Remote Sensing of Spatial and Temporal Vegetation Patterns in Two Grazing Systems

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Abstract

One constraint that range scientists must face in grazing studies is the lack of accurate and repeatable techniques for discriminating grazing effects from both temporal variability and spatial heterogeneity of vegetation. Both forms of variability contribute to inconsistent grazing system effects on vegetation response and forage production in semiarid ecosystems. Remote sensing may be an efficient tool for detecting differences in spatial and temporal patterns of grazing impact on vegetation. The purpose of this study was to evaluate the spectral data derived from satellite images as a tool for comparing grazing system impacts on spatial and temporal vegetation patterns. We evaluated the effect of two grazing systems, “Continuous” (C) and “Two-Paddocks Rest-Rotation” (TPRR), on vegetation cover from 1996 to 2006 in a semiarid ecosystem of Argentina. We compared grazing effects on vegetation cover using two indices derived from the Normalized Difference of Vegetation Index (NDVI) data from Landsat Thematic Mapper images. We observed a slight advantage in NDVI improvement for the TPRR over the C. Even though, in both grazing systems, an upward vegetation trend occurred only in areas located far from the watering points, TPRR showed higher relative vegetation cover near the watering point than C. We consider this methodology an important step for monitoring vegetation changes and making management decisions in livestock systems of semiarid regions because grazing system impacts may be compared for both spatial and temporal vegetation patterns. However, we think that the key next step is to develop procedures that discriminate between forage and nonforage components.

INTRODUCTION

Detecting grazing effects on plant communities is difficult because of temporal and spatial variability in vegetation structure and function. In arid and semiarid ecosystems the variability in plant cover and production is mainly associated with water availability, principally precipitation amount and distribution (Noy Meir 1973). Vegetation spatial patterns vary in scale from a few millimeters to many kilometers and are the result of different ecological processes (Crawley 1996). These ecological processes can be categorized as disturbances (grazing, fires, and floods), biotic processes (inseeding, individual replacement, secondary succession), and environmental constraints (microclimate, topography, soil patterns, precipitation; Levin 1978; Urban et al. 1987).

One constraint that range scientists face in grazing studies is the availability of accurate and repeatable techniques able to separate grazing effects from both temporal variability and
spatial heterogeneity of vegetation (Bastin et al. 1993). The results of grazing system effects on vegetation dynamic and forage production in semiarid ecosystems are inconsistent. Holecheck et al. (2002) suggested that rotation grazing systems had generally been more beneficial to vegetation dynamics than continuous grazing systems in the humid rangelands, but no clear differences were detected in semiarid and arid areas. In a recent review, Briske et al. (2008) demonstrates that continued advocacy for rotational grazing is based on perception and anecdotal interpretation, rather than on the preponderant experimental evidence. We think that traditional field-based monitoring may not be appropriate to detect differences in grazing system effects on arid and semiarid vegetation, because the high temporal variability and spatial heterogeneity of this type of vegetation would mask the true impacts of grazing systems.

Remote sensing–based techniques are powerful tools in solving such difficulties because they offer significant advantages related to their high temporal frequency and complete spatial coverage (Pickup et al. 1994). Vegetation indexes (i.e., Normalized Difference of Vegetation Index [NDVI]) derived from multispectral satellite images play a significant role for vegetation cover qualitative and quantitative evaluation by contrasting intense chlorophyll pigment absorption in the red against the high reflectivity of plant materials in the near-infrared (Tucker 1979). NDVI is a good estimator of synthetic parameters of vegetation structure and function, such as leaf area index and absorbed photosynthetically active radiation (Baret and Guyot 1991; Sellers et al. 1992; Gower et al. 1999; Paruelo et al. 2004) and vegetation cover (Paruelo and Golluscio 1994).

Two of the main remote sensing–based strategies that have been extensively used for grazing impact on vegetation research are the grazing gradient technique (Lange 1969; Pickup and Chewings 1994; Lind et al. 2003) and matched-pair-site technique (Bryant et al. 1990; Aguilera et al. 1998). The use of paired sites is useful for the following: 1) differences in soil type, vegetation species composition, topography, and geology are minimized and 2) the proximity of both sites minimizes meteorological differences attributable to time lags in air mass movement (Bryant et al. 1990).

Even though remote sensing techniques have been used for detecting grazing impacts on vegetation (Washington-Allen et al. 2006), these techniques have not been used in comparative studies between grazing systems. The purpose of this study was to evaluate the spectral data derived from satellite images as a tool for comparing grazing system impacts on spatial and temporal vegetation patterns.

**MATERIALS AND METHODS**

**Study Site**

This study was conducted at “Las Vizcacheras” Experimental Ranch (lat 30°27′S, long 66°11′W), located in La Rioja Province, Argentina (Fig. 1). The climate of the region is semiarid, characterized by hot summers and mild winters. January has the highest average temperature (26°C), whereas July is the coldest month (11°C; Morello et al. 1985). The frost-free period is 289 d from August to June (Bazán 1993). Long-term average annual precipitation is 469 ± 121 mm, with 80% falling between November and March (Fig. 2). According to Romero et al. (1995), soils in the site are Aridisols and Entisols. Current vegetation is characterized by a continuous shrubland with isolated trees and patches of grass. Dominant woody plant genera include Larrea, Aspidosperma, Prosopis, and Mimoyzanganthus. Dominant grass genera are Pappophorum, Trichloris, Setaria, Aristida, and Neobouteloua. The growing season generally extends from November to March, matching the seasonal precipitation distribution (Anderson et al. 1977).

We evaluated the effect of two grazing systems, “Continuous” (C) and “Two-Paddocks Rest-Rotation” (TPRR) on vegetation cover from 1996 to 2006 when C and TPRR were applied in three contiguous paddocks (Fig. 1). TPRR was applied to paddocks no. 1 and 3 (441 ha and 384 ha, respectively), and C was applied to paddock no. 2 (347 ha).
Stocking rate in each of the grazing systems was 0.104 animal units (AU)·ha⁻¹. Paddocks under TPRR alternatively received 1-yr graze and 1-yr rest, so that each paddock of the TPRR grazing system received a 0.208-AU·ha⁻¹ stocking rate during the period when each paddock was grazed. July was the paddock rotation month. Vegetation and grazing history were similar among paddocks before grazing system application (continuous grazing and stocking rate). However, the stocking rate was not always the same for the three paddocks in some years.

### Image Processing

We compared grazing effects on vegetation cover using the NDVI data from Landsat Thematic Mapper (TM) images, because the Landsat program provides long-term spectral data of high spatial resolution (Washington-Allen et al. 2006). NDVI is a good estimator of the amount of photosynthetically active radiation intercepted by the green canopy (Baret and Guyot 1991; Sellers et al. 1992; Gower et al. 1999; Paruelo et al. 2004) and hence of vegetation cover (Paruelo and Golluscio 1994). We used one scene per year (Table 1). March and April scenes were selected because these months ensured that ephemeral species were avoided, and perennial species had completed their seasonal growth but had not begun to senesce. According to Blanco et al. (2008), spatial and temporal patterns of grazing effect on vegetation can be detected during those months using NDVI data.

Image rectification and registration were performed using ERDAS Imagine software. A network of ground control points was selected throughout each scene.

We used the nearest neighbor resampling approach, which preserves recorded radiances, because it is important to compare original values in change detection studies (Jensen 1996). Registration error (mean value of all scenes) was 1.30 pixels (39 m).

We estimated the NDVI of each scene considering the atmospheric effects (Song et al. 2001) as

$$\text{NDVI} = \frac{[\text{TM}4 - \text{TM}3] - (A4 - A3)}{[\text{TM}4 + \text{TM}3] - (A4 + A3)},$$

where TM4 and TM3 are digital numbers for near-infrared and red reflectance, and A4 and A3 are the additive atmospheric effects for TM4 and TM3, respectively (Table 1). Atmospheric effects were estimated by simple dark object subtraction (Chavez 1989) as minimum digital number. Thus, A3 and A4 were selected as minimum digital number with at least 1,000 pixels in the histogram for the entire scene (Teillet and Fedosejevs 1995). The surface of Olta Lake, a deep clean water reservoir, was used as the dark object.

We observed a close relationship between NDVI (March) and precipitation (November to March) values ($P < 0.01$ and $r^2 = 0.70$; see Fig. 3). Considering that a high proportion of NDVI interannual variability is explained by the precipitation interannual variability, we need to reduce the effect of precipitation on NDVI values for detecting grazing effects. Therefore, we annually estimated two indexes. The first index, relative difference index (RDI), was calculated as

$$\text{RDI} = \left(\frac{\text{NDVI}_{\text{TPRR}} - \text{NDVI}_C}{\text{NDVI}_C}\right) \times 100.$$

RDI was estimated from 1988 to 1994 (before grazing systems started) and from 1996 to 2006 (after grazing systems started). The relationship between grazing system NDVI differences and NDVI_C allows us to reduce precipitation effects on NDVI absolute value. The second index used was NDVI/Pr, where Pr is growing season precipitation from 1 November to the date of Landsat TM scene acquisition (Prince et al. 1998; Holm et al. 2003). NDVI/Pr was estimated from 1996 to 2006 for both grazing systems. Similar to RDI, NDVI/Pr calculation allows us to reduce precipitation effects on NDVI absolute value. Moreover, NDVI/Pr can be estimated for each pixel, which allows us a detailed analysis of NDVI trend spatial patterns.

### Statistical Analysis

Linear regression analysis, considering RDI data as the dependent variable and time (yr) as the independent variable, was used to detect temporal tendencies in RDI data during the grazing systems application period (1996–2006). We performed RDI regression analysis for the whole paddock and for three zones located at different distances from the watering point: “near zone” (0 to 1,000 m), “intermediate zone” (1,000–2,000 m), and “far zone” (more than 2,000 m).

Linear regression analysis between NDVI/Pr (dependent variable) and year (independent variable) was performed for each pixel in both grazing systems. We considered the straight-line slope value for each pixel as annual NDVI/Pr change rate.

### Table 1. Landsat Thematic Mapper scenes list that includes acquisition date and minimum digital number for the red and near-infrared wavelengths of band widths (0.63–0.69 μm and 0.76–0.90 μm, respectively) used for Normalized Difference of Vegetation Index estimations.

<table>
<thead>
<tr>
<th>Growth period</th>
<th>Acquisition date</th>
<th>Red digital number</th>
<th>Infrared digital number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995–1996</td>
<td>7 March 1996</td>
<td>12</td>
<td>31</td>
</tr>
<tr>
<td>1996–1997</td>
<td>27 April 1997</td>
<td>10</td>
<td>18</td>
</tr>
<tr>
<td>1998–1999</td>
<td>17 April 1999</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>1999–2000</td>
<td>18 March 2000</td>
<td>13</td>
<td>8</td>
</tr>
<tr>
<td>2001–2002</td>
<td>17 April 2002</td>
<td>13</td>
<td>26</td>
</tr>
<tr>
<td>2002–2003</td>
<td>20 April 2003</td>
<td>13</td>
<td>17</td>
</tr>
<tr>
<td>2003–2004</td>
<td>26 February 2004</td>
<td>17</td>
<td>34</td>
</tr>
<tr>
<td>2005–2006</td>
<td>22 February 2006</td>
<td>17</td>
<td>22</td>
</tr>
</tbody>
</table>

1 Scenes Landsat ETM+, where digital number was corrected following radiometric cross-calibration proposed by Teillet et al. (2001).
Then we estimated the relative frequency distribution of annual NDVI/Pr change rate for each of the grazing systems. Finally, the difference in frequency distribution of annual NDVI/Pr change rate between grazing systems was tested with the Kolgomorov-Smirnov $z$ procedure.

We categorized the annual NDVI/Pr change rate for each pixel as positive or negative ($P < 0.10$), and even ($P > 0.10$) to visualize spatial patterns of vegetation dynamics. In addition, we used linear regression to analyze the relationship between annual NDVI/Pr change rate (dependent variable) and watering point distance (independent variable) on each of the grazing systems.

Our experiment was lacking true replicates (Hurlbert 1984). We are conscious this makes our results conditional, particularly if vegetation dynamics showed a relative difference between paddocks before the study started. So to partially solve this situation, we performed linear regression between RDI (dependent variable) and time (yr; independent variable) for the 1988–1994 period.

**RESULTS**

No RDI tendency ($P > 0.05$) was detected either for the whole paddock or for each of the three zones referred to the watering point before the start of the grazing systems (Table 2). An RDI positive trend ($P < 0.05$) was detected for the whole paddock and for each of the three zones (Table 2) since the start of the grazing systems. A RDI positive trend means that NDVI of TPRR improved in relative terms with respect to NDVI of C, but does not indicate NDVI absolute positive change of each of the grazing systems. Line regression slope for the whole paddock (Table 2) was 0.65% per yr; hence NDVI of TPRR relatively improved 7% in respect to NDVI of C, from 1996 to 2006. Similarly, NDVI of TPRR improved relatively in respect to NDVI of C in the three zones (Table 2). Nevertheless, the RDI trend was greater ($P < 0.05$) for the “near zone” (1.13% per yr) than for the “intermediate zone” and the “far zone” (0.58% · yr$^{-1}$ and 0.64% · yr$^{-1}$, respectively, without significant differences between them).

The frequency distribution of NDVI/Pr annual change rate was different ($P < 0.01$) between grazing systems (Fig. 4). We detected a significant ($P < 0.10$) NDVI/Pr positive annual change on only 6% of pixels for C but on 17% of pixels for TPRR. Within TPRR, significant differences ($P < 0.10$) between paddock 1 (23% pixels) and paddock 3 (10%) were detected. In those pixels with significant NDVI/Pr positive annual change, the average of NDVI/Pr annual change rate was similar for both grazing systems (0.02597 and 0.024960 NDVI units · mm$^{-1}$ for TPRR and C, respectively).

Pixels with a NDVI/Pr positive annual change were located far away from the watering point, independently of the grazing system (Fig. 5). NDVI/Pr annual change rate showed a significant ($P < 0.01$) quadratic increase in relation to watering point distance in both grazing systems (Fig. 6). However, this relationship showed a higher intercept value ($P < 0.01$) and lineal term ($P < 0.05$) for TPRR than for C, but the quadratic term was similar ($P > 0.10$) for both grazing systems. Thus, the NDVI/Pr annual change rate was greater along all watering point distances in TPRR than in C.

**DISCUSSION**

Our findings showed a positive vegetation dynamics advantage of TPRR in respect to C, which is partially consistent with the results of some studies, conducted in other regions of the world. Van Poollen and Lacey (1979), analyzing grazing system trials...
of western US ranges, observed that a rotational grazing system increased 13% of herbage production with respect to continuous grazing systems. Holecheck et al. (2002), in a similar review, observed that forage production under a rotation grazing system averaged 7% higher than a continuous grazing system. However, these authors pointed out that, in the semiarid and desert range types, rotational grazing systems generally showed no advantage over continuous grazing on forage production and vegetation dynamics. Grazing trials performed in semiarid regions showed inconsistent results (see, e.g., Wood and Blackburn 1984; Watts et al. 1987; White et al. 1991; Guevara et al. 2002). We think that traditional field-based monitoring could not be appropriate to detect differences in grazing system effects on arid and semiarid vegetation, because the high temporal variability and spatial heterogeneity of this type of vegetation could mask the true impact of the grazing process. For example, grazing research has not adequately evaluated the effects of grazing at large paddocks (Bailey et al. 1996), in relation to path-specific dynamic. Indeed, Teague and Dowhower (2003) demonstrated that in large paddocks, rotational grazing allows recovery from and reduces degradation caused by patch overgrazing.

Remote sensing techniques seem to be an efficient tool for detecting differences in spatial and temporal patterns of grazing impact on vegetation. However, spectral indexes derived from Landsat TM or MSS (multi-spectral scanner) allow estimating of grazing effects on vegetation total cover (Pickup et al. 1994; Jano et al. 1998; Saltz et al. 1999; Karfs and Wallace 2001), but they are of limited value to quantify plant components (Bork et al. 1999).

Many authors used remote sensing for detecting grazing effect on plant cover in semiarid regions. For example, Pickup

Table 2. Linear regression analysis (equation, $P$ value, and $r^2$) performed between Relative Difference Index (RDI; dependent variable) and time (yr; independent variable). The period 1988–1994 occurred before the installation of the grazing system, and 1996–2006 occurred afterward. We performed RDI regression analysis for the whole paddock and for three zones located within paddocks at three distances from the watering point (near zone = 0–1 000 m, intermediate zone = 1 000–2 000 m, and far zone = more than 2 000 m).

<table>
<thead>
<tr>
<th>Area</th>
<th>Before period</th>
<th>After period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total paddock</td>
<td>$RDI = -10.1735 + 3.6980 \text{ yr}$</td>
<td>$RDI = -3.6756 + 0.6506 \text{ yr}$</td>
</tr>
<tr>
<td></td>
<td>$r^2 = 0.2922, P = 0.2103$</td>
<td>$r^2 = 0.5625, P = 0.0079$</td>
</tr>
<tr>
<td>Near zone</td>
<td>$RDI = 0.2381 + 0.2954 \text{ yr}$</td>
<td>$RDI = -5.6223 + 1.1286 \text{ yr}$</td>
</tr>
<tr>
<td></td>
<td>$r^2 = 0.0162, P = 0.7857$</td>
<td>$r^2 = 0.6131, P = 0.0044$</td>
</tr>
<tr>
<td>Intermediate zone</td>
<td>$RDI = -0.3274 + 0.4445 \text{ yr}$</td>
<td>$RDI = -5.7115 + 0.5776 \text{ yr}$</td>
</tr>
<tr>
<td></td>
<td>$r^2 = 0.0357, P = 0.6847$</td>
<td>$r^2 = 0.2815, P = 0.0931$</td>
</tr>
<tr>
<td>Far zone</td>
<td>$RDI = 19.7465 - 2.3825 \text{ yr}$</td>
<td>$RDI = -1.3515 + 0.6405 \text{ yr}$</td>
</tr>
<tr>
<td></td>
<td>$r^2 = 0.0599, P = 0.5969$</td>
<td>$r^2 = 0.4563, P = 0.0225$</td>
</tr>
</tbody>
</table>

Figure 4. Frequency distribution of NDVI/Pr annual change (indicated by the straight-line slope of linear regression analysis pixel by pixel between NDVI/Pr and year from 1996 to 2006). Vertical line indicates lower limit of significant upward trend ($P < 0.10$). NDVI indicates Normalized Difference of Vegetation Index; Pr, precipitation fallen between 1 November and the Landsat scene acquisition date; C, continuous grazing system; and TPRR, two-paddocks rest-rotation grazing system.

Figure 5. Spatial patterns of annual change in NDVI/Pr. Dark gray pixels show significant ($P < 0.10$) NDVI/Pr annual increments greater than 2%. Light gray pixels showed nonsignificant ($P > 0.10$) NDVI/Pr annual increments less than 2%. NDVI indicates Normalized Difference of Vegetation Index; Pr, precipitation fallen between 1 November to acquisition date of Landsat scene. Gray squares indicate locations of watering points.
and Chewing (1994), Lind et al. (2003), and Blanco et al. (2008) observed that the grazing effect on vegetation cover varies according to watering point distance, and that these grazing gradients differed between years. However, these previous studies used remote sensing to analyze spatial patterns in grazing impact during some years but not to evaluate spatial patterns in vegetation dynamics. So we decided to focus our spatial pattern analysis of vegetation dynamics on grazing gradients. Martin and Ward (1969), in a semiarid rangeland of Arizona, observed that utilization of perennial grasses near a watering point can be reduced and herbage production increased by periodically closing the watering point in the summer (growth period). In addition, Martin and Severson (1988) reported that the “Santa Rita” grazing system can accelerate range improvement if the initial condition is poor or fair but may show little benefit if the initial condition is good. Considering that generally range conditions are related to watering point distance (near = poor, intermediate = fair, and far = good), our results are partially in agreement with the findings of Martin and Severson (1988). Even though both grazing systems showed only significant positive NDVI/Pr annual change in far watering point pixels (Figs. 5 and 6), the greatest NDVI relative differences between grazing systems occurred in the “near zone” (Table 2).

**MANAGEMENT IMPLICATIONS**

Multitemporal satellite data combined with the methodological approach for processing spectral information (relative difference index and NDVI/Pr) used in the present study allows us to compare grazing system impacts on spatial and temporal vegetation patterns in a semiarid ecosystem. Our analysis would remove some limitations of traditional field sampling techniques, particularly those related to grain and extent of the spatial pattern and the spatial-time interactions of the grazing process.

We observed a slight advantage in vegetation response improvement for the TPRR over the C. According to RDI values, plant cover uptrend in TPRR was 7% higher than in C, considering the 11-yr study period (1996–2006). Moreover, the percentage of pixels with positive NDVI/Pr annual change was higher in TPRR (17%) than in C (6%). Even though, in both grazing systems, positive NDVI/Pr annual change occurred only in areas farthest from watering points, TPRR showed higher relative vegetation cover (RDI) near watering points than C.

We consider this methodology to be an important advance for monitoring vegetation dynamics and making management decisions in grazed ecosystems of semiarid regions. However, we think that the critical advance for this methodology is to develop procedures that discriminate between forage and nonforage components of the vegetation, to base future management decisions on forage availability instead of total vegetation cover.

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**LITERATURE CITED**


