SELECTING CONTROL SITES FOR POST-FIRE ECOLOGICAL STUDIES USING BIOLOGICAL CRITERIA AND MODIS TIME SERIES DATA

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ABSTRACT

Wildland fires play a key role in the functioning and structure of vegetation. The availability of sensors aboard satellites, such as Moderate Resolution Imaging Spectroradiometer (MODIS), makes possible the construction of a time series of vegetation indices (VI) and the monitoring of post-fire vegetation recovery. One of the techniques used to monitor post-fire vegetation is the comparison of a burned site with an adjacent unburned control site. However, to date, there is no objective method available for selecting these unburned control sites. We propose three biological criteria that the unburned sites must meet to be considered control sites, as well as statistical methods based on the analysis of the properties of the Quo-

RESUMEN

Los incendios juegan un rol clave en el funcionamiento y estructura de la vegetación. La disponibilidad de sensores a bordo de satélites tales como el MODIS, hacen posible la construcción de series de tiempo de índices de vegetación (VI) y el monitoreo de la recuperación de la vegetación post fuego. Una de las técnicas usadas para monitorear la vegetación post fuego de un sitio quemado es su comparación con otro adyacente sin quemar. Por supuesto y hasta el presente, no existe un método objetivo disponible para seleccionar lugares sin quemar que sirvan de testigo. Nosotros proponemos tres criterios biológicos que los lugares sin quemar deberían cumplir para ser considerados como sitios testigo, como así también métodos estadísticos basados en el análisis de las propiedades de las series de tiempo del índice de cociente de vege-

tient Vegetation Indices time series (QVI), to detect unburned sites that meet the proposed criteria. We also test the performance of the proposed method by checking the pre-fire difference between burned and unburned sites, assuming that the higher the number of met criteria, the greater the similarity. Therefore, we compare the differences between VI time series of burned sites and VI time series of unburned sites with the same vegetation cover that meet three, two, one, and none of the proposed criteria. In addition, we compare the quality of QVI time series that meet three, two, one, and none of the proposed criteria. Our results show that, for Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data, the difference between the time series of burned and unburned sites gradually decreases with the increase of met criteria. A gradual increase is also observed in the quality of the QVI time series with the increase of met criteria. Despite the limitations present in the proposed method, our model represents an advance from the conceptual and methodological standpoints, since this is the first proposal of a statistical method for selecting unburned control sites based on biological criteria.

tación (QVI), para detectar sitios no quemados que cumplan con los criterios propuestos. También probamos el desempeño del método propuesto mediante la prueba de las diferencias previas al incendio entre lugares quemados y no quemados, suponiendo que cuanto mayor es el número de criterios concordantes, mayor será la similitud entre sitios. En base a eso, comparamos las diferencias entre las series de tiempo (VI) de los sitios quemados con aquellos (VI) de los no quemados con el mismo tipo de cobertura de vegetación que cumplirían con tres, dos, uno, o ninguno de los criterios propuestos. Adicionalmente comparamos la calidad de las series de tiempo (QV) que cumplían con tres, dos, uno, o ninguno de los criterios propuestos. Nuestros resultados muestran que para datos del índice normalizado de vegetación (NDVI) y del índice de vegetación extendido (EVI), la diferencia entre las series de tiempo de sitios quemados y no quemados disminuye gradualmente con el incremento de los criterios concordantes. Un incremento gradual se observa también en la calidad de las series de tiempo (QVI) con el incremento de los criterios concordantes. A pesar de las limitaciones del método propuesto, nuestro modelo representa un avance tanto desde el punto de vista conceptual como metodológico, dado que es la primera propuesta de un método estadístico para seleccionar sitios testigo no quemados, basados en criterios biológicos.

INTRODUCTION

Wildland fire is a widespread disturbance in terrestrial ecosystems (Flannigan *et al.* 2013) and plays a key role in the structure and function of vegetation (Bond and Keeley 2005). In the last century, ecological equilibrium has been threatened in many ecosystems, since changes that occurred in climatic and anthropogenic factors have triggered an increase in fire frequency and intensity (Mckenzie *et al.* 2011). Therefore, robust post-fire monitoring

tools are needed to understand the post-fire recovery process (Van Leeuwen *et al.* 2010), which is necessary to design forest management strategies (Casady *et al.* 2010, Di Mauro *et al.* 2014).

Wildland fires generally occur as unplanned trials because the time and place of occurrence can seldom be accurately predicted (Ayanz *et al.* 2003). In this context, satellites are useful tools to monitor fire events because the spectral information captured by on-board sensors makes it possible to obtain information about the fire including the date, location, extent of intensity and severity, and post-fire ecosystem functioning of a fire (Perez-Cabello *et al.* 2009, Di Bella *et al.* 2011). The availability of satellites with high temporal resolution and low spatial resolution, such as Moderate Resolution Imaging Spectroradiometer (MODIS), allows daily data collection (Huete *et al.* 2002). This temporal resolution allows us to build time series datasets (Gitas *et al.* 2012) and obtain metrics to characterize the post-fire vegetation functioning (Hicke *et al.* 2003, Goetz *et al.* 2006, Van Leeuwen 2008, Casady *et al.* 2010, Di Mauro *et al.* 2014). Consequently, information generated by this satellite is essential to understanding post-fire vegetation recovery processes and the effect of fires on ecosystem functioning. Despite the significant vegetation variability within each MODIS pixel due to its low spatial resolution, current evidence suggests that Normalized Difference Vegetation Index (NDVI) calculated with MODIS data has a good correlation with NDVI field data (Kovalskyy *et al.* 2012).

The use of vegetation index (hereafter VI) images obtained from satellite data is one of the most widely used methods to study post-fire vegetation recovery (Gitas *et al.* 2012). These indices have a strong relationship with the amount of biomass (Gasparri *et al.* 2010), leaf area index (Baret *et al.* 1989, Baret and Guyot 1991), and the above-ground net primary production (Paruelo and Lauenroth 1998, Paruelo *et al.* 2001). Therefore, VIs have high

correlation with ecosystem functions, (i.e., ecosystem processes that determine the flow rates of energy and matter; Cabello *et al.* 2012). By far, the most widely used remote sensing VI to assess post-fire recovery is the NDVI (Normalized Difference Vegetation Index; Gitas *et al.* 2012). Empirical evidence shows that, despite the well-known problems associated with saturation and background signal, NDVI is the VI with the greatest correlation between field measurements taken in different studies of post-fire vegetation recovery (Gitas *et al.* 2012, Veraverbeke *et al.* 2012). Another useful VI to characterize vegetation functioning is the Enhanced Vegetation Index (EVI). This index was developed to optimize the vegetation signal since it has improved sensitivity in regions with high biomass and is less affected by both the atmospheric conditions and the canopy background signal (Huete *et al.* 2002).

One technique used to monitor the time that vegetation needs to return to a similar functional pre-fire state is the comparison of a burned site with an adjacent unburned control site (Gitas *et al.* 2012, Di Mauro *et al.* 2014). This method assumes that, without fire, a burned site should exhibit the same vegetation structure and functional behavior as the control site (Lhermitte *et al.* 2010). Therefore, it is necessary to detect control sites not only with the same vegetation structure before the fire event, but also with a VI time series of similar functional behavior (e.g., Di Mauro *et al.* 2014). Several field approaches to detect control sites were reported in literature. These studies were based on data about vegetation structure, biodiversity, environmental conditions, plant phenology, and the distance between burned and control sites (Diaz Delgado and Pons 1999, Riaño *et al.* 2002, Wittenberg *et al.* 2007, Di Mauro *et al.* 2014). However, the inaccessibility to some remote and wild study sites complicates the direct field measurements of structural and phenological similarities in ecosystem-scale studies. In addi-

tion, ecosystem functions have a shorter response time than vegetation structure; so, variations in ecosystem functioning are seldom reflected in vegetation maps because they are oriented to detect structural attributes of vegetation (Paruelo *et al.* 2001). Therefore, some studies used vegetation maps with a good spatial resolution as complementary information to MODIS time series imagery to ensure structural similarity between burned and control sites (Van Leeuwen 2008, Casady *et al.* 2010, Di Mauro *et al.* 2014). In these studies, the authors dealt with the problem of functional similarity by comparing the value of the arithmetic mean of all VI time series of burned sites with the arithmetic mean of all VI time series of unburned control sites. However, the main limitation of this approach is that, by averaging values of the burned area, the intrinsic spatial variability is lost (Gitas *et al.* 2012). In other studies, such as Lhermitte *et al.* (2010), authors proposed selecting control sites based on the pre-fire Euclidian distance between the VI time series of burned and unburned sites. However, statistical distance between different time series does not provide information about the nature of the difference or similarity between series (Cuadras 1989, Lhermitte *et al.* 2011). Hence, in sites with high spatial heterogeneity, selecting the most similar sets of unburned sites does not guarantee a similar vegetation behavior between control and burned sites.

Overall, there are several techniques to compare or measure differences between time series. However, there are no objective criteria for selecting unburned control sites based on the vegetation functional behavior that minimizes the differences between the VI time series of burned and unburned control sites (Gitas *et al.* 2012). Accordingly, the specific aims of this study were to: 1) propose criteria for selecting control sites that have VI time series of the same functional behavior, 2) propose a statistical method for detecting control sites that meet the set criteria, and 3) test the perfor-

mance of the proposed method using data obtained from burned and unburned sites.

METHODS

Study Area

We performed the study in the Dry Chaco region, in Santiago del Estero province, Argentina (Figure 1), between 22°S and 31°S, and between 59°W and 66°W (Kunst *et al.*
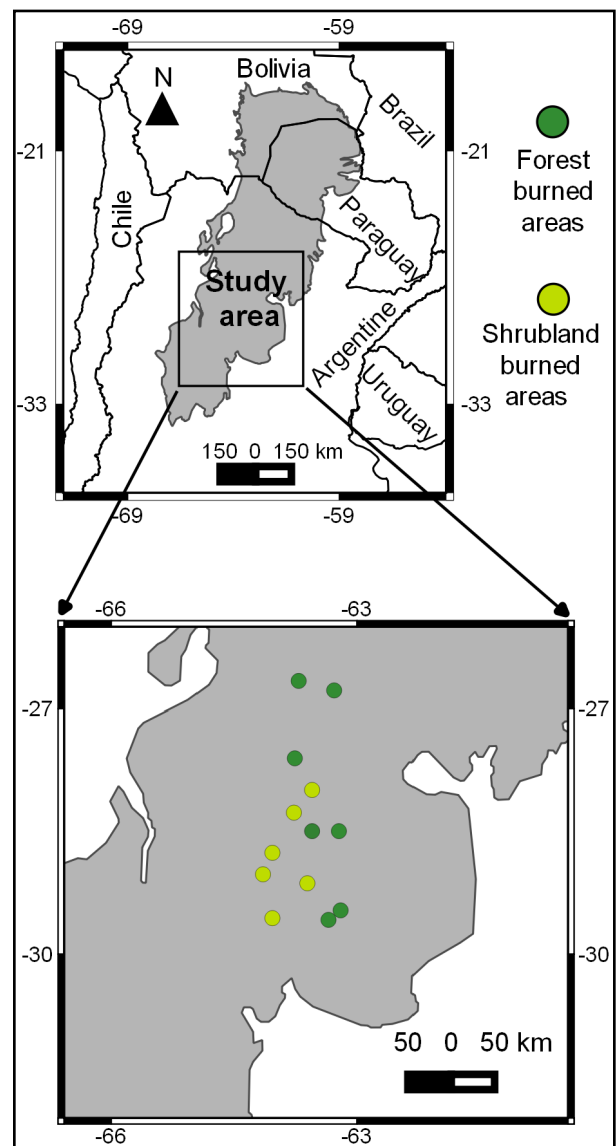

Figure 1. Location of study area. Dark green circles: forest burned areas, light green circles: shrubland burned areas. Grey area: Dry Chaco region.

2003). The annual rainfall ranges from 400 mm to 800 mm (Arambarri *et al*. 2011). The vegetation is composed of forest, shrubland, and grassland (Kunst *et al*. 2003, Atala *et al*. 2008, Bravo *et al*. 2014). The forest canopy is 6 m to 9 m in height and the cover ranges from 15 % to 80 %; it is mainly composed of the evergreen species *Aspidosperma quebracho-blanco* Schltdl. and the deciduous trees *Prosopis* spp. L. (Kunst *et al*. 2003). The shrubland consists of short woody vegetation and an herbaceous layer resulting from excessive logging and grazing; it is mainly composed by *Acacia praecox* Griseb., *Celtis chichape* (Wedd.) Miq.*,* and *Schinus fasciculatus* (Griseb) I.M. Johnst. (Kunst *et al.* 2003). Nomenclature follows Zuloaga and Morrone (1999). The woody species are 3 m to 5 m in height and the cover ranges from 35 % to 80 % (Atala *et al*. 2008).

Satellite Data

Time series construction. We used data from MODIS Terra imagery (MOD13Q1) to construct NDVI and EVI time series. We downloaded images from the Oak Ridge National Laboratory Distributed Active Archive Center's MODIS Land Product Subsets (https://daac.ornl.gov/MODIS/). This product is atmospherically corrected to surface reflectance and has a spatial resolution of 250 m × 250 m, with a temporal resolution of 16 days, resulting in 23 images per year. Since NDVI MODIS Terra dataset has been available from 18 February 2000, we decided to use VI time series that spanned three years before fire events, from 18 February 2000 to the date corresponding to an image prior to each fire event, from August to December 2003.

Fire detection. To detect burned areas, we used the Normalized Burn Ratio (NBR) index (Key and Benson 1999), calculated from Landsat 5 TM images (scenes 229-79 and 229-80 from 12 December 2003, resolution 30 m × 30 m). We downloaded georeferenced and or-

thorectified images from the US Geological Survey (EarthExplorer; http://earthexplorer.usgs.gov/). In order to validate detected burned areas, we overlapped the MODIS (MCD14L) vector Thermal Anomalies Fire product shapefile (Giglio 2010) with NBR images (Figure 2). This product has a spatial resolution of 1 km × 1 km and a temporal resolution of 6 hr, and was downloaded from NASA FIRMS (National Aeronautics and Space Admin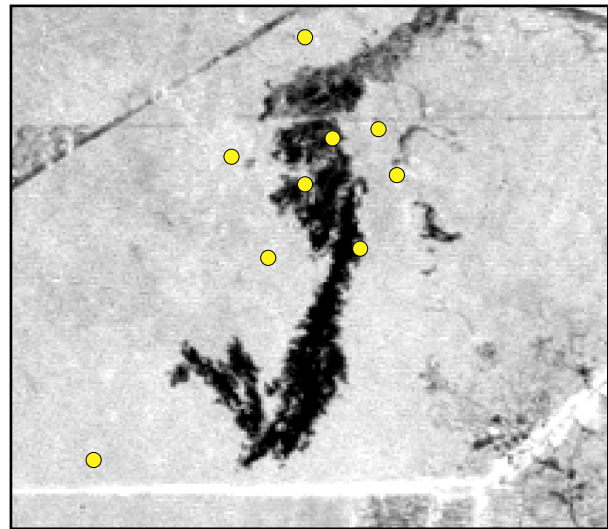istration Fire Information for Resource Management System; https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms).

Figure 2. NBR Landsat 5 TM image of a burned area. Yellow circles: MODIS (MCD14L) vector Thermal Anomalies Fire product.

Vegetation map. We used Globcover 2000 vegetation map (Joint Research Centre) to assign vegetation cover to unburned and burned sites. This map is a global vegetation product, has a spatial resolution of 1 km × 1 km (Eva *et al*. 2002), and incorporates vegetation field data, NDVI data from SPOT VEGETATION (Saint 1994). This NDVI product has a spatial resolution of 1 km × 1 km, with a temporal resolution of 10 days. Besides, Globcover 2000 incorporates ATSR2 (Závody *et al*. 1994) satellite data to characterize seasonal behavior of forests, JERS-1 (Rosenqvist 1996) radar

data to characterize the hydrodynamics of forests, and GTOPO30 topographic data (USGS 2005).

Proposed Criteria and Statistical Methods

As a first step, we proposed to calculate the point-by-point ratio between the VI time series of one pixel of the burned area of interest (TS_b), and the VI time series of one pixel of the unburned area (TS_{ub}). This unburned area was randomly selected in a buffer area around each burned site (Equation 1; Figure 3, step 1):

$$QVI_{TS_b/TS_{ub}} = \frac{TS_b}{TS_{ub}} , \qquad (1)$$

where TS_b is the VI time series of the burned site, and TS_{ub} is the VI time series of the unburned site

Then, we represented the new time series $QVI_{TS_b/TS_{ub}}$ according to a classical additive statistical model for time series (Morettin and Castro Toloi 1987, Brockwell and Davis 2002), which is presented in Equation 2:

$$QVI_{TS_b/TS_{ub}} = Me_{QVI} + T_{QVI} + S_{QVI} + a_{QVI}, (2)$$

where Me_{QVI} is the arithmetic mean; T_{QVI} is the tendency component, the function that expresses the rate of change of $QVI_{TS_b/TS_{ub}}$ over time; S_{QVI} is the seasonality component, the function that expresses the seasonal component of $QVI_{TS_b/TS_{ub}}$; and a_{QVI} is the random effect component.

Next, we analyzed the properties of the $QVI_{TS_b/TS_{ub}}$ time series to test if they met the following proposed criteria. As the first criterion, we proposed that, before the fire, the mean level of photosynthetic activity of the unburned site should not have statistically significant differences from the mean level of photosynthetic activity of the burned site. To detect these unburned sites, we proposed that pre-fire $QVI_{TS_b/TS_{ub}}$ time series had $Me_{QVI} = 1$ (Figure 3, step 2), because if Me was 1, then

TS_b and TS_{ub} had the same mean. To test that $Me_{QVI} = 1$, we proposed using μ as an estimator (Efron 1979, Efron and Tibshirani 1986) with a 95 % confidence interval. To break the temporal autocorrelation of the data, the lower and upper limits of Me_{QVI} were estimated by bootstrapping with replacement (Efron 1979, Efron and Tibshirani 1986), using 1000 iterations and extracting 50 % of the data from each iteration.

As a second criterion, we proposed that the slope of the VI time series of burned and unburned sites should not have statistically significant differences (Figure 3, step 3), because differences in this parameter indicate that the photosynthetic activity of both sites evolved differently in magnitude or direction over time. To test this criterion, we proposed that $QVI_{TS_b/TS_{ub}}$ should exhibit a null T_{QVI}. To test if T_{QVI} was null, we proposed using the nonparametric Spearman Rank Correlation Test (Morettin and Castro Toloi 1987, McLeod et al. 1991, Yue et al. 2002).

As a third criterion, we proposed that, in each season of the year, burned and unburned sites should have a mean level of photosynthetic activity without statistically significant differences (Figure 3, step 4), since these differences indicate that burned and unburned sites have a different functional behavior for at least one season of the year. To test this criterion, we proposed that $QVI_{TS_b/TS_{ub}}$ should have a null S_{QVI}, because the existence of differences between burned and unburned sites in the mean of VI for at least one season of the year would generate a seasonal pattern in the $QVI_{TS_b/TS_{ub}}$ time series. To test if S_{QVI} was null, we proposed testing that each season of the year had an arithmetic mean of $QVI_{TS_b/TS_{ub}}$, without statistically significant differences, by applying the nonparametric Friedman test (Morettin and Castro Toloi 1987, Sutradhar et al. 1995). To implement the test, we used each season as a treatment (four treatments) and the year as a block (three blocks); thus, the Friedman test was implemented using 12 data
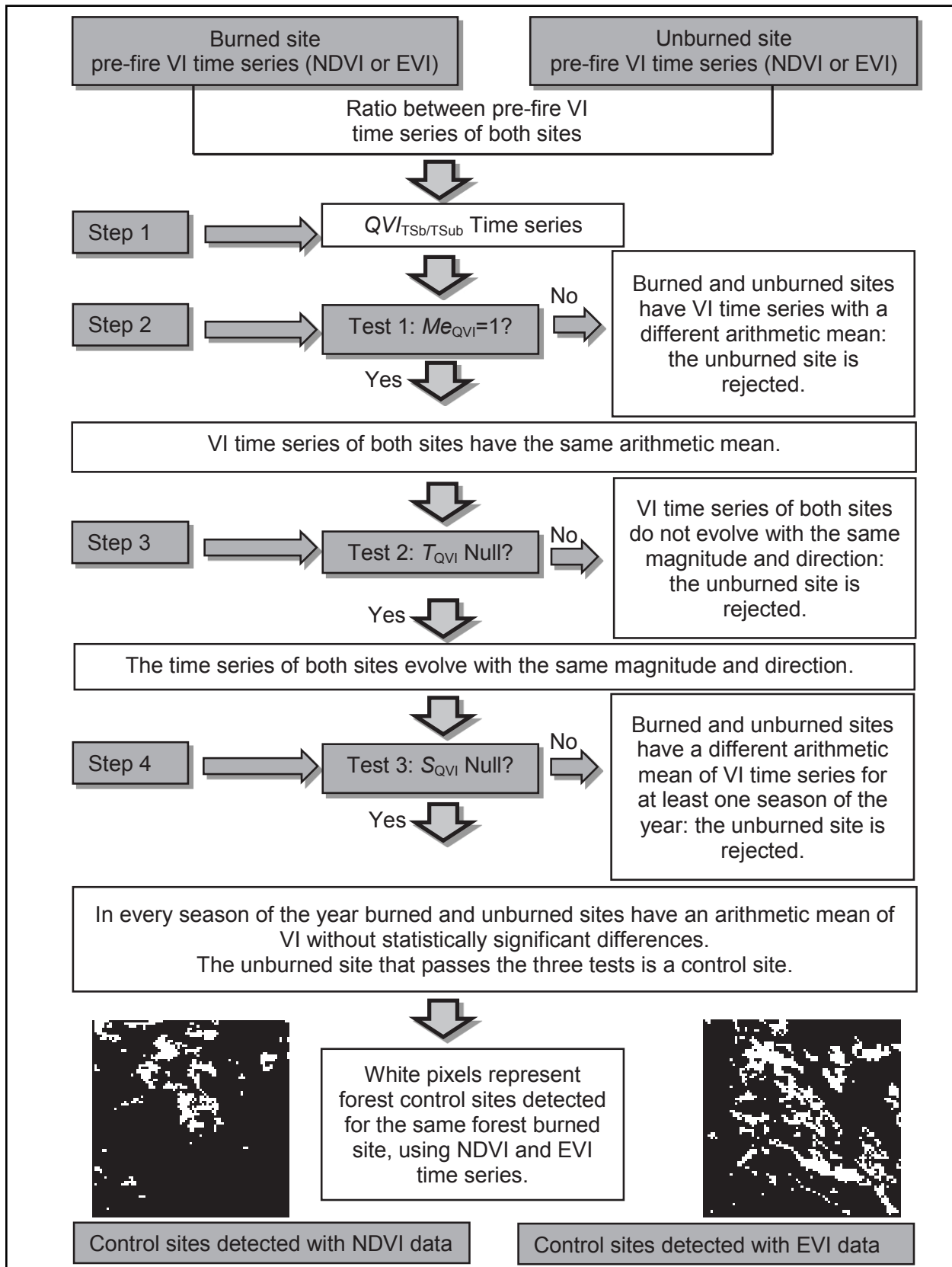
Burned site pre-fire VI time series (NDVI or EVI)	Unburned site pre-fire VI time series (NDVI or EVI)

Ratio between pre-fire VI
time series of both sites

Step 1 → $QVI_{TSb/TSub}$ Time series

Step 2 → Test 1: $Me_{QVI}=1$? — **No** → Burned and unburned sites have VI time series with a different arithmetic mean: the unburned site is rejected.

Yes ↓

VI time series of both sites have the same arithmetic mean.

Step 3 → Test 2: T_{QVI} Null? — **No** → VI time series of both sites do not evolve with the same magnitude and direction: the unburned site is rejected.

Yes ↓

The time series of both sites evolve with the same magnitude and direction.

Step 4 → Test 3: S_{QVI} Null? — **No** → Burned and unburned sites have a different arithmetic mean of VI time series for at least one season of the year: the unburned site is rejected.

Yes ↓

In every season of the year burned and unburned sites have an arithmetic mean of VI without statistically significant differences.
The unburned site that passes the three tests is a control site.

White pixels represent forest control sites detected for the same forest burned site, using NDVI and EVI time series.

Control sites detected with NDVI data	Control sites detected with EVI data

Figure 3. Flowchart of the proposed method.

points. To obtain each data point, we averaged the $QVI_{TS_b/TS_{ub}}$ data corresponding to each season. We used this nonparametric test to avoid the correlation between repetitions, because, in this way, we increased the time lag between replicates of each treatment to one year instead of one data point every 16 days (Franzini and Harvey 1983, Morettin and Castro Toloi 1987, Sutradhar *et al.* 1995). The $QVI_{TS_b/TS_{ub}}$ time series that met the three proposed criteria could be considered as a random noise with µ = 1, since the classical additive statistical model assumes that a time series without tendency and seasonality is a random noise (Morettin and Castro Toloi 1987, Brockwell and Davis 2002).

The unburned sites generating $QVI_{TS_b/TS_{ub}}$ that met the three proposed criteria could be considered control sites because they not only had the same vegetation cover as the burned sites, but also the same functional behavior. Figure 4 shows the vegetation structure of actual burned and unburned sites that met the three proposed criteria. Figure 5A shows that the NDVI time series of a burned site and of an unburned site that met the three proposed criteria had the same behavior with occasional differences. And figure 5B shows that the $QVI_{TS_b/TS_{ub}}$ that met the three proposed criteria was centered around 1 and only a few data points were as high as 10 %.

Testing the Performance of the Proposed Method

To test the performance of the method, we assumed that, if it is correct, the pre-fire functional similarity between burned and unburned sites would increase with the increase of met criteria of unburned sites. Therefore, we compared the differences between VI time series of burned sites and VI time series of unburned sites with the same vegetation cover that met three, two, one, and none of the proposed criteria. In addition, we expected that the quality of $QVI_{TS_b/TS_{ub}}$ time series would increase with
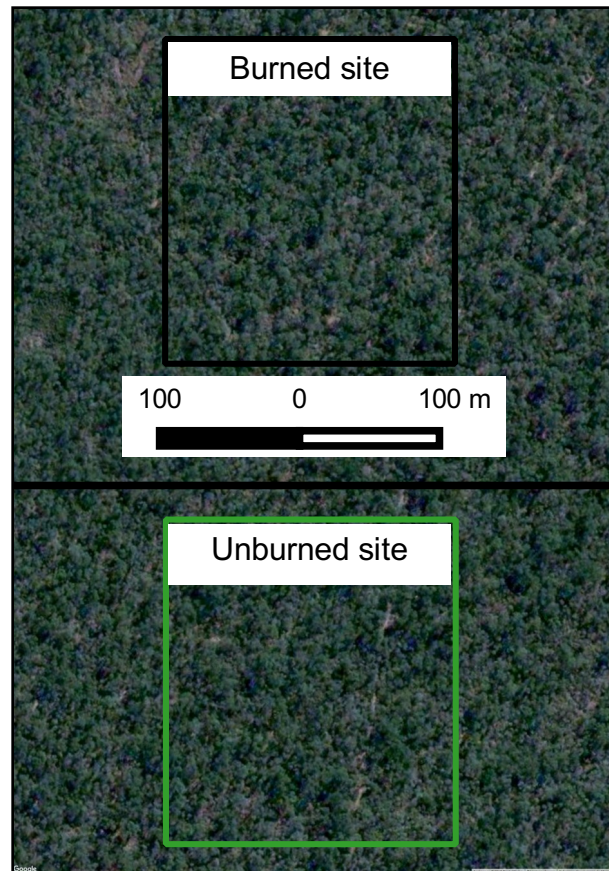

Figure 4. Structure of actual burned and unburned sites that met the three proposed criteria.

the increase of met criteria of unburned sites. Therefore, we compared the width of the confidence interval for $QVI_{TS_b/TS_{ub}}$ time series that met three, two, one, and none of the proposed criteria. Finally, we expected a decrease in the variability of VI time series of unburned sites with the increase of met criteria, because the VI time series of unburned sites that met the three proposed criteria should be very similar to the VI time series of the burned sites. In turn, VI time series of unburned sites that did not meet the three proposed criteria could be similar or dissimilar to the VI time series of the burned sites.

For this study, we constructed VI time series from forest and shrubland covers using NDVI and EVI data sets (Huete *et al.* 2002). We used forest and shrubland areas because
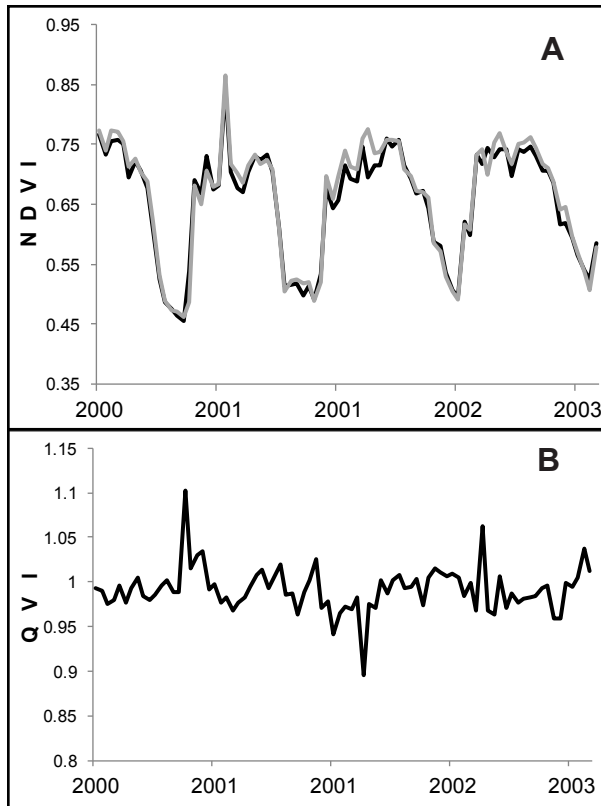
Figure 5. A) NDVI time series of a burned site (black) and an unburned site (gray) that met the three proposed criteria. B) QVI time series that met the three proposed criteria.

they are the largest land covers in the region and exhibit VI time series with different inter- and intra-annual behaviors (Clark *et al.* 2010). We also used NDVI and EVI datasets because they exhibit differences in the range of variation and in the sensitivity to vegetation structure, chlorophyll activity, and soil water status (Huete *et al.* 2002, Clark *et al.* 2010, Paruelo *et al.* 2014), thus providing different types of biological information to select the control sites. We manually selected 20 burned forest sites distributed across seven burned areas, and 20 burned shrubland sites distributed across six burned areas (Figure 1). Each burned site had an area of 250 m × 250 m (1 MODIS pixel). We detected each burned area by visually analyzing the NBR images and the vector Thermal Anomalies Fire product shapefile (Figure 2). All areas were burned in 2003

at different points across an area of 50 000 km² of the Chaco region. For each burned site, we randomly selected 40 unburned sites with VI time series that met the three proposed criteria and had the same vegetation cover before the fire, 40 that met two criteria, 40 that met one criterion, and 40 that did not meet any criteria. We used a total of 12 840 VI time series for this work: 40 time series of burned sites plus 12 800 VI time series of unburned sites (2 plant cover × 20 burned plots × 40 unburned sites per number of met criteria × 4 number of met criteria × 2 vegetation indices = 12 800). Unburned sites were selected from a buffer area of 10 km around each burned site. Unburned site selection and statistical tests were performed automatically using IDL 71 (ITT Visual Information Solutions 2009).

Comparison of Time Series

We measured the pre-fire differences between VI time series of each burned site and unburned sites that met three, two, one, and none of the proposed criteria using two measures: 1) Mean Proportional Difference (MPD; Equation 3), and 2) Mean Square Error (MSE; Equation 4)—the latter being more sensitive to outliers than the former (Lhermitte *et al.* 2010, Lhermitte *et al.* 2011). The quality of the $QVI_{TS_b/TS_{ub}}$ time series generated from the possible control sites was measured using the Width of the Confidence Interval (WCI) of Me_{QVI}.

$$MPD = \frac{\sum_{i=0}^{n=1} \frac{\text{Abs}(Sb_i - Sub_i)}{Sb_i}}{N} \quad , \qquad (3)$$

and

$$MSE = \sqrt{\frac{\sum_{i=0}^{n=1}(TSb_i - TSub_i)^2}{N}} \quad , \qquad (4)$$

where TSb_i is the VI value at time i of the burned site time series, $TSub_i$ is the VI value at the i of the unburned site time series, N is the

number of observations in the time series, and Abs is the absolute value function.

Data Analysis

We used the nonparametric Kruskal-Wallis test (Sheskin 2004) to compare MPD and MSE differences and WCI of $QVI_{TS_b/TS_{ub}}$ time series, using the number of met criteria as treatment. We verified that VI time series variability of unburned sites decreased with the increase of met criteria by unburned sites. For this, we performed an *F* test for homogeneity of variances to compare the variability of MPD and MSE differences and WCI values obtained for each set of time series (Sheskin 2004), using the number of met criteria as treatment.

RESULTS

In forests, average differences between VI time series of burned and unburned sites gradually decreased with the increase of met criteria (Figure 6; MPD_{NDVI} $P < 0.0001$, $\chi^2 = 1025.4$; MPD_{EVI} $P < 0.0001$, $\chi^2 = 383.4$; MSE_{NDVI} $P < 0.0001$, $\chi^2 = 273.4$; MSE_{EVI} $P < 0.0001$, $\chi^2 = 234.6$). In the NDVI data set, VI time series that met the three criteria had a MPD and a MSE nearly 50 % smaller than the series that did not meet any criteria. For the EVI data set, we observed that these reductions were close to 30 % for MPD and MSE. The WCI values measured for the $QVI_{TS_b/TS_{ub}}$ series followed a similar reduction pattern (WCI_{NDVI} $P < 0.0001$, $\chi^2 = 357.4$; WCI_{EVI} $P < 0.0001$, $\chi^2 = 217.1$). In the NDVI data set, the WCI values of the time series that met the three criteria were about 29 % smaller than series that did not meet any criteria; whereas for the EVI data set, this reduction was close to 17 %. Unburned sites showed a gradual decrease in the variability of the time series with the increase of met criteria (Table 1). The variability measured for unburned sites that met the three criteria were five to ten times smaller than the measured variability of the
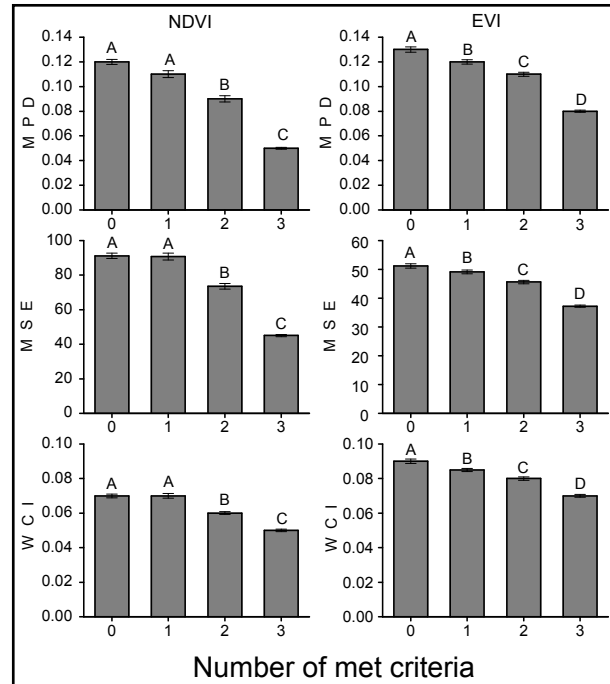

Figure 6. Mean value and standard deviation of MPD (Mean Proportional Difference) and MSE (Mean Square Error) differences, and WCI (Width of the Confidence Interval) obtained for forest VI time series that met three, two, one, and none of the proposed criteria. Different letters indicate significant differences (Kruskal-Wallis test, $P < 0.05$).

unburned sites that did not meet any criteria (Table 1).

Results obtained for shrubland VI time series were similar to those of the forest VI time series. The differences between the VI time series of burned and unburned sites gradually decreased with the increase of the met criteria (Figure 7; MPD_{NDVI} $P < 0.0001$, $\chi^2 = 495$; MPD_{EVI} $P < 0.0001$, $\chi^2 = 270.6$; MSE_{NDVI} $P < 0.0001$, $\chi^2 = 452.3$; MSE_{EVI} $P < 0.0001$, $\chi^2 = 273.4$). For the NDVI data set, VI time series that met the three criteria had a MPD 45 % smaller and a MSE 36 % smaller than series that did not meet any criteria. For the EVI data set, these reductions were about 30 % for MPD and 36 % for MSE. The WCI values measured for $QVI_{TS_b/TS_{ub}}$ series followed a similar reduction pattern (WCI_{NDVI} $P < 0.0001$, χ^2

Table 1. Variance measured for MPD (Mean Proportional Differences) and MSE (Mean Square Error) differences, and WCI (Width of the Confidence Interval) obtained for forest time series that met three, two, one, and none of the proposed criteria. Different letters indicate significant differences (*F* test, *P* < 0.05).

Number of met criteria	MPD		MSE		WCI	
	NDVI	EVI	NDVI	EVI	NDVI	EVI
0	3.5×10^{-3} a	3.7×10^{-3} a	1867 a	536.2 a	1×10^{-3} a	13×10^{-3} a
1	0.01 b	2.6×10^{-3} b	3316 b	313.9 b	1.5×10^{-3} b	7×10^{-4} b
2	4×10^{-3} c	2.2×10^{-3} c	2286.4 c	277.1 c	5×10^{-4} c	8×10^{-4} c
3	4×10^{-4}	8×10^{-3} d	340.9 d	108.5 d	4×10^{-4} d	5×10^{-4} d

= 116.88; WCI_{EVI} P < 0.0001, χ^2 = 109.22). In the NDVI data set, the WCI values of the time series that met the three criteria were about 25 % smaller than series that did not meet any criteria; whereas, for the EVI data set, this reduction was close to 29 %. Unburned sites showed a gradual decrease in the variability of the time series with the increase of met criteria (Table 2). The variability measured for sites that met the three criteria were two to five times smaller than the variability measured for unburned sites that did not meet any criteria (Table 2). The only exception to this pattern was the WCI of the EVI data set.
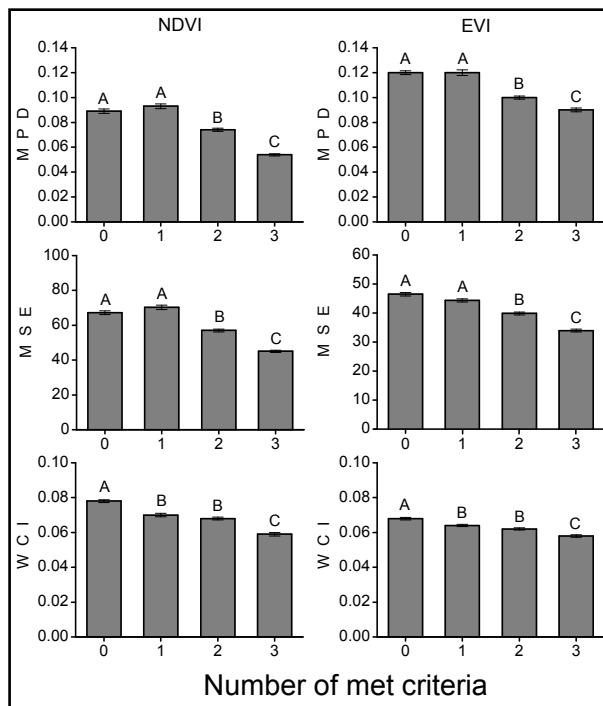
DISCUSSION

The biological criteria and statistical method proposed herein to select control sites yielded satisfactory results. We observed a gradual decrease in MPD, MSE, and WCI values with the increase of met criteria. This pattern indicates that the similarity of VI time series between burned and unburned sites increased with the increase of met criteria. Hence, the functional similarity also increased, because the VI are related to biomass, green cover, leaf area index, and fraction of absorbed photosynthetically active radiation (Huete *et al*. 2002, Paruelo 2008). We also observed a gradual reduction in the variability of MPD, MSE, and WCI values with the increase of met criteria, which means that VI time series that met the three criteria were very similar to the VI time series of the burned sites; whereas, VI time series of unburned sites that did not meet the three proposed criteria were similar or dissimilar to the VI time series of the burned sites.

The comparison of the average values of MPD, MSE, and WCI values obtained for NDVI and EVI time series showed similar pat-

Figure 7. Mean value and standard deviation of MPD (Mean Proportional Difference) and MSE (Mean Square Error) differences, and WCI (Width of the Confidence Interval) obtained for shrubland VI time series that met three, two, one, and none of the proposed criteria. Different letters indicate significant differences (Kruskal-Wallis test, *P* < 0.05).

Table 2. Variance measured for MPD (Mean Proportional Differences) and MSE (Mean Square Error) differences, and WCI (Width of the Confidence Interval) obtained for the shrubland time series that met three, two, one, and none of the proposed criteria. Different letters indicate significant differences (*F* test, $P < 0.05$).

Number of met criteria	MPD		MSE		WCI	
	NDVI	EVI	NDVI	EVI	NDVI	EVI
0	2.2×10^{-3} a	3.5×10^{-3} a	959.7 a	272.7 a	7×10^{-4} a	4×10^{-4} a
1	2.9×10^{-3} a	2×10^{-3} b	1255 b	274.8 a	8×10^{-4} a	3×10^{-4} a
2	1.1×10^{-3} a	1.5×10^{-3} c	479 c	166.6 b	5×10^{-4} b	3×10^{-4} a
3	4×10^{-4} b	1.4×10^{-3} c	218.9 d	163.9 c	6×10^{-4} b	4×10^{-4} a

terns of variation (Figures 6 and 7). However, for both forest and shrubland covers, the average MPD and WCI values for the NDVI data were about half of the values for the EVI data. These differences may be attributed to the information contained in each index. The NDVI index provides information not only about plant photosynthetic activity, but also about the characteristics and water status of the substrate (Huete *et al*. 2002, Paruelo 2008). Therefore, by using the NDVI time series, we can select sites with greater similarity in photosynthetic activity, type of substrate, and soil water dynamics than by using the EVI time series. On the other hand, the EVI index is more sensitive to structural canopy variations, including leaf area index, canopy type, plant physiognomy, and canopy architecture (Gao *et al*. 2000, Huete *et al*. 2002), than NDVI. Therefore, for ecological studies, we recommend selecting as control sites those unburned sites that meet the three criteria with both VI time series. As a consequence, the functional similarity between sites will be maximized

Comparing the results obtained between forest and shrubland, we observed that variability was the main difference. The probability to select an unburned site that meets the three proposed criteria and has a great difference from the time series of a burned site was smaller for forests than for shrublands. This is because, in forests, the reduction in the variance was twice higher than in shrublands (Tables 1 and 2). Consequently, the results from the method obtained for shrubland covers need

to be examined more carefully. These differences between cover types may be attributed to the different levels of degradation and high spatial heterogeneity typical of shrublands (Atala *et al*. 2008), which are characterized by a high percentage of a herbaceous plant cover and bare soil (Kunst *et al*. 2003, Arambarri *et al*. 2011). Hence, due to the phenology of annual and deciduous plants, shrubland VI time series have sharper seasonal variations than forest VI time series, as well as a sharper and more rapid response to climatic conditions (Clark *et al*. 2010, Arambarri *et al*. 2011). These kinds of variations in VI time series might generate $QVI_{TS_b/TS_{ub}}$ time series with high noise levels and abrupt variations. The presence of high noise levels in time series can reduce the probability to detect significant results in traditional tests, such as the Spearman test used to detect trends (Yue *et al*. 2002). Therefore, the method might be affected by the inter- and intra-annual differences in behavior of forest and shrubland covers.

The proposed method is only based on functional similarity; however, structural similarity should be taken into account if we want to obtain unburned control sites highly similar to burned sites. Therefore, the availability of vegetation maps with good accuracy and few misclassified pixels is a key issue in implementing the proposed method successfully. Nevertheless, it is necessary to distinguish the effect of omission and commission errors. Omission errors have no effect on the results obtained by the tests used in the proposed

method since they are pixels of a given vegetation cover, but were classified as a different vegetation cover (Lillesand *et al.* 2008). In other words, if the method looks for forest data, pixels of this vegetation cover incorrectly labeled will be ignored. Nevertheless, the presence of omission errors in the vegetation map reduces the number of potential candidate sites to be tested, and this could be a problem if the vegetation cover under study is scarce. The presence of commission errors in the vegetation map could generate problems in the results obtained by the tests used in the proposed method. The commission errors are pixels that were mistakenly classified as the determined vegetation cover (Lillesand *et al.* 2008).

This situation represents a problem only if the $QVI_{TSb/TSub}$ series calculated from VI series obtained from different vegetation covers successfully meets the three proposed criteria. Nevertheless, since the dominant vegetation covers of our system have very different structural (Atala *et al.* 2008, Arambarri *et al.* 2011) and functional (Clark *et al.* 2010) characteristics, we expect that only a small quantity of $QVI_{TSb/TSub}$, constructed with VI time series of different vegetation covers, meet the three proposed criteria. However, this could generate problems in systems in which the different vegetation covers have similar structural and functional characteristics. Therefore, we recommend checking the results with free, very high spatial resolution images, like GeoEye or QuickBird (Google Earth, https://www.google.com/earth//).

The mode of implementing the proposed statistical tests may have some drawbacks. The Friedman test was implemented using 12 averaged data points (four seasons and three years) to reduce autocorrelation problems (Morettin and Castro Toloi 1985, Sutradhar *et al.* 1995). However, this procedure implies losing some of the information contained in the time series. The limitations mentioned would generate problems in the method implementation since Friedman test often fails to

detect statistically significant differences in data sets with high variance (Yue *et al.* 2002), as is expected for shrubland QVI time series. Thus, the method would select unburned sites with VI time series that did not meet the proposed biological criteria and with extreme differences from the VI time series of the burned site. To avoid selecting unburned sites with VI time series showing extreme differences from the VI time series of the burned site, Lhermitte *et al.* (2010) proposed to remove these kinds of time series using Limit Values obtained through MSE (i.e., an empirical threshold estimated from the distribution of the data pool, which is used as a rule of thumb to accept or reject time series). Better results may be obtained by calculating the Limit Value using the WCI data, since this measure presents a proportional reduction smaller than MPD and MSE differences (Figures 6 and 7). We propose to use the median of the WCI data as Limit Value (between 0.05 and 0.08 for this work), which ensures the selection of the best quality data and the rejection of only half of the possible unburned control sites. However, we emphasize that the need to use arbitrary Limit Values to obtain satisfactory results implies that some of the biological information still has not been correctly modeled. As a consequence, some $QVI_{TSb/TSub}$ time series that meet the three proposed criteria were not pure random noise a_{QVI}, as we expected for time series that lack seasonality and trend components (Morettin and Castro Toloi 1987, Brockwell and Davis 2002). Further research will be needed to determine if this is due to the need for additional biological criteria or the need for improvements in the statistical tests.

CONCLUSIONS

This method represents an advance from the conceptual and methodological standpoints; it can be used to select control sites for the study of fires as well as other disturbances such as floods, insect infestation, and droughts

in different ecosystems. In addition, the proposed criteria can also be used to determine when the sites will recover after the fire. The biological criteria proposed in this study can provide a complete analysis since they allow us to test the mean value of $QVI_{TS_b/TS_{ub}}$, its slope, and seasonal behavior separately, providing detailed information about the recovery process. However, the statistical slope test still needs to be adapted to detect when the slope of the $QVI_{TS_b/TS_{ub}}$ curve becomes null.

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