, EVI and EVI2 had an intermediate predictive capacity, which was very similar among them, while DVI was generally weaker predictors of the attributes evaluated. Finally, the poorest performance was achieved by NDWI (Tables 2–6).

NDVI explained about 30% and 40% of the variability found in plant species richness (Table 3 and Fig. 2b) and basal cover (Table 2 and Fig. 2a), respectively. Models fitted to the LFA indices were significant in the 100% of cases, and explained about 38% and 50% of the variability found in the infiltration and nutrient cycling indices, respectively (Tables 5 and 6, Fig. 2d and e). The stability index was weakly related to VIs, as NDVI was able to predict ~15% of its variability, and only 63.6% of the validation models were significant (Table 4 and Fig. 2c). For the other structural and functional attributes measured, the models fitted were successfully validated, as the relationships between predicted and observed values were significant in over 90% of cases. Predictions made through NDVI showed a similar mean than that found in the observed dataset (bias was near zero in all cases) and lower variability (variance ratio range between 0.56 and 0.69; Tables 2–6).

4. Discussion and conclusions

In this study, several VIs were compared for their abilities to estimate spatial variability of ecosystem structure and functioning attributes (Table 1). NDVI was the better predictor for basal cover of vegetation. This was likely due to the failing of other VIs to improve the limitations of NDVI. SAVI was developed as an attempt to reduce one of these limitations: the effect of soil background on spectral data. This index includes an adjustment factor L, which is a function of vegetation density. The value of factor L is critical to minimize the effects of soil optical properties effects on vegetation reflectance. Huete (1988) suggested an optimal value of $L = 0.5$ to account for intermediate vegetation cover values. However, this assumption was not very appropriate for our study area because: (i) the geology and soils of the Patagonian steppe are very heterogeneous (del Valle, 1998), and different soils have different reflectance spectra and (ii) vegetation cover was very variable throughout the study area (Appendix II). Thus, this variability in soils and vegetation cover will reduce the reliability of SAVI values. In an attempt to improve SAVI, Qi et al. (1994) developed MSAVI2, where the factor L is not constant and varies inversely with the amount of vegetation present. However, this improvement does not seem to avoid the noise caused by different soil types. RVI is mathematical equivalent to NDVI, but Jackson and Huete (1991) showed that NDVI is more sensitive to sparse vegetation densities than is the RVI, but is less sensitive to high vegetation densities. In our study area, where 73.7% of sites have less than 40% of vegetation cover, NDVI does not saturate and, therefore, is better predictor than RVI. Roujean and Breon (1995) found that DVI was

Table 2
Summary of the 300 models conducted to predict and validate the relationships between vegetation indices (VIs) and the ground cover of vegetated patches. b and a denote the intercept and slope of the model. The acronyms of the VIs are defined in Table 1. Data represent means ± SE.

	NDVI	RVI	DVI	NDWI	SAVI	MSAVI	ARVI	EVI	EVI2
Prediction[a]									
R^2	0.39 ± 0.03	0.31 ± 0.04	0.18 ± 0.03	0.01 ± 0.01	0.25 ± 0.03	0.23 ± 0.03	0.32 ± 0.04	0.25 ± 0.03	0.24 ± 0.03
% significant ($p < 0.05$) models	100.0	100.0	100.0	2.0	100.0	100.0	100.0	100.0	100.0
b	1.88 ± 1.34	−19.45 ± 3.18	9.47 ± 1.60	30.60 ± 0.98	6.36 ± 1.61	8.27 ± 1.57	32.03 ± 2.49	7.27 ± 1.56	7.58 ± 1.57
a	154.31 ± 14.42	33.69 ± 2.17	386.03 ± 43.64	−11.29 ± 21.45	235.92 ± 25.07	257.81 ± 28.06	120.51 ± 12.08	246.19 ± 26.19	246.61 ± 26.48
Validation[b]									
R^2	0.39 ± 0.13	0.30 ± 0.14	0.18 ± 0.10	0.07 ± 0.07	0.25 ± 0.11	0.22 ± 0.11	0.32 ± 0.13	0.25 ± 0.11	0.24 ± 0.11
% significant ($p < 0.05$) models	98.7	97.4	81.2	24.0	90.9	87.0	96.8	91.6	90.3
RMSE	14.65 ± 1.39	15.63 ± 1.73	16.99 ± 1.75	18.95 ± 2.54	16.29 ± 1.66	16.52 ± 1.69	15.48 ± 1.59	16.29 ± 1.68	16.36 ± 1.67
CV RMSE	0.48 ± 0.04	0.51 ± 0.05	0.55 ± 0.05	0.61 ± 0.07	0.53 ± 0.05	0.54 ± 0.05	0.50 ± 0.05	0.53 ± 0.05	0.53 ± 0.05
Bias	−0.03 ± 2.62	−0.07 ± 2.74	−0.09 ± 2.94	−0.14 ± 3.32	−0.09 ± 2.83	−0.09 ± 2.86	−0.06 ± 2.73	−0.08 ± 2.83	−0.09 ± 2.84
Variance ratio	0.61 ± 0.10	0.53 ± 0.13	0.43 ± 0.09	0.06 ± 0.07	0.49 ± 0.10	0.47 ± 0.10	0.56 ± 0.10	0.49 ± 0.10	0.48 ± 0.10

[a] $n = 154$.
[b] $n = 40$.

Table 3
Summary of the 300 models conducted to predict and validate the relationships between vegetation indices and perennial plant species richness. Rest of legend as in Table 2.

	NDVI	RVI	DVI	NDWI	SAVI	MSAVI	ARVI	EVI	EVI2
Prediction[a]									
R^2	0.31 ± 0.05	0.30 ± 0.05	0.21 ± 0.04	0.02 ± 0.02	0.26 ± 0.04	0.25 ± 0.04	0.30 ± 0.05	0.27 ± 0.04	0.26 ± 0.04
% significant ($p < 0.05$) models	100.0	100.0	100.0	51.0	100.0	100.0	100.0	100.0	100.0
b	5.52 ± 0.56	−1.73 ± 1.14	6.35 ± 0.66	13.53 ± 0.31	5.71 ± 0.64	6.16 ± 0.63	13.55 ± 0.62	5.88 ± 0.62	6.03 ± 0.62
a	40.97 ± 4.66	10.02 ± 0.80	123.99 ± 16.63	11.14 ± 6.12	72.35 ± 9.02	80.54 ± 10.27	34.74 ± 4.02	76.57 ± 9.50	76.17 ± 9.57
Validation[b]									
R^2	0.30 ± 0.16	0.29 ± 0.16	0.22 ± 0.14	0.07 ± 0.09	0.27 ± 0.15	0.25 ± 0.15	0.29 ± 0.16	0.27 ± 0.16	0.26 ± 0.15
% significant ($p < 0.05$) models	88.3	86.4	77.3	24.7	85.1	81.8	88.3	85.1	85.1
RMSE	4.65 ± 0.63	4.66 ± 0.60	4.96 ± 0.64	5.56 ± 0.82	4.81 ± 0.62	4.85 ± 0.62	4.69 ± 0.61	4.78 ± 0.61	4.82 ± 0.61
CV RMSE	0.35 ± 0.05	0.35 ± 0.05	0.37 ± 0.05	0.42 ± 0.05	0.36 ± 0.05	0.37 ± 0.05	0.35 ± 0.05	0.36 ± 0.05	0.36 ± 0.05
Bias	0.00 ± 0.81	0.01 ± 0.82	−0.03 ± 0.89	−0.04 ± 1.04	−0.02 ± 0.85	−0.02 ± 0.87	−0.01 ± 0.82	−0.02 ± 0.85	−0.02 ± 0.86
Variance ratio	0.56 ± 0.11	0.55 ± 0.14	0.46 ± 0.12	0.14 ± 0.07	0.52 ± 0.13	0.50 ± 0.13	0.55 ± 0.12	0.52 ± 0.13	0.51 ± 0.13

[a] $n = 154$.
[b] $n = 40$.

Table 4
Summary of the 300 models conducted to predict and validate the relationships between vegetation indices and the stability index. Rest of legend as in Table 2.

	NDVI	RVI	DVI	NDWI	SAVI	MSAVI	ARVI	EVI	EVI2
Prediction[a]									
R^2	0.13 ± 0.02	0.10 ± 0.02	0.09 ± 0.02	0.00 ± 0.00	0.11 ± 0.02	0.10 ± 0.02	0.13 ± 0.02	0.12 ± 0.02	0.11 ± 0.02
% significant ($p < 0.05$) models	100.0	100.0	100.0	0.0	100.0	100.0	100.0	100.0	100.0
b	35.53 ± 1.14	28.57 ± 2.60	36.37 ± 1.20	44.76 ± 0.49	35.66 ± 1.22	36.30 ± 1.20	45.31 ± 1.11	35.77 ± 1.21	36.11 ± 1.20
a	49.69 ± 6.89	10.93 ± 1.74	153.29 ± 23.84	−5.16 ± 6.18	88.67 ± 13.20	97.80 ± 15.08	43.70 ± 6.18	94.91 ± 14.24	92.73 ± 14.09
Validation[b]									
R^2	0.15 ± 0.09	0.14 ± 0.09	0.11 ± 0.08	0.02 ± 0.03	0.13 ± 0.09	0.12 ± 0.08	0.14 ± 0.10	0.14 ± 0.09	0.13 ± 0.09
% significant ($p < 0.05$) models	63.6	59.7	46.1	3.2	57.8	51.9	71.4	59.7	56.5
RMSE	9.95 ± 0.86	10.12 ± 0.91	10.17 ± 0.94	10.65 ± 0.97	10.05 ± 0.92	10.10 ± 0.93	9.91 ± 0.86	10.02 ± 0.93	10.07 ± 0.92
CV RMSE	0.22 ± 0.02	0.23 ± 0.02	0.23 ± 0.02	0.24 ± 0.02	0.22 ± 0.02	0.23 ± 0.02	0.22 ± 0.02	0.22 ± 0.02	0.22 ± 0.02
Bias	−0.11 ± 1.87	−0.09 ± 1.90	−0.11 ± 1.89	−0.07 ± 2.02	−0.11 ± 1.88	−0.11 ± 1.88	−0.10 ± 1.87	−0.10 ± 1.87	−0.11 ± 1.88
Variance ratio	0.35 ± 0.10	0.31 ± 0.13	0.29 ± 0.09	0.04 ± 0.04	0.33 ± 0.10	0.31 ± 0.10	0.35 ± 0.11	0.33 ± 0.10	0.32 ± 0.10

[a] $n = 154$.
[b] $n = 40$.

less affected by the soil background than NDVI, especially at low values of vegetation cover. However, the DVI was more affected by the spectral and directional canopy properties than the NDVI. The sites studies here range from short grass steppes to tall shrublands with very different canopy properties, which can have a strong effect on the DVI. To minimize atmospheric-induced variations in NDVI due to variations in atmospheric aerosol content, Kaufman and Tanre (1992) developed the ARVI, which included corrections for molecular scattering and ozone absorption. ARVI is most useful in regions of high atmospheric aerosol content, including tropical regions contaminated by soot from slash-and-burn agriculture. This is not the case of the Patagonian steppe, where the atmosphere during the growing season is relatively transparent. The EVI provides improved sensitivity in dense vegetation regions, where the NDVI can become saturated, while correcting at the same time for soil background signals and reducing atmospheric influences by using the blue reflectance (Huete et al., 2002). The EVI2 is similar to the EVI, but does not require the blue band reflectance; it takes advantage of non-physically based mathematical relationships between surface reflectance in the red and blue wavelengths (Jiang et al., 2008). The EVI and EVI2 are thus most useful in those regions with high biomass and/or high atmospheric aerosol contents. The

Table 5
Summary of the 300 models conducted to predict and validate the relationships between vegetation indices and the infiltration index. Rest of legend as in Table 2.

	NDVI	RVI	DVI	NDWI	SAVI	MSAVI	ARVI	EVI	EVI2
Prediction[a]									
R^2	0.36 ± 0.04	0.33 ± 0.04	0.16 ± 0.03	0.02 ± 0.01	0.25 ± 0.03	0.22 ± 0.03	0.34 ± 0.04	0.24 ± 0.03	0.24 ± 0.03
% significant ($p < 0.05$) models	100.0	100.0	100.0	39.0	100.0	100.0	100.0	100.0	100.0
b	34.51 ± 0.54	26.12 ± 0.95	37.25 ± 0.66	44.62 ± 0.33	35.79 ± 0.62	36.54 ± 0.61	44.65 ± 0.19	36.17 ± 0.62	36.23 ± 0.60
a	52.49 ± 2.76	12.18 ± 0.62	128.14 ± 12.12	11.45 ± 6.69	82.51 ± 5.92	89.16 ± 6.91	43.72 ± 2.46	85.43 ± 6.32	86.08 ± 6.32
Validation[b]									
R^2	0.38 ± 0.13	0.35 ± 0.13	0.18 ± 0.11	0.06 ± 0.08	0.26 ± 0.12	0.24 ± 0.12	0.36 ± 0.14	0.26 ± 0.12	0.25 ± 0.12
% significant ($p < 0.05$) models	99.4	98.7	72.1	18.2	92.9	85.1	98.7	90.3	90.3
RMSE	5.02 ± 0.56	5.15 ± 0.57	5.83 ± 0.68	6.43 ± 0.77	5.51 ± 0.61	5.61 ± 0.63	5.10 ± 0.54	5.53 ± 0.60	5.54 ± 0.61
CV RMSE	0.11 ± 0.01	0.12 ± 0.01	0.13 ± 0.02	0.14 ± 0.02	0.12 ± 0.01	0.13 ± 0.01	0.11 ± 0.01	0.12 ± 0.01	0.12 ± 0.01
Bias	−0.20 ± 0.90	−0.21 ± 0.94	−0.22 ± 1.07	−0.23 ± 1.20	−0.22 ± 1.00	−0.22 ± 1.02	−0.22 ± 0.92	−0.22 ± 1.00	−0.22 ± 1.01
Variance ratio	0.61 ± 0.11	0.57 ± 0.13	0.41 ± 0.09	0.12 ± 0.05	0.50 ± 0.11	0.47 ± 0.10	0.58 ± 0.10	0.49 ± 0.11	0.49 ± 0.11

[a] $n = 154$.
[b] $n = 40$.

Table 6
Summary of the 300 models conducted to predict and validate the relationships between vegetation indices and the nutrient cycling index. Rest of legend as in Table 2.

	NDVI	RVI	DVI	NDWI	SAVI	MSAVI	ARVI	EVI	EVI2
Prediction[a]									
R^2	0.49 ± 0.03	0.41 ± 0.03	0.28 ± 0.03	0.01 ± 0.01	0.37 ± 0.03	0.33 ± 0.03	0.45 ± 0.04	0.36 ± 0.03	0.35 ± 0.03
% significant ($p < 0.05$) models	100.0	100.0	100.0	98.3	100.0	100.0	100.0	100.0	100.0
b	14.99 ± 0.60	3.85 ± 1.37	17.66 ± 0.73	29.03 ± 0.45	16.18 ± 0.73	17.18 ± 0.72	29.56 ± 1.26	16.68 ± 0.74	16.84 ± 0.71
a	74.31 ± 6.79	16.83 ± 0.94	203.81 ± 21.38	2.32 ± 9.74	123.01 ± 12.27	134.40 ± 13.73	61.78 ± 5.83	128.06 ± 13.04	128.36 ± 12.96
Validation[b]									
R^2	0.50 ± 0.11	0.43 ± 0.12	0.29 ± 0.11	0.06 ± 0.06	0.38 ± 0.12	0.35 ± 0.12	0.46 ± 0.13	0.38 ± 0.12	0.37 ± 0.12
% significant ($p < 0.05$) models	100.0	100.0	96.8	23.4	100.0	100.0	79.0	100.0	100.0
RMSE	5.74 ± 0.58	6.19 ± 0.63	6.89 ± 0.75	8.24 ± 1.03	6.44 ± 0.69	6.60 ± 0.71	5.96 ± 0.64	6.46 ± 0.69	6.49 ± 0.69
CV RMSE	0.20 ± 0.02	0.21 ± 0.02	0.24 ± 0.03	0.28 ± 0.03	0.22 ± 0.02	0.23 ± 0.02	0.21 ± 0.02	0.22 ± 0.02	0.22 ± 0.02
Bias	−0.02 ± 1.02	0.02 ± 1.10	−0.06 ± 1.21	−0.12 ± 1.42	−0.04 ± 1.12	−0.04 ± 1.15	−0.01 ± 1.06	−0.04 ± 1.13	−0.04 ± 1.13
Variance ratio	0.69 ± 0.12	0.63 ± 0.17	0.51 ± 0.11	0.07 ± 0.04	0.59 ± 0.12	0.56 ± 0.12	0.66 ± 0.13	0.59 ± 0.13	0.58 ± 0.12

[a] $n = 154$.
[b] $n = 40$.

NDWI vary according to the relative water content of leaves (Gao, 1996), and thus could be useful in the detection of water stress or drought. The water status of vegetation can change considerably in the short-term (Schwinning and Sala, 2004) and, therefore, this VI is not a good indicator of more "slow" variables such as those measured here. This could explain why NDWI yielded the poorest performance as predictor of basal cover of vegetation.

In drylands, vegetation cover has been found to be related to different indicators of ecosystem functioning such as soil nutrient cycling and storage (Maestre and Escudero, 2009), microbial activity (Smith et al., 1994) and soil water infiltration and runoff (Vásquez-Méndez et al., 2010). Therefore, it is not surprising to find that VIs (mainly NDVI) are related to the LFA indices. Paredes (2011) analyzed, in 18 sites in southern Patagonia, the relationship between plant biomass and cover with some of the VIs used in this study (NDVI, RVI, EVI, SAVI, MSAVI2 and NDWI) and others not evaluated here (OSAVI – Rondeaux et al., 1996 and IPVI – Crippen, 1990), and also noted that the NDVI was the VI most correlated to these vegetation attributes. García-Gómez and Maestre (2011) calibrated LFA indices and vegetation cover with NDVI obtained from the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) sensor, in semi-arid steppes of central Spain. When validating the models fitted, these authors found R^2 values ranging from 0.53 to 0.75. In our study, NDVI was linearly related to LFA indices infiltration and nutrient cycling (average $R^2 = 0.36$ and 0.49, respectively), while the relationship with the stability index was weak (average $R^2 = 0.13$). In arid conditions, vegetation provides protection against degradation processes such as wind and water erosion. However, the weak relationship between VIs and the stability index found here suggests that other factors in addition to vegetation cover influence soil stability. The stability index is associated with vegetation cover, litter, biological soil crusts (biocrusts) and coarse fragments (Tongway and Hindley, 2004). Biocrusts play a significant role in stabilizing soil and preventing erosion in drylands (Evans and Johansen, 1999). Positive relationships between NDVI and the photosynthetic activity of biocrusts have also been

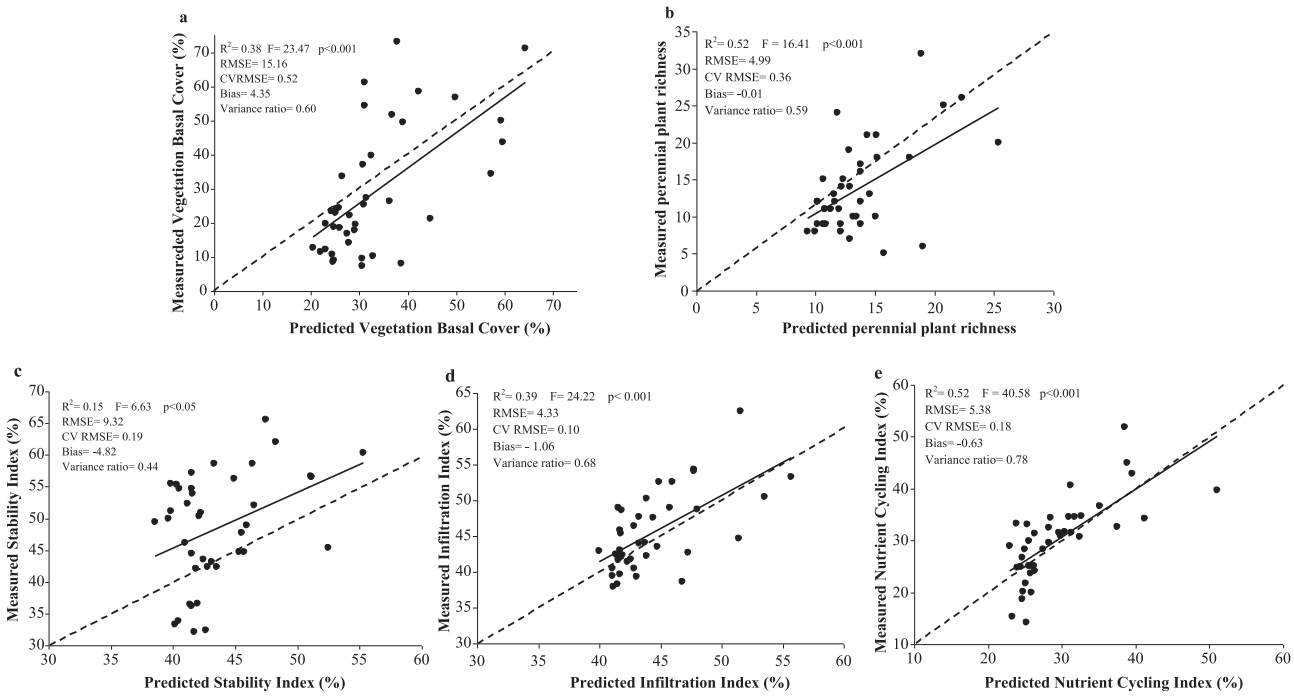

Fig. 2. Examples of regressions between field-measured values and predicted model values for vegetation basal cover (a), perennial plant richness (b) and LFA stability (c), infiltration (d) and nutrient cycling (e) indices. See Tables 2–6 for a summary of the validation models conducted. The 1:1 relationship is shown as a dotted line.

found (Burgheimer et al., 2006). This could explain the positive relationship between NDVI and the stability index found by García-Gómez and Maestre (2011), since biocrusts are prevalent in the ecosystems studied by these authors, where they can cover up to 30% of the total surface (Maestre et al., 2009; Castillo-Monroy et al., 2011). In our study area, however, biocrust cover is very low (<2% in all our study sites), as the sandy soil texture and strong winds characterizing it do not facilitate the development of biocrust communities (Belnap and Lange, 2003). Soil stability in these ecosystems can be provided by abiotic factors, such as the formation of desert pavements (Cerdà, 2001), which are very common in our study area because of the prevalence of wind erosion (Rostagno and Degorgue, 2011). Thus, sites with different vegetation cover can achieve similar values of stability index; in some cases the stability is given by the vegetation cover, and in others by the presence of desert pavements. As such, variations in the stability index are not driven by changes in vegetation cover, and thus this function cannot be satisfactorily predicted from VIs.

We found that NDVI predicts 31% of the variability in plant species richness, a result likely driven by the positive linear relationship between plant cover and species richness observed in our data ($r = 0.60$, $p < 0.001$). Plant biodiversity attributes have been found to be an important predictor of ecosystem functioning in drylands (Maestre et al., 2012), and are also related to the onset of desertification processes in these areas (Jauffret and Lavorel, 2003). The shape of the relationship between plant species richness and net primary productivity, biomass or vegetation cover, and the causal mechanism(s) behind the observed pattern(s) is a topic of great interest in ecology (Grace, 1999; Waide et al., 1999; Mittelbach et al., 2001). Species richness is often hypothesized to first increase and then decrease with productivity, producing an unimodal relationship (e.g., Grime, 1973; Rosenzweig, 1992). According to Grime (1973), optimum richness correspond to a biomass level of 500 g m^{-2}. In the Patagonian steppe, plant biomass typically ranges between 10 g m^{-2} and 400 g m^{-2} (Paruelo et al., 2004), and therefore would be found in the range with a linear relationship between plant species richness and biomass. This could explain the positive relationship found in this study between plant species richness with vegetation cover and NDVI at the regional scale. Regardless the mechanisms underlying the relationships found, which cannot be elucidated with the measurements taken in this study, our results show that VIs could be used to predict variations in plant species richness in drylands. Given the importance of biodiversity for assessing ecosystem functioning, further research on how it can be successfully monitored using remote sensing information is warranted.

Our results illustrate the potential of MODIS to assess the variability of structural and functional attributes over large areas, but it has some limitations that must be taken into account: (i) the average models produced had in all cases R^2 values below 0.50. Models with higher predictive ability could be generated by using more advanced remote sensing tools, such as sensors acquiring images in a large number of narrow spectral channels. Using hyperspectral data, VIs can be improved by using narrow bands that make them less sensitive to variations in illumination conditions, observing geometry, soil properties and atmospheric interference. Indices developed from the Medium Resolution Imaging Spectrometer (MERIS) sensor, such as MTCI (MERIS Terrestrial Chlorophyll Index, Dash and Curran, 2004) or MGVI (MERIS Global Vegetation Index, Gobron et al., 1999) may be used as an alternative to MODIS-based VIs for estimating ecosystem attributes. MERIS has 15 narrow (~10 nm) visible and near-infrared bands, moderate spatial resolution (pixel size ~300 m) and global coverage with two- to three-day repeat cycle (Rast et al., 1999). However the MERIS sensor is no longer operative (http://www.esa.int/Our_Activities/Observing_the_Earth/Envisat/ESA_declares_end_of_mission_for_Envisat), and thus future monitoring with these indices will not be possible. Others hyperspectral remote sensing sources are economically expensive and cover small areas, and thus could not be used over large areas or in those lacking the economical resources needed to use them; (ii) NDVI can change rapidly with environmental conditions (e.g. after rainfall events), and therefore may not be a good indicator of structural and functional ecosystem attributes (which change more slowly). This limitation could be reduced by using the mean NDVI of the growing season instead of a single date NDVI, as we used in our study; and (iii) another possible limitation of using MODIS is its spatial resolution (pixel size of 250 m × 250 m), which would make it inappropriate for use in ecosystems whose spatial heterogeneity of structural and functional attributes largely occurs at finer spatial scales.

Overall, the results of this study suggest that VIs obtained from MODIS, and NDVI in particular, can be used to estimate the spatial variability of important functional and structural attributes in the Patagonian steppe at the regional scale. Our results are an important step towards generalizing the use of MODIS remote sensing data, which are free and offer a good compromise between spatial resolution and temporal frequency, to monitor temporal changes in ecosystem structure and functioning that could be linked to the onset of desertification processes in drylands. For achieving this goal, the next step will be to repeat the field surveys at each site, and assess the performance of NDVI to predict temporal changes in the measured ecosystem attributes.

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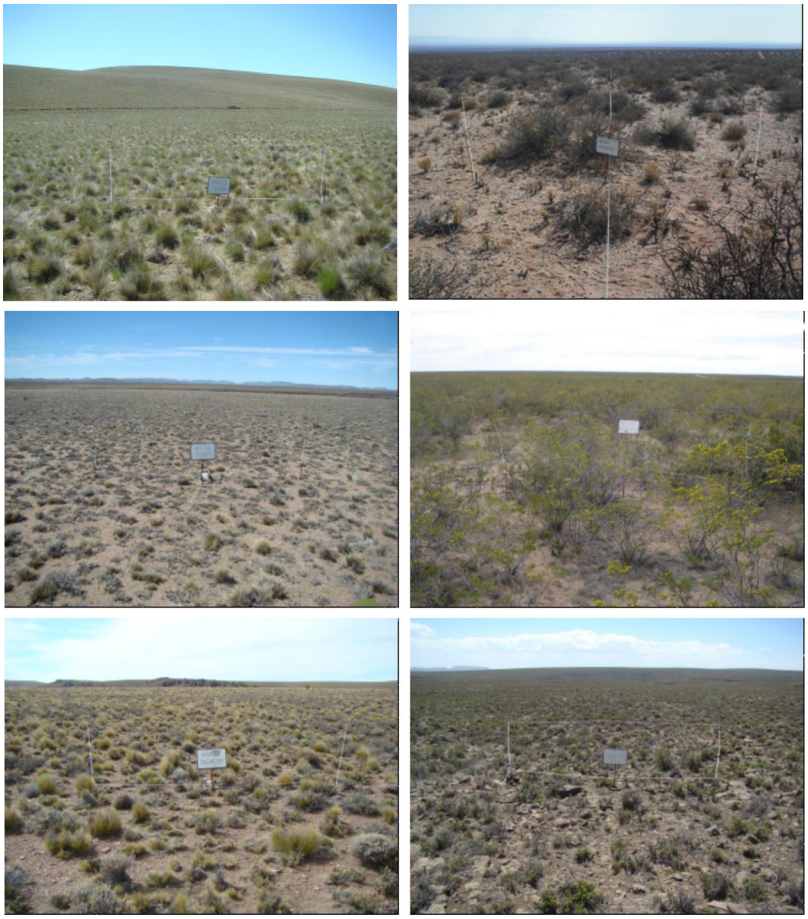
Appendix I.

Examples of some of the sampled field sites, which show that the assessed area is representative of the surrounding larger area.



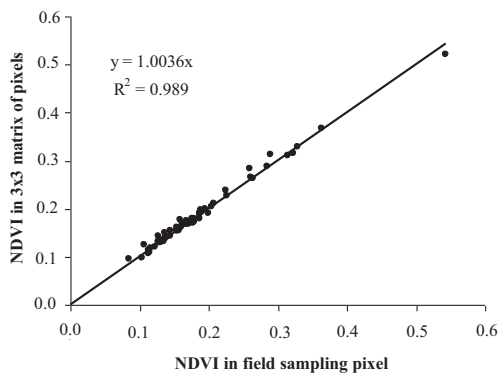
Appendix II.

Mean, standard deviation, minimum and maximum for vegetation attributes, LFA indices and spectral vegetation indices ($n = 194$). NDVI: Normalized Difference Vegetation Index. RVI: Ratio Vegetation Index. DVI: Difference Vegetation Index. NDWI: Normalized Difference Water Index. SAVI: Soil Adjusted Vegetation Index. MSAVI2: Modified Soil Adjusted Vegetation Index. ARVI: Atmospherically Resistant Vegetation Index. EVI: Enhanced Vegetation Index. EVI2: Two band EVI.

Variable	Mean	Standard deviation	Min.	Max.
Vegetation basal cover (%)	31.1	18.4	4.5	98.5
Plant species richness	13.2	5.5	2	36
Stability index (%)	44.9	10.5	17.9	68.2
Infiltration index (%)	44.4	6.4	25.5	68.5
Nutrient cycling index (%)	29.0	8.0	11.1	59.2
NDVI	0.187	0.074	0.086	0.531
RVI	1.494	0.304	1.177	3.269
DVI	0.055	0.020	0.018	0.148
NDWI	−0.027	0.066	−0.148	0.327
SAVI	0.103	0.039	0.042	0.278
MSAVI	0.087	0.034	0.033	0.246
ARVI	−0.008	0.086	−0.119	0.392
EVI	0.095	0.037	0.039	0.263
EVI2	0.094	0.037	0.038	0.263

Appendix III.

Relationship between NDVI values obtained in the pixel where the field sampling site was located and the same NDVI values calculated from a 3 × 3 matrix of pixels centered on each site location. $N = 65$ randomly. Very similar relationships were obtained for the other vegetation indices (data not shown).



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