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Influence of fuel conditions on the occurrence, propagation and duration of wildland fires: A regional approach

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ABSTRACT

Wildfires affect Earth's surface every year. Fuels conditions influence fire occurrence and behavior; therefore, their characterization is important for fire risk studies. We analyzed vegetation conditions influencing fires occurrence, spread and duration in semiarid Argentina using satellite and complementary data. MODIS spectral data and GLC2000 map were the main inputs for this study. We analyzed pre-fire vegetation spectral responses of unburned areas and sites affected by fires of different sizes and durations nearby in space and time. Fire occurrence was more influenced by fuel load in shrublands, agriculture and steppes than in forests, where fuel status was most critical. Differences among burned and unburned sites were achieved in less time in shrublands and agriculture than in the steppes and forests due to fuel thickness, type and degradation state. Vegetation conditions also varied between fire sizes. Smaller fires were preceded by high fuel accumulation. From 300 ha burned fuel conditions were not related with fire spread probably due the influence of another variables. Fire duration was clearly influenced by pre-fire fuel quantity. Based on our results, we concluded that satellite data appears as a valuable tool to study fire occurrence and behavior, and to provide useful data for fire prevention.

1. Introduction

About one million square kilometers of forests, shrublands, grasslands, savannas and steppes are affected by uncontrolled fires worldwide every year (e.g. Goldammer, 2000, Krock, 2002). Although the onset of fires is often unpredictable, their evolution, development and severity is influenced by abiotic (weather, physical barriers or topography) (Bravo et al., 2010, Liu et al., 2014) and biotic factors (fuel moisture content, fuel type and quantity) that have different degrees of predictability (Chuvieco et al., 2003, Pyne et al., 1996). Noticeably, the onset of fires can affect some of these abiotic and biotic factors as it is the case of changes in vegetation cover and growth, opening the possibility for complex feedbacks in their dynamics (Irvine et al., 2007, Knorr et al., 2012).

Fuel characteristics are very important controls of fire behavior. Higher moisture contents and larger fractions of live biomass reduce the spread and intensity of fires (Burgan, 1979, Chuvieco et al., 1999). A large contribution of fine fuels encourages fire occurrence and spread, whereas a thick fuels favor fire duration and intensity (Tanskanen, 2007). Based on this background, the characterization of fuels is an important issue for fire hazard studies (e.g. Pyne et al., 1996). The most accurate way to analyze fuel status and quantity is through field measurements which are expensive and not plausible at large scales. To solve this, indirect estimates based on meteorological variables or satellite data become more appropriate (e.g. Chuvieco et al., 1999). In this sense, remote sensing allows obtaining global and periodic spectral data of earth's surface (Chuvieco and Kasischke, 2007, Justice and Dowty, 1994). In this way it is not only possible to detect wildfires (Chuvieco and Kasischke, 2007) but to assess vegetation conditions before their onset and after their retreat (Chuvieco et al., 2003, Crutzen and Andrade, 1990). Numerous studies of fuel status have been based on spectral information using vegetation or other indices to obtain indirect fire risk data (Bowman, 1989, Chuvieco, 1990, 2000, Hunt and Rock, 1989, Mbow et al., 2004). For instance, fuel moisture content has been the most extended estimator of potential fire occurrence and propagation. This variable is widely used for fire danger assessment (Viegas et al., 1992), and has a clear impact on the rate of fire spread (Nelson, 2001). Several indices like the

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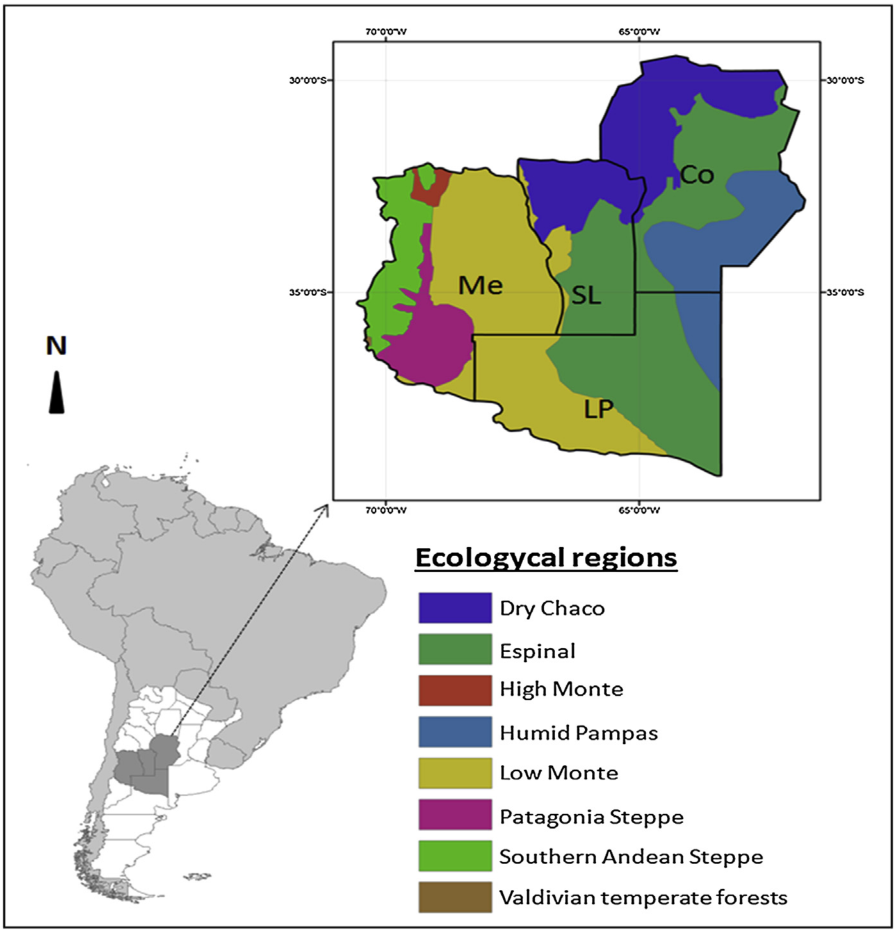

Fig. 1. Location of the study area (dark gray), which includes the provinces of Cordoba (Co), La Pampa (LP), Mendoza (Me), San Luis (SL) and detail ecological regions delimited by Olson et al., 2001.

Normalized Difference Vegetation Index -NDVI- (Rouse et al., 1974), Enhanced Vegetation Index -EVI- (Huete et al., 2002), Normalized Difference Infrared Index -NDII- (Hunt and Rock, 1989), Normalized Difference Water Index -NDWI- (Gao, 1996), among others, show a strong correlations with field measurements of fuel moisture content (Yebra et al., 2007).

In Argentina, wildfires affect a large area every year. From 2000 to 2012, more than 12,000 fires were reported every year, burning 1.3 million hectares on average (PNEF 2000–2012). While the causes of wildfires in this region are commonly unreported (~40%), most of them are attributed to the ignition by humans (~50%) (PNEF 2000–2012). The unpredictability of fires caused by humans as well as limited information on fire occurrence, behavior and environmental factors, hinder their understanding. Although the central semiarid region of Argentina is highly affected by wildfires, fires studies are scarce and field data are poor (e.g. Cabrera and Willink, 1973, Di Bella et al., 2006). Previous studies have focused on analyzing and characterizing fire events and how their spatial distribution is associated with latitude, vegetation types, land use and meteorological conditions (e.g. Di Bella et al., 2011; Fischer et al., 2012). The main objective of this paper is to address the relation between fuel conditions and fire occurrence, size and duration. This information would be relevant to apply adequate management practices to the fire control, prevention and mitigation at a regional scale.

To address our main goal we used a hotspot database to detect fire events location, their occurrence date, size and duration, satellite data of medium spatial resolution, from which we obtained vegetation indices and algorithms evaluating their temporal evolution; and a land cover/land use map. This information allows not only assessing vegetation conditions before fire occurs, but also it allows us to cover large areas with an advantage in data acquisition homogeneity.

2. Materials and methods

2.1. Study area

The study area extends over 530,000 km^2 and covers four provinces in central Argentina: Cordoba, La Pampa, Mendoza and San Luis (Fig. 1). This region is severely affected by fires every year (Fischer et al., 2012). Spatial and temporal distribution of fires is related with a significant rainfall gradient from east to west decisive in land use and land cover types (Fischer et al., 2012). Rainfall varies from 800 to 200 mm in east-west sense per year. In the east there is a significant surface under agriculture with the predominance of extensive crops (*i.e.* soybean, wheat, corn, sunflower). In the center, annual rainfall is lower than in the east, and the area is dominated by: shrublands, grasslands and several forests mainly characterized by xerophytic adaptations (Burkart, 1999, Cabrera and Willink, 1973). The predominant natural vegetation shows the production peak during the spring-summer season (September–March). Husbandry is the main land use. The western area is characterized by water deficits during most of year; hence the use

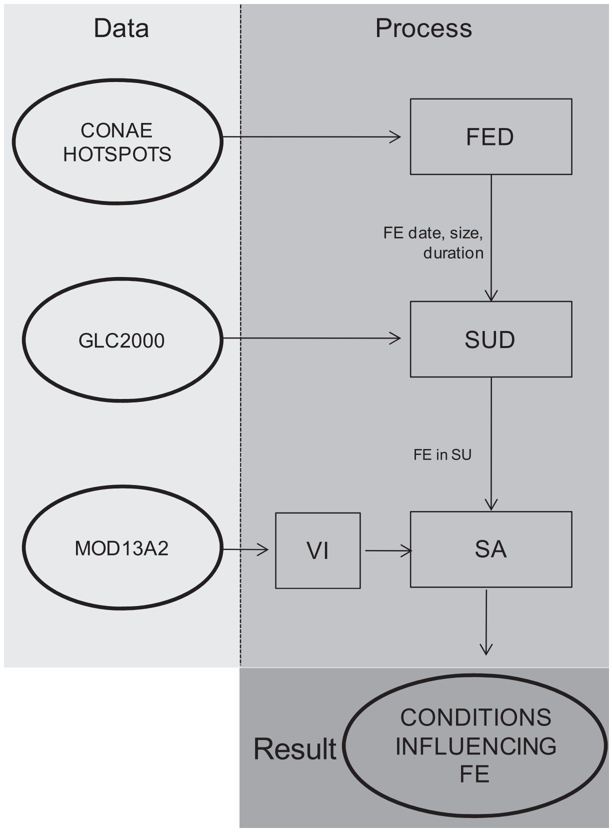

Fig. 2. Diagram representing input data and processes used in this paper to study vegetation conditions influencing the occurrence, propagation and duration of fires (FE: fire events; FED: fire event detection; SU: study units; SUD: study unit detection; VI: Vegetation Indices; SA: statistical analysis).

of these lands is scarce, except for irrigated crops (*e.g.* vines, olive trees, corn, alfalfa and soybean). The natural vegetation covers are dominated by species of shrubs and trees with xerophytes characteristics.

2.2. Satellite information

2.2.1. Hotspot and fire events

We processed daily MODIS thermal anomalies products provided by CONAE (*Comisión Nacional de Actividades Espaciales* – Argentina) for the period September 2003 to May 2006 (Fig. 2). We selected this period because there is available information about land use/cover affected by fires and moisture conditions (Fischer et al., 2012). The algorithm of MODIS hotspots product uses brightness temperatures derived from the MODIS 4-μm and 11-μm channels (Giglio et al., 2003). Information about latitude, longitude, day, month, year and platform at 1 km^2 of spatial resolution was recorded. We considered that the MODIS hotspots located near in space and time could be related to the same fire event FE (Figs. 2 and 3). In this context, we clustered the hotspots data taking into account a spatial-temporal window of 2 km and 2 days, in order to identify all Fire Events -FE- (Fig. 3; Fischer et al., 2012). From these data we obtained the occurrence, propagation (number of pixels affected per FE), and duration (number of days from the day of occurrence to the day of FE ending) of each FE.

2.2.2. Land cover map

A Global Land Cover Map of South America -GLC 2000- (Eva et al., 2004, Mayaux et al., 2006) was used to obtain data about the extent and distribution of the main land cover types with a spatial resolution of 1 km^2 (Fig. 2). In order to simplify the analysis and to generate groups extrapolated to other regions we grouped GLC classes registered in the study units (see 2.3) in the following 4 main groups: agriculture -A-, steppes -ST, shrublands –SH– and forests –FO–. Category A involved class 50, category ST grouped classes 71 and 75, Category SH involved classes 64 and 65, and category FO grouped classes 120, 170 and 20 of GLC 2000.

2.2.3. Spectral information

We downloaded the MOD11A2 product of Land surface Temperature/Emissivity composed every 8-days to 1 km spatial resolution', and MOD13A2 product of Vegetation Indices composed every 16 days to 1 km spatial resolution (NASA-http://edcimswww.cr.usgs.gov/pub/imswelcome/) between 01/06/2002 and 31/05/2006 corresponding to h12v12 tile. From this data, we obtained spectral information in blue (Band 3: 0.459–0.479 μm), red (Band 1: 0.62–0.67 μm), near-infrared (Band 2: 0.841–0.876 μm), middle-infrared (Band 7: 2.105–2.155 μm), and thermal-infrared (Band 31 and 32: 10.78–12.27 μm) bands of the electromagnetic spectrum (Fig. 2). Imagery acquired before fire occurrence was used to classify and map pre-fire vegetation patterns.

2.3. Data processing and analysis

From MODIS hotspots, the first step in data processing was to select and identify the Fire Events –FE– (Fig. 2 -FED-; Also see Section 2.2.1). Later, in order to analyze the differences of vegetation conditions that influence FE occurrence, propagation and duration, 24 units of study were selected (Fig. 3; Fig. 2). Each unit

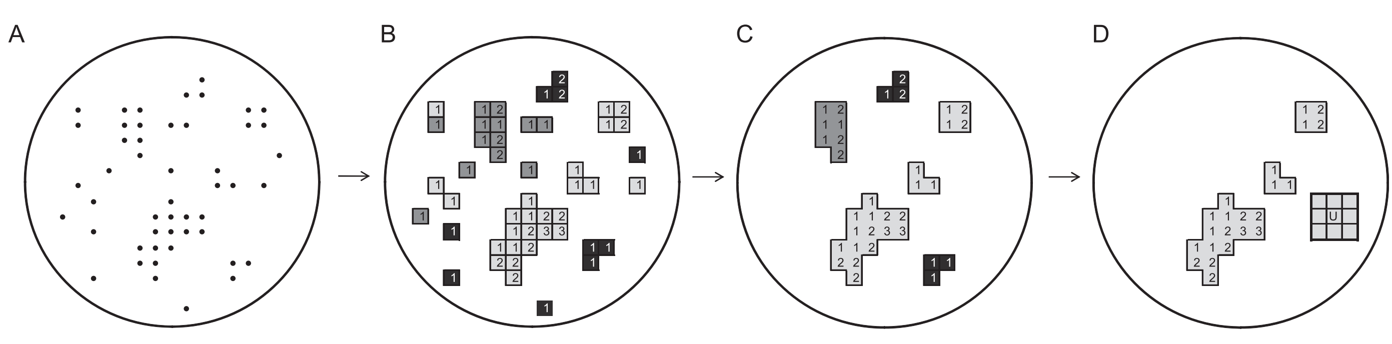

Fig. 3. Representation of process used to identify the "units of study". (A) MODIS hotspots; B) Fire Events -FE- detected in a time window of 2 days at distance lower than 10 km; C) FE superior to 200 ha; D) Final Unit of study involving FE with the same predominant land cover type (Global Land Cover 2000 map) and an unburned area of 9 km^2 represented by "U". The different numbers inside each FE represent the day of pixel burning (1: fire detections on day 1, 2: fire detection on day 2, etc).

Table 1
Spectral indices and algorithms used to study terrestrial covers and to analyze the evolution of vegetation along time.

Index	Formulas	Comments
NDVI	$NDVI = \frac{NIR-R}{NIR+R}$	The NDVI values range from −1 to 1 with the amount, type and status of vegetation cover. This index is mainly used for amount of green biomass accumulated in surface (Rouse et al., 1974). We calculated NDVI using B1 and B2 of MODIS.
SWVI	$SWVI = \frac{NIR-SWIR}{NIR+SWIR}$	The SWVI, similar to the NDVI algorithm, add the short wave infrared band (SWIR, 1.1 y 2.5 μm) replacing of the visible band. In this paper we used B7 as a portion or SWIR to replace B1 of MODIS. It is mainly used for estimating vegetation water status and to detect differences among burned and unburned areas (Fraser et al., 2000, Kaufman and Remer 1994).
NDVI-I	$NDVI - I = \sum NDVI$	This is the integral of NDVI values registered from the last growth season to the fire date. It is commonly used to estimate the total production of vegetation biomass (Paruelo et al., 1997).
SWVI-I	$SWVI - I = \sum SWVI$	This is the integral of SWVI values registered from the last growth season to the fire date. We used SWVI-I in order to analyze vegetation status in an specific period of time.
RND	$RND_{(N,D_1,D_2,i,j)} = \sum_{L=J}^{J+N}\sum_{K=L}^{I+N}\frac{NDVI_{(D_2,K,L)}-NDVI_{(D_1,K,L)}}{NDVI_{(D_1,K,L)}}$	The relative NDVI Differences -RND- (López et al., 1991) evaluate temporal evolution of vegetation cover for each pixel (k, l). D2: date where the NDVI was registered. D1: date previous to D2.

involved at least two FE at a distance less than 10 km, with the same date of occurrence, the same land use/cover class (Fig. 2), and different sizes duration (S_1: fires covering less than 300 has; S_2: fires covering between 300 and 1000 has; S_3: fires covering more than 1000 has). The distance between FE was important to reduce the climate, topography and vegetation variability. In addition, within each unit of study, we selected an unburned surface (U) of 3 × 3 pixels, 9 km^2, (Fig. 3).

From MODIS spectral data two vegetation indices (VI) were calculated: a) Normalized Difference Vegetation Index -NDVI - (Nemani et al., 1993, Rouse et al., 1974) and, b) Short Wave Vegetation Index -SWVI- (Cayrol et al., 2000, Hunt and Rock, 1989) (Table 1; Fig. 2). The NDVI is one of the most used in vegetation studies and it is based on the relationship between the reflectance in the infrared and visible red band. This index is widely assumed as an indicator of leaf area index (LAI), the fraction of the photosynthetically active radiation absorbed by vegetation - FAPAR - (Baret et al., 1989, Cristiano et al., 2012, Di Bella et al., 2004) and the annual aboveground net primary productivity —ANPP- (Paruelo et al., 1997, 2000). The SWVI, similar to NDVI algorithm, was calculated replacing the visible band by the Band 7 of MODIS, involving the short wave infrared band -SWIR-. Certain studies have shown that the addition of this band is useful to assess leaf water content, variable associated to fuel combustibility (Bowman, 1989, Cohen, 1991, Fraser et al., 2000, Hunt and Rock, 1989).

In addition, we calculated the "annual integral of NDVI" (NDVI-I) (Paruelo et al., 1997, Paruelo and Larenroth, 2003), the "annual integral of SWVI" (SWVI—I) and the Relative NDVI Differences -RND- (López et al., 1991) as a proxy of biomass productivity or fuel moisture content (Table 1). The NDVI-I represents the accumulation of green biomass during a period analyzed, while RND evaluate the temporal evolution of NDVI. Low values of these two indices are related to low contents of leaf moisture content, increasing the existing fuel flammability and the fire risk (López et al., 1991; Illera et al., 1996).

These algorithms were also integrated into the: growing season -G_n- (September, October, December, January, February, March), including spring and summer season, and wintering season —W_n—, including autumn-wintering season (April, May, June, July, August).

Linear Regression analysis and ANOVA tests were used for this study (Tukey, 1977). A nested statistical design was considered in order to make these comparisons. This type of analysis took into account factors that influence the response variables (vegetation indices and algorithms), such as unit of study, fire occurrence, fire size and fire duration (Fig. 2).

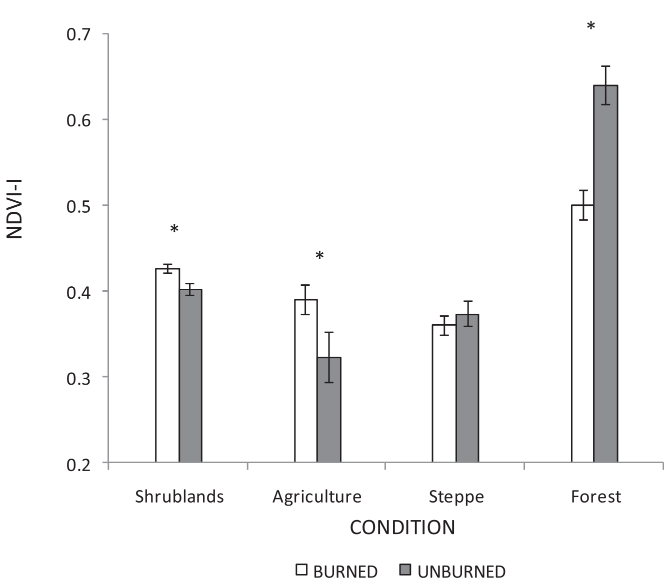

Fig. 4. Response of pre-fire integral NDVI (NDVI-I) for burned and unburned sites from the growing season before fire to the fire date, among different land use/cover sites corresponding to burned and unburned situations. Dots indicate significant differences between condition and vegetation type (LSD test, 5%).

3. Results and discussion

3.1. Fire event occurrence

Vegetation conditions before the onset of fires varied between burned and unburned sites, showing opposite trends in forests vs.

Table 2
Values of spectral indices evaluated between areas affected by fires and areas non affected. Significant differences are indicated by asterisks.

Index	Vegetation type		Burned	Unburned
NDVI-I	Shrubland	*	0.427	0.402
NDVI-I	Agriculture	*	0.390	0.327
NDVI-I	Steppe		0.361	0.374
NDVI-I	Forest	*	0.501	0.641
SWVI-I	Shrubland	*	0.106	0.095
SWVI-I	Agriculture	*	0.053	0.043
SWVI-I	Steppe	*	0.061	0.204
SWVI-I	Forest	*	0.206	0.338
RND	Shrubland	*	−0.614	0.642
RND	Agriculture	*	−0.522	−0.677
RND	Steppe		−0.632	−0.625
RND	Forest	*	−0.486	−0.361

the rest of the cover types (Fig. 4). In shrublands and agricultural areas we observed significant higher values of the annual integral of NDVI (NDVI-I) in burned sites (Fig. 4). The integral of SWVI (SWVI–I) and the RND showed the same tendency as NDVI-I over these covers. In the steppes, we observed the same trend although the results were significant only for SWVI-I (Table 2). The significant higher values of these vegetation indices in burned sites suggested that a higher buildup of fuel stocks during the previous year favored the onset of fires. Several studies have shown the sensitivity of vegetation indices, such as NDVI, to detect the active biomass accumulated in prairies, grasslands, savannas, among others (Moreau et al., 2003, Chen et al., 2011), and to demonstrate that the accumulated vegetation biomass correspond to high fuel load, and this variable is directly related with the fire risk. In our area, increased levels of NDVI-I in burned sites of shrublands and steppes are predictable because wildfires are mainly caused by humans with the goal of reducing the buildup of biomass and to promote vegetation re-growth for livestock. In forests we observed an opposite trend with NDVI-I as well as SWVI-I and RND showing lower values in burned sites regarding unburned sites (Table 2). The inverse response observed in forests could be related to the fact that the fuel load was not a limiting factor for ignition in this land covers, because the biomass is accumulated year after year without limitations in forests. In this case, the fuel status probably was the main control for FE occurrence, as noted by other authors (Yebra et al., 2007). In this sense, we observed lower values of vegetation indices before fire occurrence, probably indicating an increase of the level of dryness of biomass. Beyond the trigger for wildfires, which may be natural or anthropogenic, the presence of large fires in these covers was due to the characteristics of fuel status and the slope of the sites where they were usually located (hillsides) (Mendes-Lopes et al., 2003).

In addition, we observed that the vegetation differences between burned and unburned areas varied seasonally. In shrublands, the differences between burned and unburned sites were observed during the two previous winters (W2, W1) and during the growing season (G0) in the year of fire onset (Fig. 5). In agricultural areas, the differences were observed since the previous growing season (G1) until the current one (G0). In steppes major differences occurred during the penultimate growing and winter seasons (G2, W2). Forests showed differences during the whole span of our analysis which included two full years (Fig. 5). Large differences between burned and unburned sites in this land cover could be associated with the presence of forests structurally different in each sites with different condition. In field, wildfires affect “more degraded forests” than “protected, vigorous and closed forests” (Kyereh et al.,

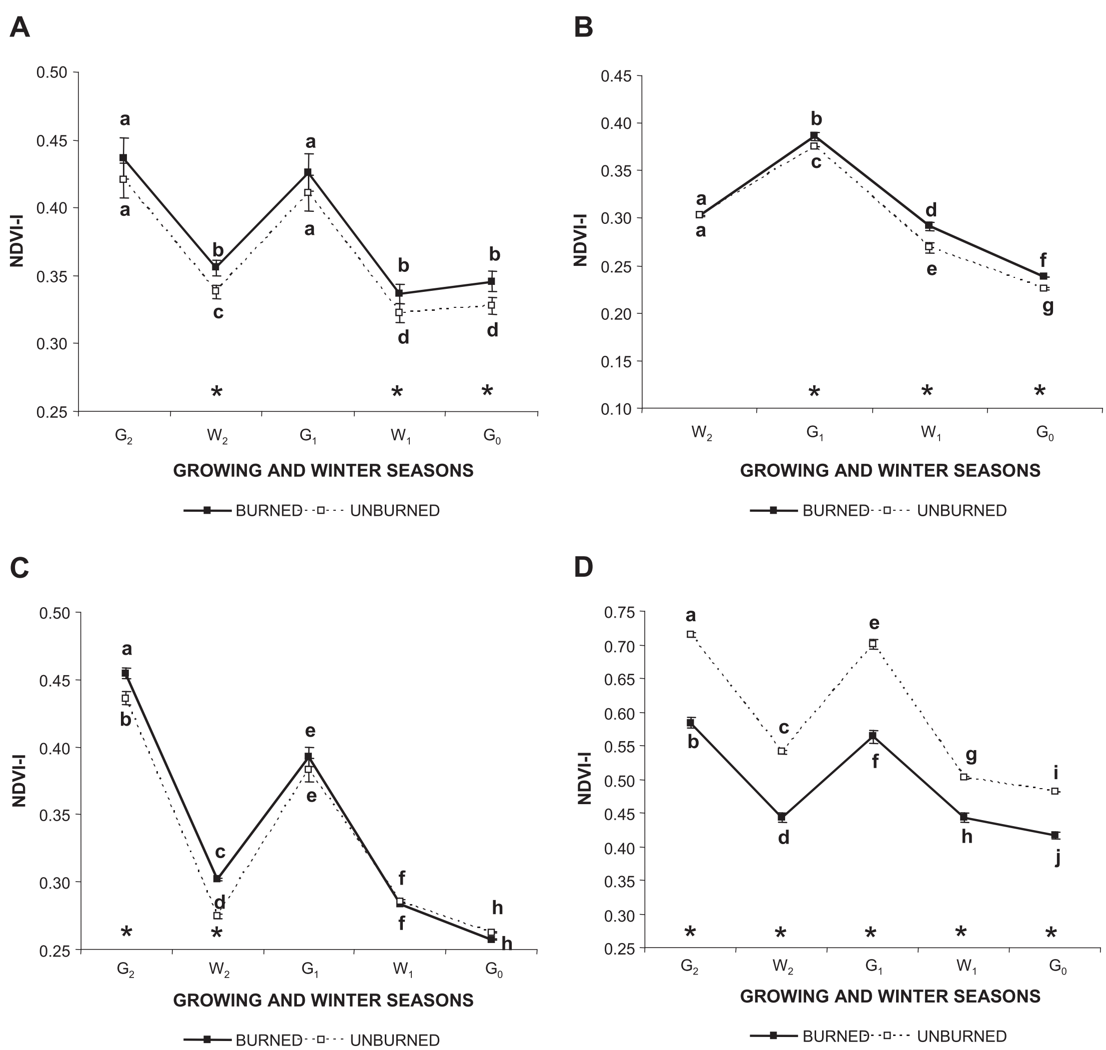

Fig. 5. Response of the NDVI-I before fire date for growing (G) and winter (W) seasons among burned and unburned sites, and between vegetation types: shrublands (A), agriculture (B), steppes (C) and forests (D). Different letters indicate significant differences between treatments (LSD test, 5%). The number subscripts of seasons indicate the year before fire occurrence, from 0 when fire occurred to 2 indicating two years before fire.

2006). Forest affected and not affected by fires differ in structure and involved different species, so it is consistent that the spectral response of each one (burned, unburned) differ widely throughout all study period. In forests, regarding the rest of land covers, structural changes should be slow and deep to reach optimal fuel condition that influence fire regime. In this sense, several authors have published that the rate of moisture loss varies according to tissue thickness, status, type and density (Chuvieco et al., 2004, Jurdao et al., 2012). For instance, Jurdao et al., 2012 distinguished between fine and coarse fuel thicknesses, indicating that shrubs were less dependent on weather conditions so their moisture decrease much more slowly, while fine fuels (such us grasses) were more susceptible to rapid moisture changes. The live:dead biomass ratio is also important in determining the probability of ignition and fire behavior (Cheney et al., 1998, Chuvieco et al., 2004). This ratio varies among degraded and not-degraded forests. While moisture content in dead fuels can change very rapidly, depending on the relative humidity of the air and precipitation, in live fuels the moisture content changes but at a much slower rate (UtahState University 2011). Therefore, this process is one of those affecting the period of time required to reach suitable fuel conditions for fire occurrence.

3.2. Fire event propagation

The NDVI-I was the index that showed the most significant differences between fire events of different sizes: S1 (100–300 ha), S2 (300–1000 ha), S3 (>1000 ha). S1 showed significant highest NDVI-I values in shrubs and steppes ($n = 4{,}669$, $p < 0.001$); S2 showed lowest values in the four covers; and NDVI-I of S3 was greater than S2 (Fig. 6). The SWVI-I ($n = 4.669$, $p < 0.001$) and RND ($n = 4.669$, $p < 0.001$), not shown in figures, responded in the same way that the NDVI-I. Highest values of NDVI-I of smallest FE (S1) could be related with a higher biomass accumulation before fires against FE bigger than 300 ha. This trend could be related with the fact that S1 fires are commonly intentional and they are caused in sites with important accumulation of biomass in order to reduce fuel load. Fires bigger than 300 ha didn't shown a clear trend. When we analyzed fire by fire, in the four classes of vegetation, we observed different behaviors of NDVI-I before fire in fires S2 and S3, probably due to different conditions of fuel or another variables. The vastness of these fire events brings different surfaces, with structural and functional changes in vegetation cover and probably different fire control strategies, or climate conditions. These variable responses of vegetation indices probably indicate that fires spread not only depend on vegetation fuel but also on another variables like wind speed, wind direction, the presence or the absence of physical barriers, the most or less effective control tasks and suppression of fires, environmental policies, among others. For this reason we considered that fuel load or quality reflected by spectral indices is not a limiting factor for fire spread at least above 300 ha fires.

The differences between the events fire sizes were also analyzed between seasons (growth and winter). In shrublands, the significant differences between S_1 and S_3 were detected since the growing season from two years before FE date (G_2) to the growing season previous to fire (G_1) (Fig. 7). However, in steppes, S_1 and S_3 were significantly different only in the growing season of two years

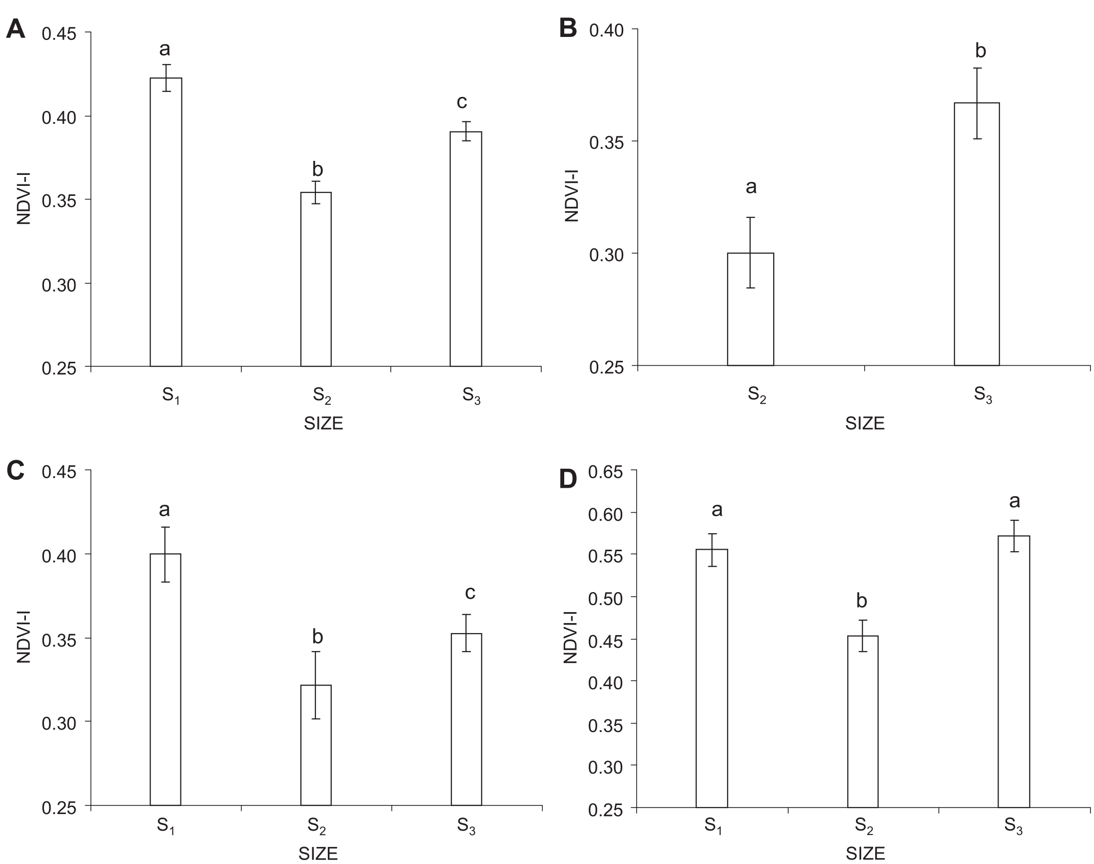

Fig. 6. Condition of the NDVI-I before the onset of fires of different size ($S_1 < 300$ ha, S_2: 300–1000 ha, $S_3 > 1000$ ha), and between vegetation types: shrublands (A), agriculture (B), steppes (C), forest (D). Different letters indicate significant differences (ANOVA test, $p < 0.01$).

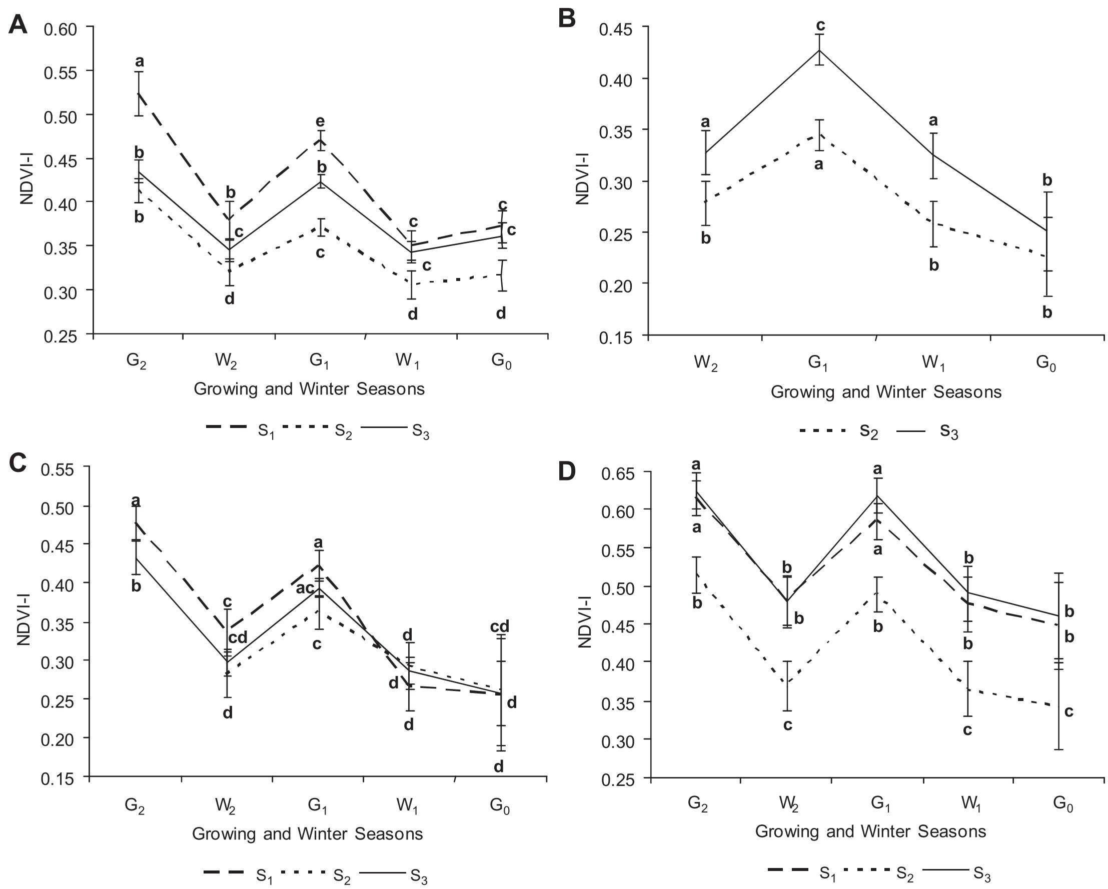

Fig. 7. Response of the NDVI-I by seasons before fire date (G, W) in sites affected by fires of different sizes (S_1, S_2 and S_3) between vegetation covers: shrublands (A), agriculture (B), steppes (C), forests (D). Different letters indicate significant differences between treatments (ANOVA test, $p < 0.01$).

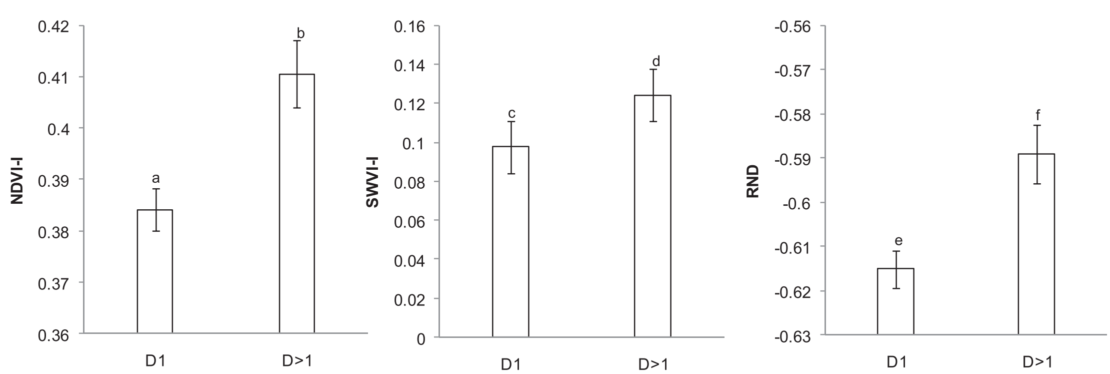

Fig. 8. Response of the NDVI-I, SWVI-I and RND among sites affected by fires of one day of duration (D1) and fires of long duration (D > 1). Letters show significant differences between indices values among D1 and D > 1.

before the wildfire (G_2). We also observed that the differences between S_2 and the rest of the sizes of FE occurred during whole study period, remaining below the rest. From these data we infer that fires among 300 and 1000 ha (S_2) show a particular behavior probably related to the presence of dry fuel in surface burnt. Fuel status could be a driver for fire spread in that scale, as mentioned above.

3.3. Fire events duration

The duration of Fire Events (FE) was related with fuel features; in agreement with several authors who have indicated the relationship between the fires behavior and the type, size, quantity, arrangement, and dead:live ratio of fuels (Fitzgerald 1957, Schwela et al., 1999, Soho, 2002). In this paper, we observed that FE which lasted more than one day (D > 1) were detected in places that showed higher pre-fire values of NDVI-I, SWVI-I, and RND in comparison with areas where they lasted only one day -D1- (Fig. 8). It seems that the duration of fires is more influenced by the amount of fuel than fuel status (Fig. 8). Previous works also observed that FE with longest duration were more frequent in forests (Fischer et al., 2012). In this land covers, places affected by durable FE presented significant high NDVI-I during whole period before FE occurrence in comparison with places affected by FE of shorter duration

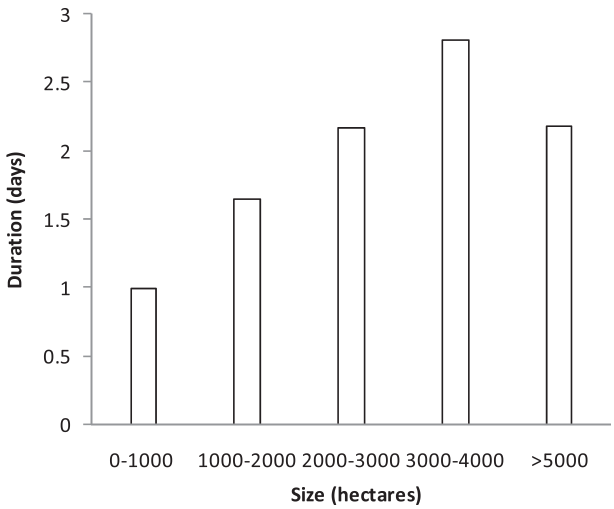

Fig. 9. Mean duration of fire events (days) by 5 classes of size (0–1000; 1000–2000; 2000–3000; 3000–4000; >5000 ha).

($n = 181$, $p < 0.001$). On this regard, the vegetation quantity accumulated before occurrence could be influencing FE duration. Nevertheless, in shrublands the FE with long duration mainly present lower values of NDVI-I, indicating that the amount of dry biomass increased the durability of FE in shrubs.

The duration of FE was also related with FE size (Fig. 9). FE grouped in five classes of size (0–1000 ha, 1000–2000 ha, 2000–3000 ha, 3000–4000 ha, >5000 ha), showed an increase mean duration, in exception for the last class, where the median duration lowered probably associated with the control of such disturbances.

4. Conclusions

Our results show that vegetation indices provide useful information to identify areas that are more vulnerable to experience wildfires. We observed that fuel load or fuel status had different effects depending on the vegetation types. A significant buildup of biomass during the year previous to fire was important in shrublands and agriculture for fire occurrence. In forests, however, fuel quantity was not the limiting factor for fire occurrence; in this case, FE occurrence was directly influenced by fuel status and likely presence of degraded forests. The period for reach adequate conditions of fuel also varied according fuel thickness and live:dead biomass. Furthermore, fire propagation was strongly influenced by vegetation quantity. Large and durable wildfires were more frequent in places with a greater amount of dry biomass and low live:dead ratio according to the vegetation covers.

Based on the results obtained, it can be concluded that in the semiarid region of Argentina fire behavior is not only the response to human interventions, but also the response to several natural factors. The knowledge about the vegetation conditions, fuel status and load obtained from satellite data was an important tool for estimating the risk of occurrence, propagation and duration of fires. These results will be useful for fire fighting and for authorities in order to make right decisions and to reduce the environmental impacts of the wildfires.

Our results made it possible to distinguish the vegetation conditions that influenced the fire occurrence and its behavior, providing useful information for prevention, control and mitigation of these events. Moreover, taking into account that fires are often a common practice with agricultural purposes in the study region, it would be possible to adjust its use to the appropriate conditions of vegetation in order to reduce the probability of uncontrolled fire events. The direct observation of vegetation quantity and quality is essential for early warning systems and agricultural practices planning.

Acknowledgments

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