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By Luciana Ghermandi, Antonio Lanorte, Facundo Oddi & Rosa Lasaponara

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Assessing Fire Severity in Semiarid Environments with the DNBR and RDNBR Indices

Luciana Ghermandi [α], Antonio Lanorte [σ], Facundo Oddi [ρ] & Rosa Lasaponara [ω]

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I. Introduction

Shape and dimension of fires at landscape scale are the result of complex interactions among climate, topography, vegetation and ignition sources. Factors related to fire, such as structure and moisture content of vegetation (considered as fuel), exhibit substantial spatial and temporal variability (Turner and Romme, 1994). After fire, we observe a mosaic of patches with different degree of fire severity and such heterogeneity determines important implications in ecosystem recovery and possibility of land uses (Lentile et al., 2006; French et al., 2008; Keeley et al., 2008). For instance, ecosystem resilience may be low in more severely burned patches because no remnant vegetation (Chuvieco et al., 2006; Lentile et al. 2006) and land managers and political decision makers need to know fire severity impact on ecosystems because it can trigger processes like soil erosion, desertification or faunal pauperization (French et al., 2008; Keeley, 2009).

Fire severity terminology has been used in confused manner in ecology and remote sensing literature (Lentile et al., 2006) and to remediate this, Jain et al. (2004) proposed a conceptual framework, called *fire disturbance continuum*. More recently Keeley (2009) tried to clarify the use of fire intensity, fire severity, burn severity and ecosystem responses and proposed to define fire severity as the aboveground and belowground organic matter consumption excluding post-fire ecosystem responses. For example, in Mediterranean perennial grasslands of northwestern Patagonia, fire mortality, that is an indicator of fire severity, can be assessed only after the first post-fire growth season because the dominance of sprouting species (Ghermandi et al., 2004; Gittins et al., 2011).

Fire intensity represents the energy released during a fire. Topography, fuel load, fuel condition (size and surface/volume ratio, degree of compaction, moisture content, and chemical composition) and wind magnitude, are the decisive factors in determining fire intensity (Heward et al., 2013). Fire residence time is inversely proportional to fire rate of spread and directly proportional to flame height. Therefore fire intensity and fire residence time take opposed meaning in presence of a given amount of fuel which burns fast (Rothermel and Deeming, 1980; Alexander 1982). Consequently, a high-intensity fire with low residence time may not be severe and may not lead to high plant mortality. On the other hand, low-intensity fires can damage soil more than vegetation when smoldering combustion of litter or peat produces long duration heating (Hartford et al., 1991; Watts, 2013; Atwood et al., 2016).

Plant vulnerability to fire and post-fire responses are related to a set of features that characterize the two functional groups of shrubs, seeders and sprouters that dominate the Mediterranean environments (Bond and Van Wilgen, 1996; Keeley et al., 2012). However, interactions between fire severity, vegetation and environmental factors are poorly known, in particular in large fires because the traditional methods of recording fire severity involve expensive and time-consuming field surveys. For this reason remote sensing products are

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frequently utilized in the monitoring of post-fire vegetation and soil at landscape and regional scales (Epting et al., 2005; Soverel et al., 2010).

Indices derived from spectral bands have been extensively used to estimate the fire severity from remote sensing datasets. Multi-decadal estimate of fire severity can be achieved using the radio metrically consistent temporal archive of Land sat images captured with the TM, ETM+ and OLI instruments since 1982 at near global coverage (Smith et al., 2005; Keeley et al., 2012). The normalized burn ratio (NBR), for example, has been extensively used for multi-date differenced NBR (dNBR) classification of fire severity and to infer the degree of post-fire ecological change (Key, 2006; Parker et al., 2015).

Fire causes changes in spectral behavior of vegetation. The reflectance in the midinfrared, which is sensitive to water content of soil and vegetation, increases after fire, while in the near infrared region a reflectance decline occurs because of the drop of the live vegetation chlorophyll content. The NBR index has been created to assess fire severity considering these characteristics (Miller and Thode, 2007; Lanorte et al., 2013).

Nevertheless to map fire severity in heterogeneous landscapes may be required predisturbance and post-disturbance images and the delta-NBR (dNBR) and the relative delta- NBR (RdNBR) have been developed to remove biasing of the pre-fire vegetation present in the uni-temporal approach (Miller and Thode, 2007; Miller et al., 2009). The dNBR shows the absolute change value whereas the RdNBR is a relative index that allows certain independence from pre-fire condition of vegetation. However, the results about the indexes suitability in different ecosystems, are not conclusive. Some studies defined that RdNBR is more accurate than dNBR (Key, 2006; Miller and Thode, 2007) whereas others found that RdNBR not improves the estimations of fire severity and showed similar correlations between both indices and field data (Roy et al., 2006; Soverel et al., 2010). For example, in black spruce forests RdNBR produced a classification with less omission and commission errors for high severity fires (Hoy et al., 2008) whereas in Californian chaparrals, dNBR correlated better with field data than RdNBR (Keeley et al., 2008). Moreover, several studies show that RdNBR is more sensitive to vegetation mortality and dNBR to soil burn severity (Zhu et al., 2006; Safford et al., 2008; Miller et al., 2009).

Most of the fire severity assessments using remote sensing has been done in forest ecosystems and are few the studies carried out in semiarid ecosystems dominated by grasslands and shrublands. The difficulty can be that pre and post-fire conditions in these environments present a low spectral contrast due to the lower fuel load compared with forests (Collins et al., 2009; Norton 2009). Researchers reported lower correlations of non forest compared with forest ecosystems and some of them were forced to remove herbaceous/shrubby areas from the analysis due to the complexity of result interpretation (Epting et al., 2005; Collins and Stephen, 2010).

The Patagonia extra-Andean landscape is heterogeneous, the climate is Mediterranean, with rains concentrated in autumns-winters and dry summers (Paruelo et al., 1998). For this reason the fire regime presents a strong seasonality and fires occur principally during the summer months (Oddi and Ghermandi, 2016). The Andes chain provokes an of wide world most abrupt west-east precipitations gradient that is reflected in the vegetation that change from mesic forests to semiarid grasslands and arid shrublands in a few kilometers (Soriano, 1983). In this region we recorded a strong relationship between large wildfires and ENSO phenomena (Ghermandi et al., 2010). During 1997-1999 occurred one of these concatenated effects: a strong El Niño (rainy year that increased the biomass production) followed by a strong La Niña (dry year that dried the biomass) followed by a very devastating wildfire in January 1999 (summer). The fire was provoked by two highlights and burned 22000 ha, 16000 of these belonging to San Ramón ranch (Defossé and Dentoni, 1999) being largest fire occurred in the region from ’70 decade (Oddi and Ghermandi, 2016).

San Ramón is a productive ranch in which the land uses are the extensive stockbreeding and forestations. For this reason we rely on a pre-fire detailed vegetation map, made from aerial photos (Anchorena and Cingolani, 2002) and technical reports that estimate the biomass load before and after the 1999 wildfire (Golluscio et al., 1993; Bran et al., 2006). In the same study site we had also studied the patterns of vegetation recovery (Ghermandi et al., 2004; Gonzalez and Ghermandi, 2008; Ghermandi and Gonzalez, 2009; Ghermandi et al., 2010) focusing in post-fire shrub encroachment (Ghermandi et al., 2013) and in the post-fire response of dominant grasses and shrubs (Gonzalez et al., 2015 a; Gonzalez et al., 2015 b). This signifies that we had an important previous knowledge about ecological processes linked with fire, which had had useful in the interpretation of fire severity in the study area. The general objective of the present study is to assess the fire severity in semiarid ecosystems dominated by herbaceous vegetation using detailed pre-fire vegetation maps, biomass load data and pre-fire/post-fire Landsat images. The specific objectives are: a) to compare the behavior of the dNBR and RdNBR indexes in four vegetation communities: grassland, shrubland, meadow and forestation; b) to evaluate the sensibility of the indexes to assess fire severity in the three communities characterized by low biomass production (grassland, shrubland and meadow); c) to interpret the results on the basis of the previous and detailed knowledge of the biomass load.

In the case of the meadows, that are ecosystems whit a shallow water table, we also consider, for the interpretation of the results, the water content.

II. Material and Methods

In 1999, during five days (25-29 January), a large and severe fire affected the San Ramón ranch (Northwestern Patagonia, Argentina) (Fig. 1). The extension of fire was of 22000 ha, 16000 (60%) of which within San Ramon ranch (Defossé and Dentoni, 1999). Fire burned grasslands and shrublands of different species composition and structure. We assessed fire severity only in San Ramon ranch due to the preexistence of a detailed vegetation map that helped us in the identification of vegetation types (Anchorena and Cingolani, 2002).

a) Study area

The study area (San Ramon ranch) is located 30 km east from Bariloche (Argentina) (latitude -41° 04'; longitude -70° 51') (Fig. 1). The topography of the landscape is characterized by smooth plains and sierras with a large number of rocky outcrops (Anchorena and Cingolani, 2002). The soils are Mollisols (Haploxerolls) characterized by sandy-loam texture and superficial horizon containing a moderate amount of organic matter (Bran et al., 2006). The climate is Mediterranean (60% of precipitation from May to August), temperate with a mean annual temperature of 8.6 °C and 586 mm of annual accumulate precipitation (San Ramón ranch meteorological station, unpublished data).

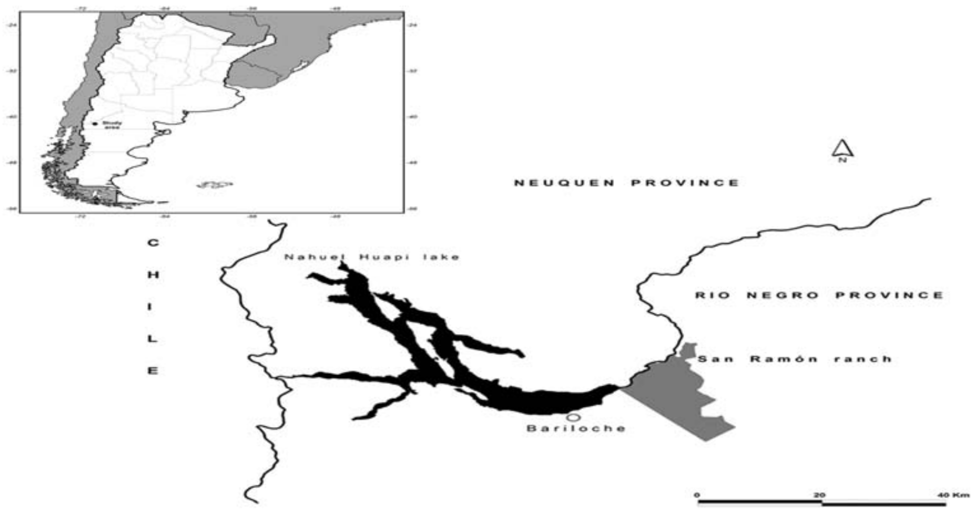

Figure 1: Study area

The area belongs to the phytogeographyc Subandine District of the Patagonian Province (Cabrera, 1971) that is characterized by the presence of perennial grasslands dominated by the *Festuca pallescens* and *Pappostipa speciosa* tussock grasses. Some sectors are occupied by monospecific shrublands of the native species *Fabiana imbricata*, *Discaria articulata* and *Colliguaja integerrima*. The most oriental groups of the native tree *Austrocedrus chilensis* grow in the outcrops (Pastorino et al., 2006). The meadows (*mallin,* is the local term) had flat-concave relief which receive superficial or sub-superficial water inputs. This high water availability leads to temporary water logging that allows the development of productive communities. In the meadows the soil is deep (greater than 120 cm) with abundant organic matter and the water table oscillates between 0 and 80 cm of depth (Bran et al., 2006).

Table 1: Vegetation classes, communities, dominant species, forage availability (from Bran et al., 2006), and fuel load (from Defossé and Dentoni, 1999; Siffredi et al., 2015).

Vegetation class	Communities	Dominant species	Forage availability (kg dry biomass ha^{-1} $year^{-1}$)	Fuel load (kg dry biomass ha^{-1})
Shrubland	Wet (shrubs in meadows)	Berberis buxifolia, Escallonia virgata	1500	16000
	Dry	Berberis spp., Schinus patagonicus	400	7600
Meadow	Very wet	Juncus balticus, Descampsia caespitosa, Cyperaceae	3500	3500

	Wet	Juncus spp., Poa pratensis, Trifolium repens, Holcus lanatus	6000	6000
	Sub-wet	Juncus spp., Poa pratensis, Trifolium repens, Festuca pallescens, Azorella trifurcata	2500	2500
	High and sub-wet	Taraxacum officinale, Festuca pallescens	800	800
Grassland	*Festuca* very good	Total cover: 60-70%. Festuca pallescens cover: 50-60%	1500	1500
	Festuca good	Total cover: 50-60%. Festuca pallescens cover: 30-40%	600	1250
	Pappostipa regular	Total cover: 50-60%	300	1500
	Pappostipa poor	Total cover: 40-50%	75	1200
Forestation	Pine	Pinus ponderosa, P. contorta, P. radiata, Pseudotsuga menziesii	-	44174

We used the vegetation classification made with the objective of evaluating the productivity of the natural grassl and to determinate the cattle receptivity. This classification determined four principal vegetation categories (grassland, shrubl and, meadow and forestation) and 11 sub-categories (see Table 1).

b) Image processing

Landsat TM images are considered among the most appropriate source of data to assess fire severity (Keeley, 2009). We used Landsat TM images of the path/row 230/88 to evaluate the behavior of the dNBR and RdNBR fire severity indices. TM data are sensed in six reflectance bands simultaneously with the instantaneous field of view (IFOV) of 30m x 30m, which capture the heterogeneity in a large fire (Lentile et al., 2006).

We used a pre-fire image of January 9, 1999 (16 days before fire) and a post-fire image of 10 February, 1999 (11 day after fire) (Fig 2). These images were selected because they fulfilled with two conditions: to be the closest to fire and to be totally free of clouds.

We used atmospherically corrected Landsat TM surface reflectance CDR imagery (USGS Product guide Landsat 4-7: climate data record surface reflectance) downloaded from the US Geological Survey website (USGS Earth Explorer). Each image was geometrically corrected. Raw digital numbers (DN) were scaled to spectral radiance values (Chander et al., 2007; Chander et al., 2009) using the coefficients supplied by the USGS in the metadata. Then, radiance values were converted to reflectance according to Chander and Markham (2003). We applied also a terrain illumination correction model (Teillet et al., 1982; Tan et al., 2013) in order to make a topographic normalization. The Landsat TM imagery processing was performed with ENVI 4.7 software.

The NBR index was applied to both pre and post-fire images (Fig. 3a and 3b). In Landsat TM images, NBR is calculated as [(Band4 – Band7) / (Band4 + Band7)], where 4 is the near infrared reflectance (NIR) and 7 is the shortwave infrared reflectance (SWIR).

Further, we applied the difference between pre- and post-fire NBR for obtains the dNBR as Eq. (1) and calculated the relativized dNBR or RdNBR (Fig. 3c and 3d) as Eq. (2):

$$dNBR = NBR_{prefire} - NBR_{postfire} \quad (1)$$

$$RdNBR = \frac{dNBR}{\sqrt{ABS[\frac{NBR_{prefire}}{1000}]}} \quad (2)$$

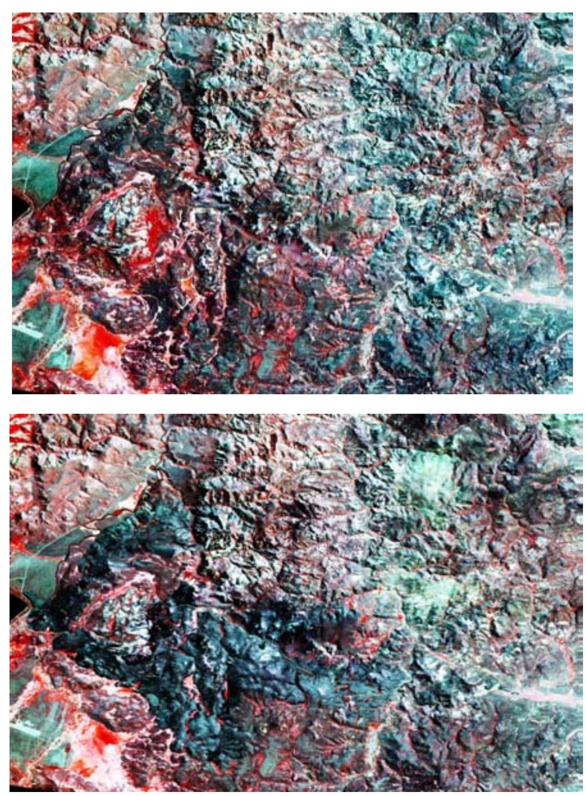

Figure 2: (a)Landsat-TM January 9, 1999 – RGB 432; (b) Landsat TM February 10, 1999 – RGB 432

In order to infer the fire severity degree we categorized dNBR and RdNBR values. Because dNBR/RdNBR ranges values are basically site-specific, we not apply fixed thresholds but adopt the Holden and Evans (2010) classification approach. They applied an unsupervised fuzzy c-means clustering algorithm to objectively assign fire severity classes to dNBR (or RdNBR) on the base of an iterative partitioning of the data (Hartigan et al., 1979; Bezdek, 1981; Roubens, 1982; Odeh et al., 1992). This approach has benefits such as objectivity, possibility of use in case of unavailability of field data and minimizing the problems involved by outliers. In this study we selected six classes of dNBR and RdNBR: unburned, very low, low, moderate, high and very high.

c) Vegetation map

We utilized the map of vegetation built from the Landsat TM image, SRTM DEM of 25 January, 2005 and the map of ranch paddocks of San Ramón ranch (Bran et al., 2006). We summarized the information in Table 1. The map allowed us to interpret the fire severity categories at the same spatial resolution.

d) Data analysis

We superimposed the dNBR and RdNBR on map vegetation and generated a database where each observation (i.e., pixel cell) contains: dNBR/RdNBR values; dNBR/RdNBR severity degree, vegetation class and community.

Then the analysis aimed to obtain:

- Statistical correlation (Pearson coefficient) between dNBR and RdNBR values within each vegetation class and community, taking into account: a) all pixels with dNBR or RdNBR values between unburned and very-low b) all pixels with dNBR or RdNBR values between low and very-high.
- Mean and standard deviation of dNBR/RdNBR in each vegetation class and community.
- Number of pixels, by vegetation class and by community, detected as burned (pixels classified between very-low and very-high severity degree) for both indexes.

The similarity between the indexes was evaluated with the Pearson correlation coefficient. We performed correlation analyses for each vegetation class and community.

Correlations were carried out on two dataset (a and b) due to is expected a similar spectral behavior on unburned or only scorched areas. Moreover, dNBR and RdNBR detect spectral change and therefore to use all pixels together could confuse the interpretation of their behavior.

Finally, vegetation classes and communities were described and compared on the basis of: the dNBR/RdNBR mean and standard deviation and the percentage of pixels of each fire severity degree in both indexes. Our analyses are based on assumption that pixels with categories between very-low and very-high severity had been really burned.

Table 2: Range of dNBR and RdNBR values for the different severity classes

Communities	Fire severity Class	dNBR Range	RdNBR Range
Wet shrubland	Very low	0.028-0,228	0.43-0.729
	Low	0.228-0.375	0.729-1.016
	Moderate	0.375-0.57	1.016-1.287
	High	0.57-0.83	1.287-1.565
	Very high	0.83-1.06	1.565-3.1
Dry shrubland	Very low	0.024-0.227	0.43-0.738
	Low	0.227-0.326	0.729-0.979
	Moderate	0.326-0.439	0.979-1.208
	High	0.439-0.587	1.208-1.543
	Very high	0.587-0.926	1.543-2.91
Very wet meadow	Very low	0.045-0.204	0.46-0.661
	Low	0.204-0.335	0.661-0.892
	Moderate	0.335-0.449	0.892-1.098
	High	0.449-0.576	1.098-1.3
	Very high	0.576-0.863	1.3-1.58
Wet meadow	Very low	0.017-0.178	0.405-0.673
	Low	0.178-0.316	0.673-0.956
	Moderate	0.316-0.443	0.956-1.22
	High	0.443-0.581	1.22-1.561
	Very high	0.581-0.864	1.561-2.12
Sub-wet meadow	Very low	0.013-0.179	0.33-0.676
	Low	0.179-0.315	0.676-0.965
	Moderate	0.315-0.447	0.965-1.241
	High	0.447-0.603	1.241-1.884
	Very high	0.603-0.974	1.884-8.157

High and sub-wet meadow	Very low Low Moderate High Very high	0.038-0.162 0.162-0.273 0.273-0.39 0.39-0.498 0.498-0.655	0.33-0.69 0.69-0.997 0.997-1.27 1.27-1.775 1.775-4.438
Festuca very good grassland	Very low Low Moderate High Very high	0.016-0.104 0.104-0.171 0.171-0.243 0.243-0.323 0.323-0.624	0.25-0.54 0.54-0.848 0.848-1.2 1.2-1.897 1.897-5.45
Festuca good grassland	Very low Low Moderate High Very high	0.021-0.118 0.118-0.202 0.202-0.297 0.297-0.399 0.399-0.638	0.28-0.602 0.602-0.925 0.925-1.264 1.264-1.96 1.96-6.05
Pappostipa regular grassland	Very low Low Moderate High Very high	0.018-0.13 0.13-0.23 0.23-0.354 0.354-0.54 0.54-1.095	0.25-0.561 0.561-0.875 0.875-1.207 1.207-1.845 1.845-6.43
Pappostipa poor grassland	Very low Low Moderate High Very high	0.013-0.137 0.137-0.238 0.238-0.359 0.359-0.568 0.568-1.104	0.31-0.634 0.634-0.935 0.935-1.257 1.257-1.872 1.872-6.962
Pine forestation	Very low Low Moderate High Very high	0.045-0.283 0.283-0.493 0.493-0.712 0.712-0.905 0.905-1.197	0.43-0.615 0.615-0.795 0.795-0.97 0.97-1.112 1.112-1.31

III. Results

The Table 1 shows the vegetation characteristics derived from the literature (Bran et al., 2006; Siffredi et al., 2015) and from the consultations with the range managers. The Table 2 shows the values of dNBR and RdNBR fire severity classes obtained by the unsupervised fuzzy c-means clustering algorithm. Both indexes generated different spatial patterns of fire severity and RdNBR showed a spatial configuration markedly more heterogeneous than dNBR (Fig.3).

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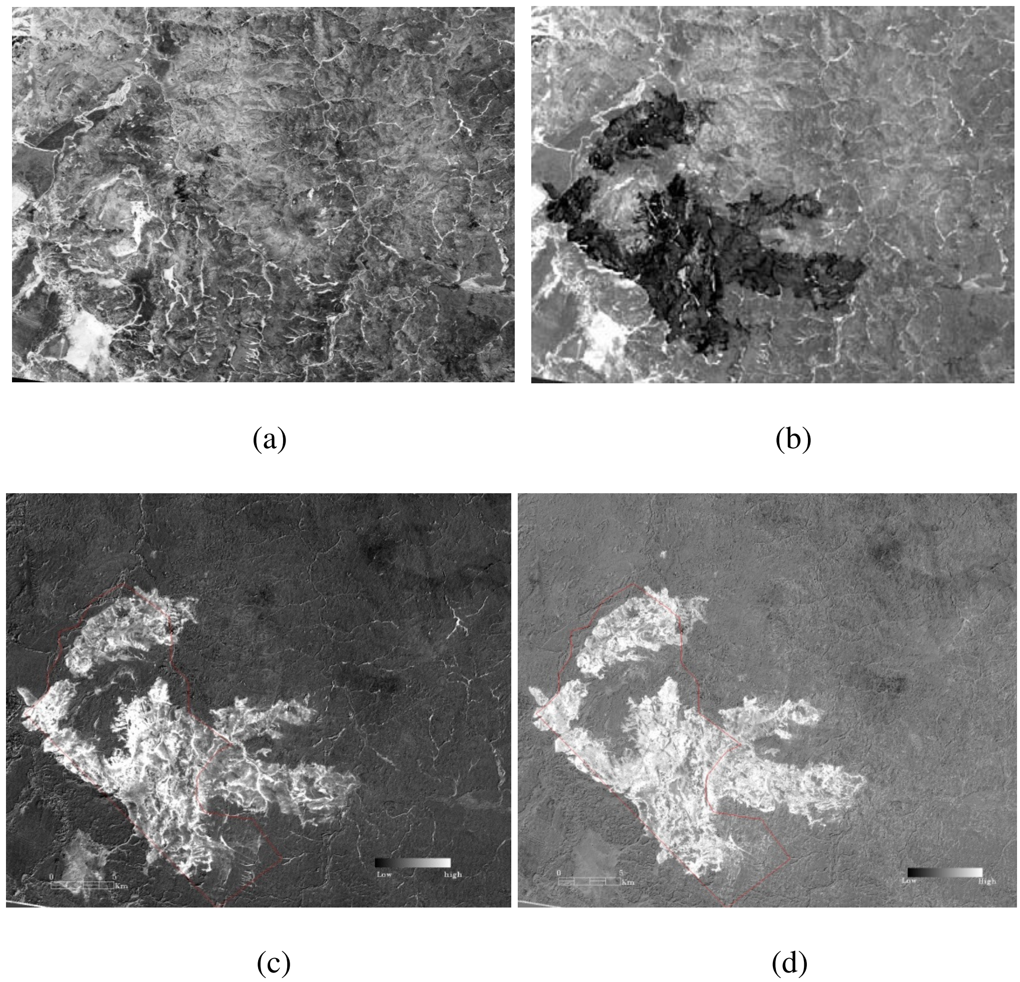


(a) (b) (c) (d)

Figure 3: (a) NBR January 9, 1999;(b) NBR February 10, 1999; (c) dNBR San Ramon fire (in red: San Ramon ranch perimeter); (d) RdNBR San Ramon fire (in red: San Ramon ranch perimeter)

Table 3: Correlations between dNBR and RdNBR

Vegetation class	Communities	dNBR-RdNBR correlation (unburned pixels)	dNBR-RdNBR correlation (burned pixels)
Shrubland	Wet	0.61	0.00
	Dry	0.48	0.00
Meadow	Very wet	0.42	0.14
	Wet	0.26	0.11
	Sub-wet	0.33	0.00
	High sub-wet	0.3	0.00
Grassland	*Festuca* very good	0.59	0.47
	Festuca good	0.47	0.31
	Pappostipa regular	0.56	0.20
	Pappostipa poor	0.38	0.08
Forestation	Pine	0.72	0.39

When we considered the complete set of pixels classified as burned, the correlations values were good for all typologies, with the r value varying from 0.26 in wet meadow to 0.72 in forestation (Table 3).

a) Behaviour of dNBR and RdNBR indices among and within vegetation classes

The dNBR index discriminate better the vegetation classes than RdNBR index (Fig. 4). More precisely, the dNBR differenced clearly grassland and forestation from the other classes (high values for forestation and low for grassland) whereas shrubland and meadow classes showed more similar values. The dNBR and RdNBR indexes showed opposite pattern in some classes. For instance, in grassland the RdNBR mean was always higher than the overall average while dNBR was always below (Fig. 4).

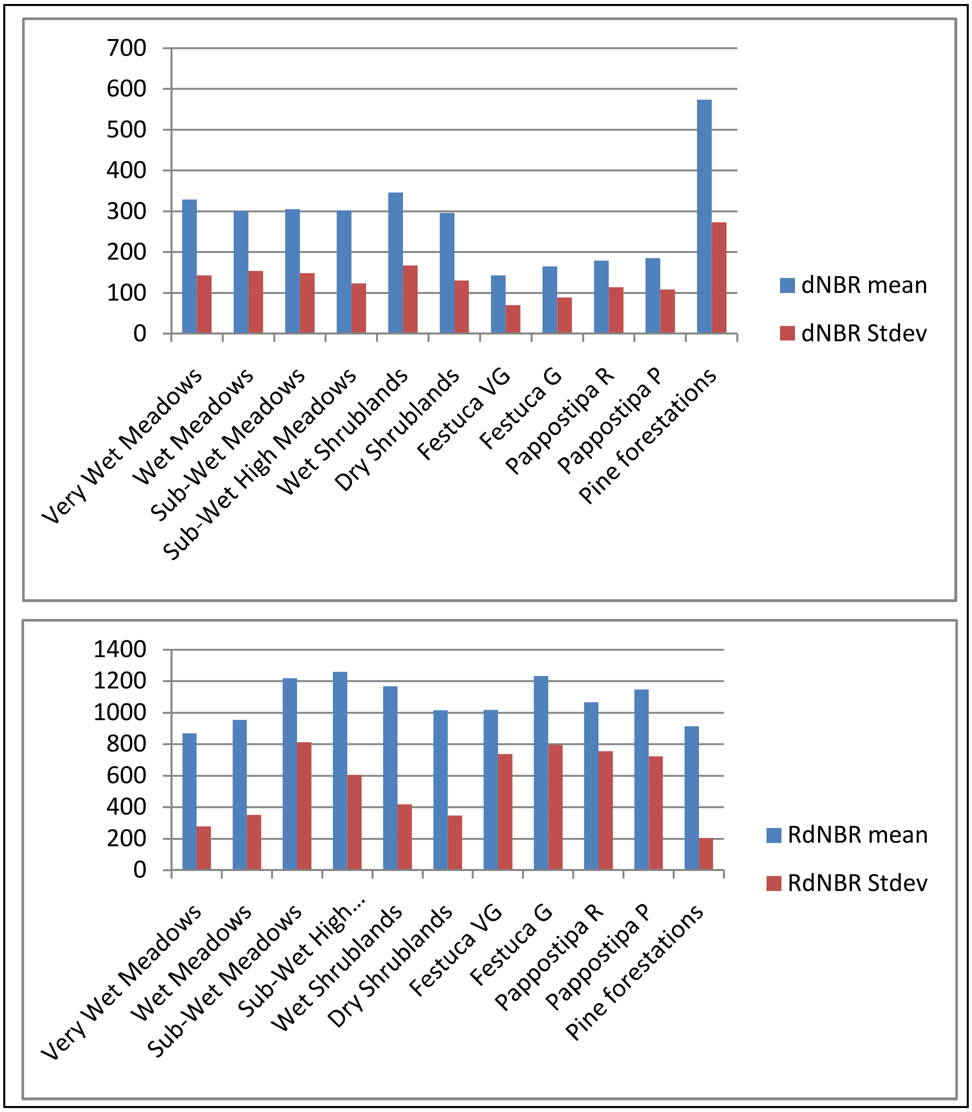


Figure 4: Top: dNBR mean values (x 100) and dNBR standard deviation values (x 100).
Bottom: RdNBR mean values (x 1000) and RdNBR standard deviation values (x 1000).

Within each vegetation classes the trends of both indexes depended on the class analyzed:

– *Grassland* (Fig. 5): Respect to the *Festuca* grasslands, the RdNBR mean value of *Festuca* good condition (*Festuca* G) is higher than *Festuca* very good condition (*Festuca* VG). Moreover, according to RdNBR index the percentage of pixels classified as high and very high fire severity was significantly higher in *Festuca* VG than in *Festuca* G. We observed the same behavior comparing *Pappostipa. Pappostipa* poor grassland (*Pappostipa* P) had lower fuel load, lower vegetation cover, greater cover of shrubs and higher RdNBR mean value than *Pappostipa* regular grassland (*Pappostipa* R).

The Fig. 5 also shows that the RdNBR mean values of the two *Pappostipa* grasslands are lower than the RdNBR mean value of *Festuca* G. Moreover, *Festuca* G showed the greater percentage of surface affected by the highest RdNBR fire severity categories compared to the other three typologies of grasslands. In those severity categories, the *Pappostipa* grasslands have percentages similar to *Festuca* VG. The dNBR index showed a trend to increase the mean value if the vegetation cover decreases and the shrubs cover increases (from *Festuca* VG to *Pappostipa* P).

- *Meadows* (Fig. 6): The mean values of RdNBR index shows an inverse relation with the gradient of humidity in the meadows whereas the mean values of dNBR index are very similar in all communities. The high sub-wet meadow, presents a percentage of the surface in highest fire severity categorie significantly higher than that of the other meadow communities.
- *Shrublands* (Fig. 7): Wet shrubland shows the highest mean value of RdNBR and dNBR. However, RdNBR index follows the expected trend (in the wet shrubland high/very high severity percentages are higher than those of dry shrubland), whereas for dNBR we found the opposite relation.

Forestations (Fig. 8): This category showed the second lowest RdNBR mean value (0.91) and the highest dNBR mean value (0.57). However, despite the relatively low mean value of RdNBR and the relatively very high mean value of dNBR, the histogram shows that over 45% of the area falls within the high/very-high RdNBR severity classes.

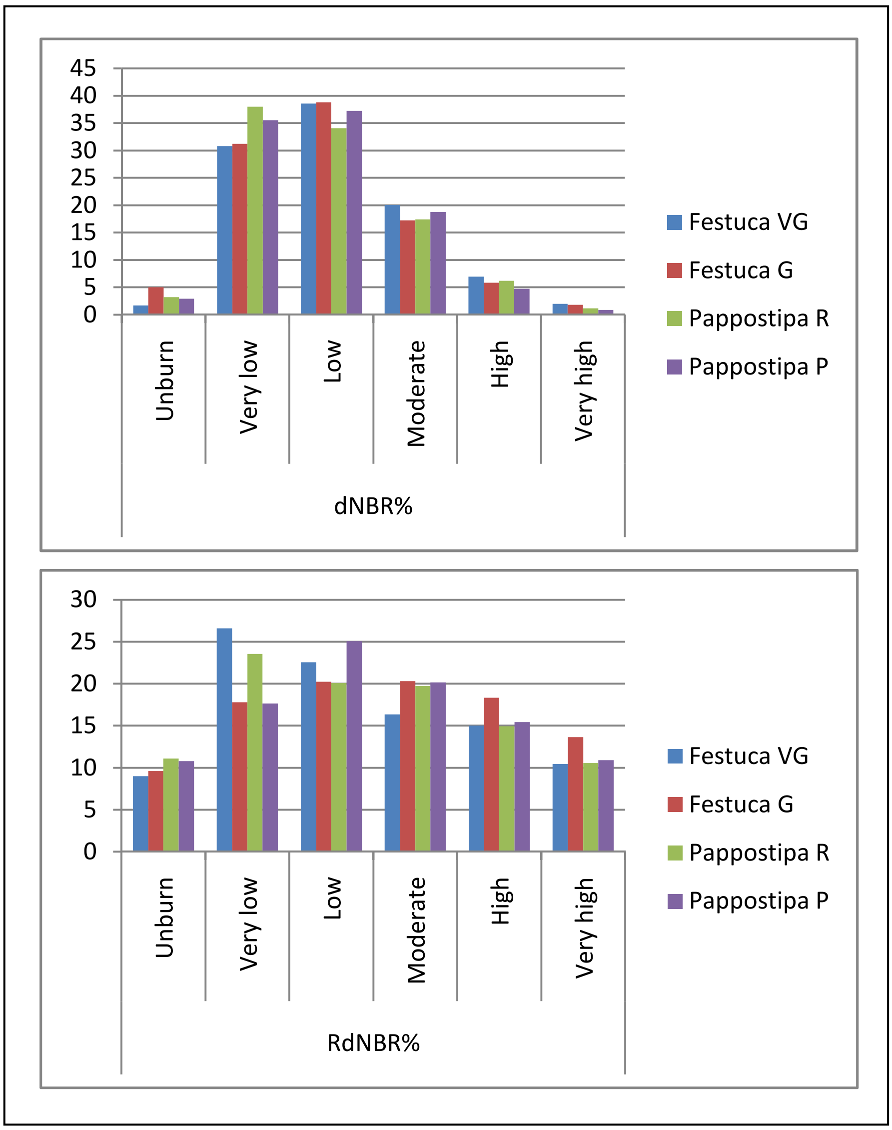


Figure 5: Grassland severity classes.

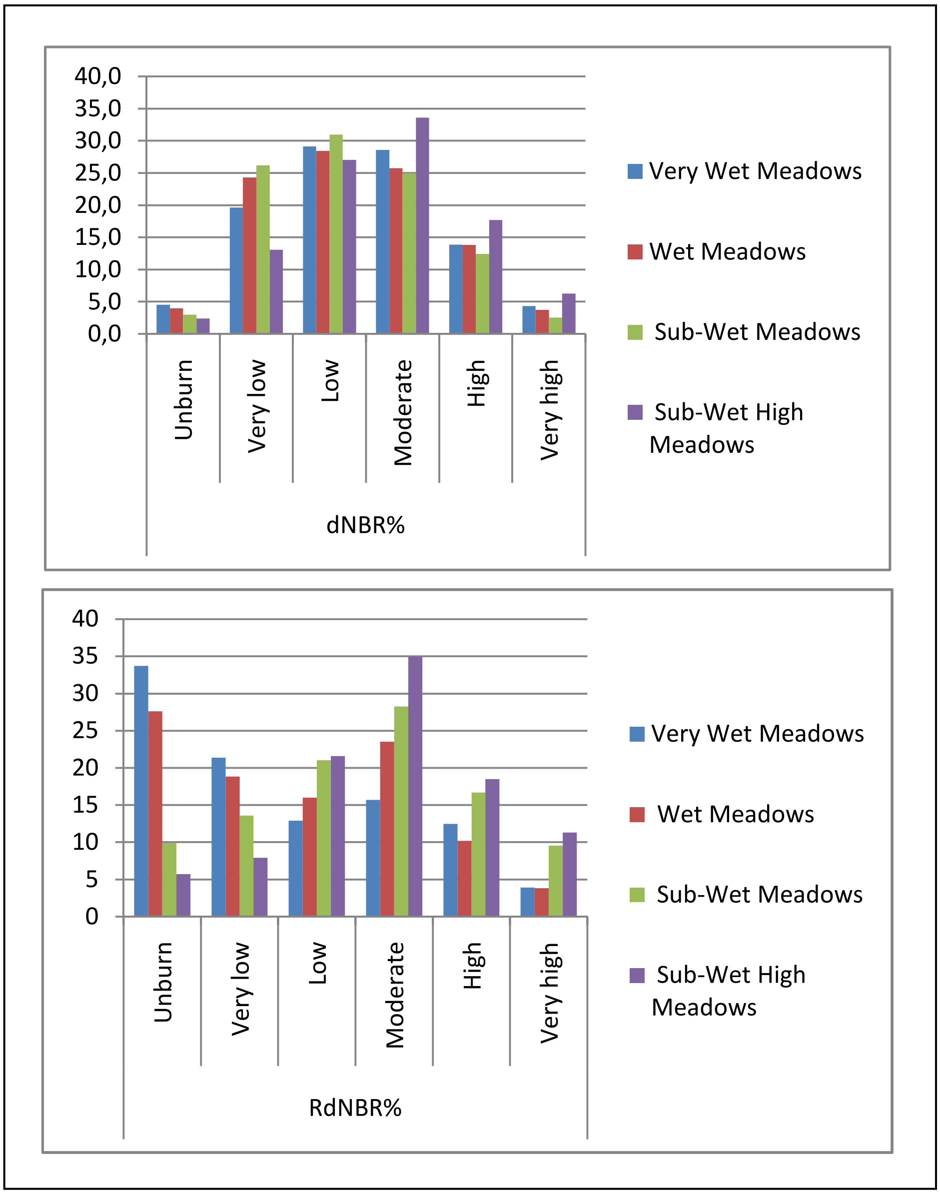


Figure 6: Meadow severity classes.

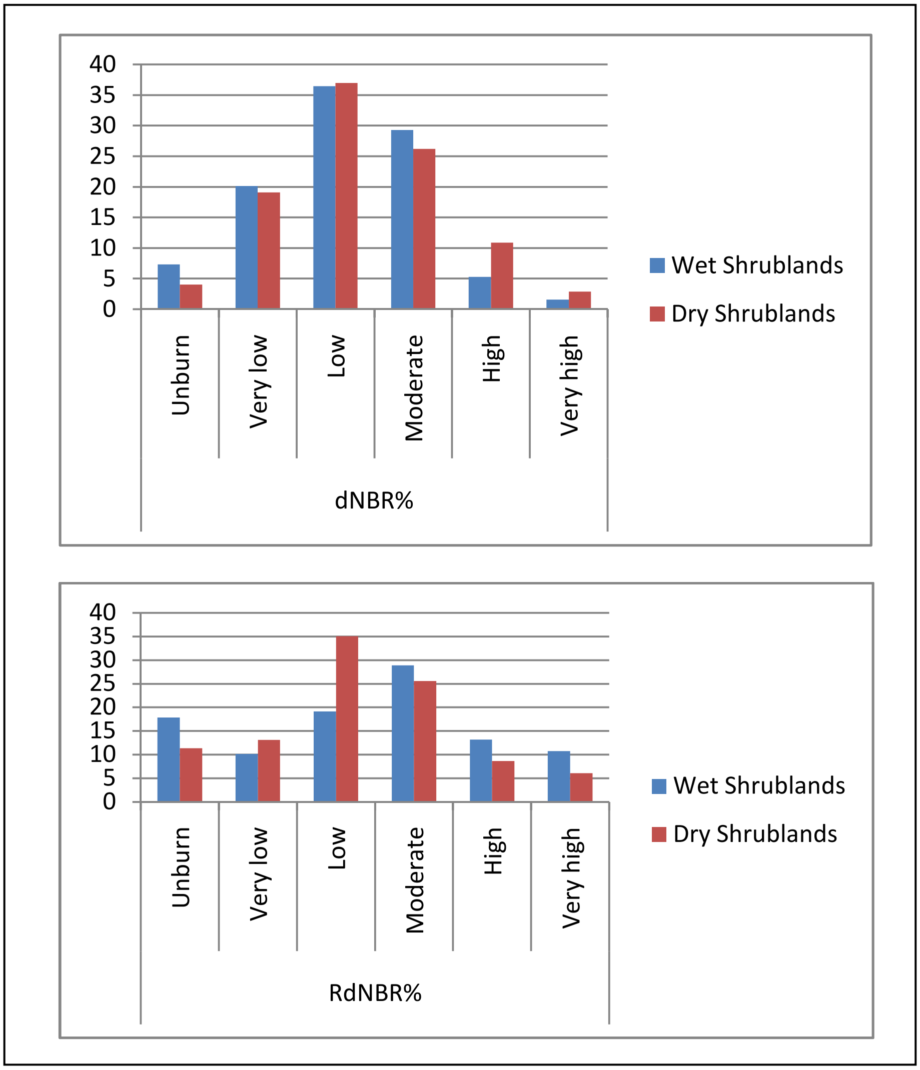


Figure 7: Shrubland severity classes.

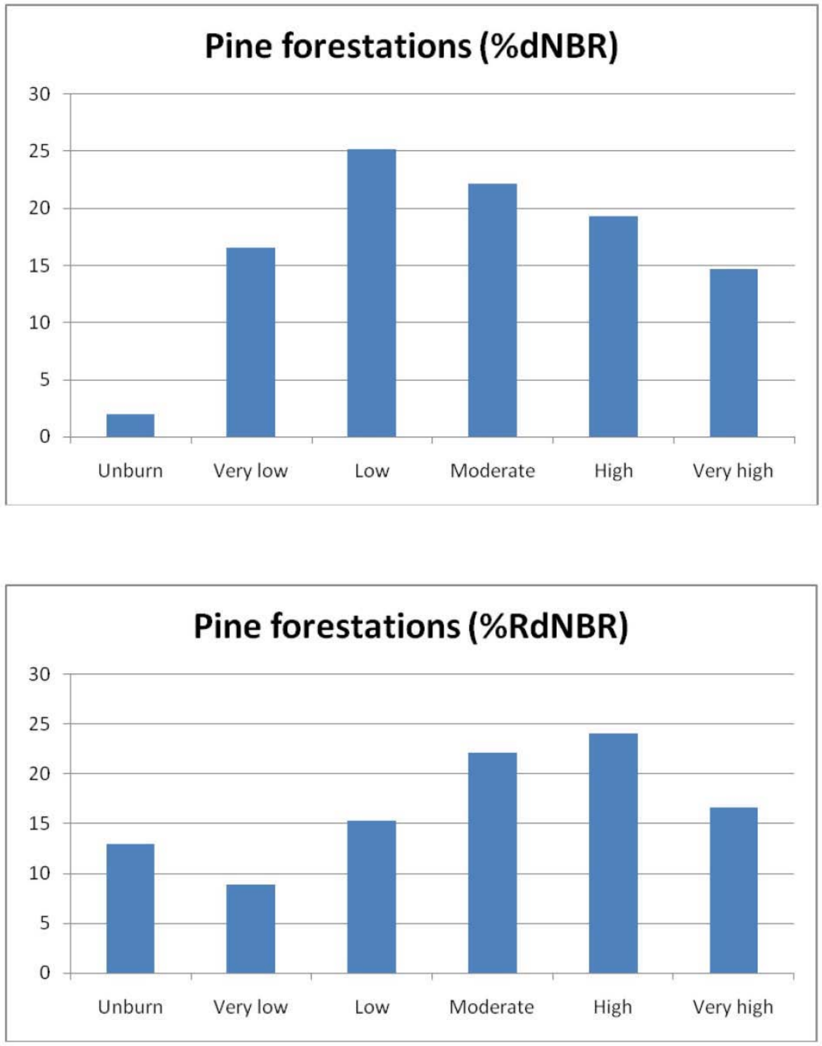
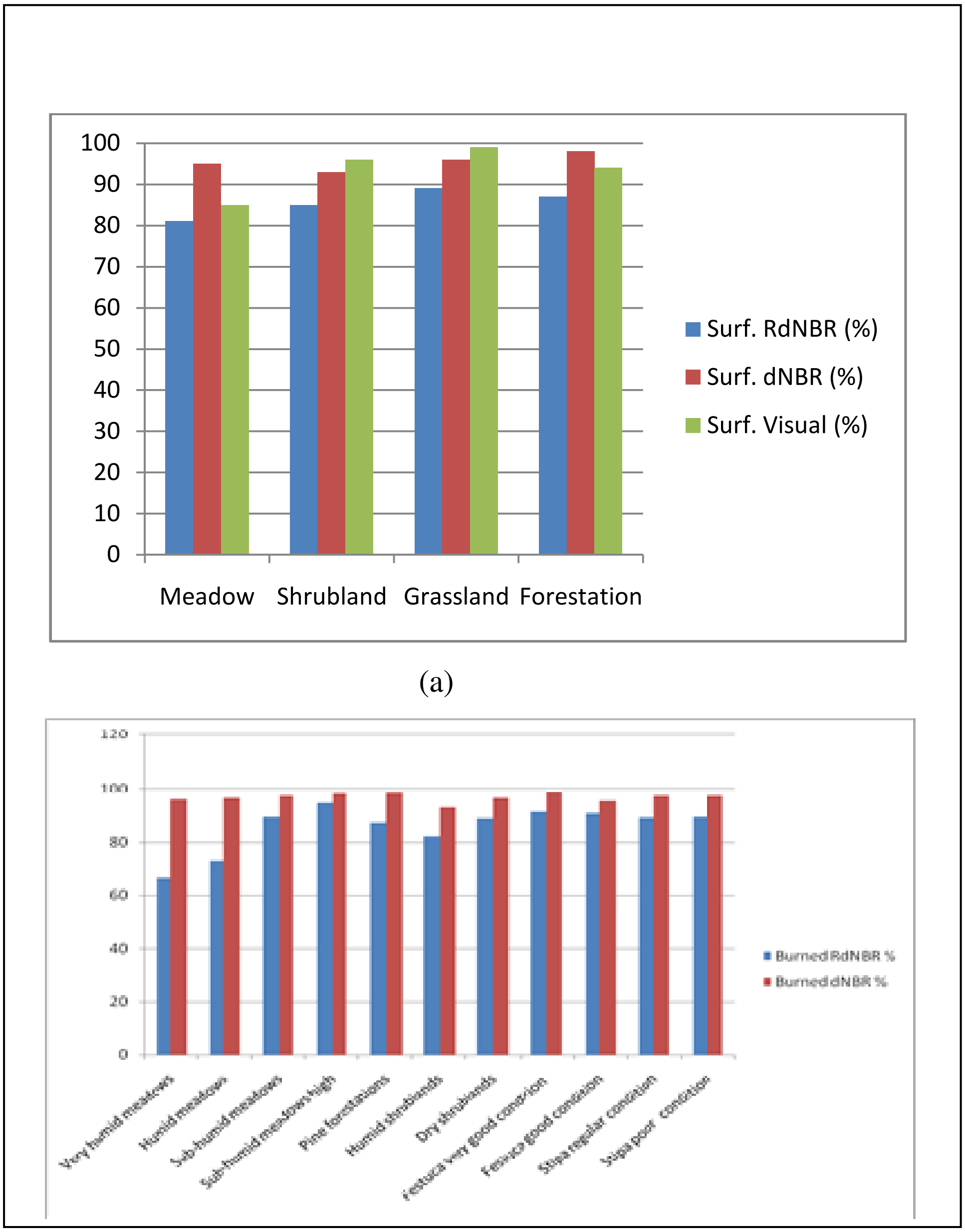


Figure 8: Forestation severity classes

b) *Percentage of pixels detected as burned by dNBR and RdNBR.*

Comparing among vegetation classes, RdNBR and dNBR showed different patterns respect to the percentage of pixels classified as burned (Fig 9a). According to RdNBR, grassland was the vegetation class with most burned surface (89%) followed by forestation (87%), shrubland (85%) and meadow (81%). According to dNBR, the four vegetation classes showed similar surface affected by fire (from 93% to 98%). Fig. 9a show comparison between the percentage of burned areas arising from dNBR, RdNBR and visual analysis (Oddi and Ghermandi, 2016).



(a)

(b)

Figure 9: (a) Comparison of burned areas percentage (dNBR, RdNBR and visual analysis) among vegetation classes; (b) Comparison of burned areas percentage (dNBR and RdNBR) among communities.

This comparison shows that in three vegetation classes (shrubland, grassland and forestation) the surface classified as burned by the dNBR processing was very close to those obtained from visual analysis, whereas for the meadow only the RdNBR percentage of burned area was close to the value obtained from the visual analysis.

Both indexes showed a different behavior when communities were compared (Fig. 9b). The dNBR index showed similar burned area for all the communities within each class.

Vice versa, RdNBR index showed different fire impact in the communities within each class, except in the grassland class. RdNBR classified as burned a higher proportion of pixels in the dry shrublands than in the wet shrublands (89 vs 82%) and in meadow class this index showed increasing burned surfaces as the moisture content decreases (high subwet meadows, 94%; sub-wet meadows,89%; wet meadows, 72% and very wet meadows, 66%).

The Fig. 10 we showed the percentage of surface that fell into the two higher RdNBR fire severity classes (calculated excluding the unburned areas) for each communities. First, the analysis confirmed that in the pine forestation the percentage of surface classified as high and very-high severity was the highest.

Particularly interesting is also the result for dry shrubland that showed the lowest surface percentage classified by RdNBR/dNBR as high and very-high severity classes. The dry shrubland, and even more the humid shrubland, were placed in a position of modest relevance also as regards the severity threshold provided by dNBR. Pine forestation was clearly the type with the highest severity according to dNBR (almost 35% of the burned area is classified as high or very high severity), whereas all meadows typologies (in particular high sub level of dNBR severity greater than the shrubland. When dNBR index was used, 8% of the burned surface of grassland was classified as high and very high severity.

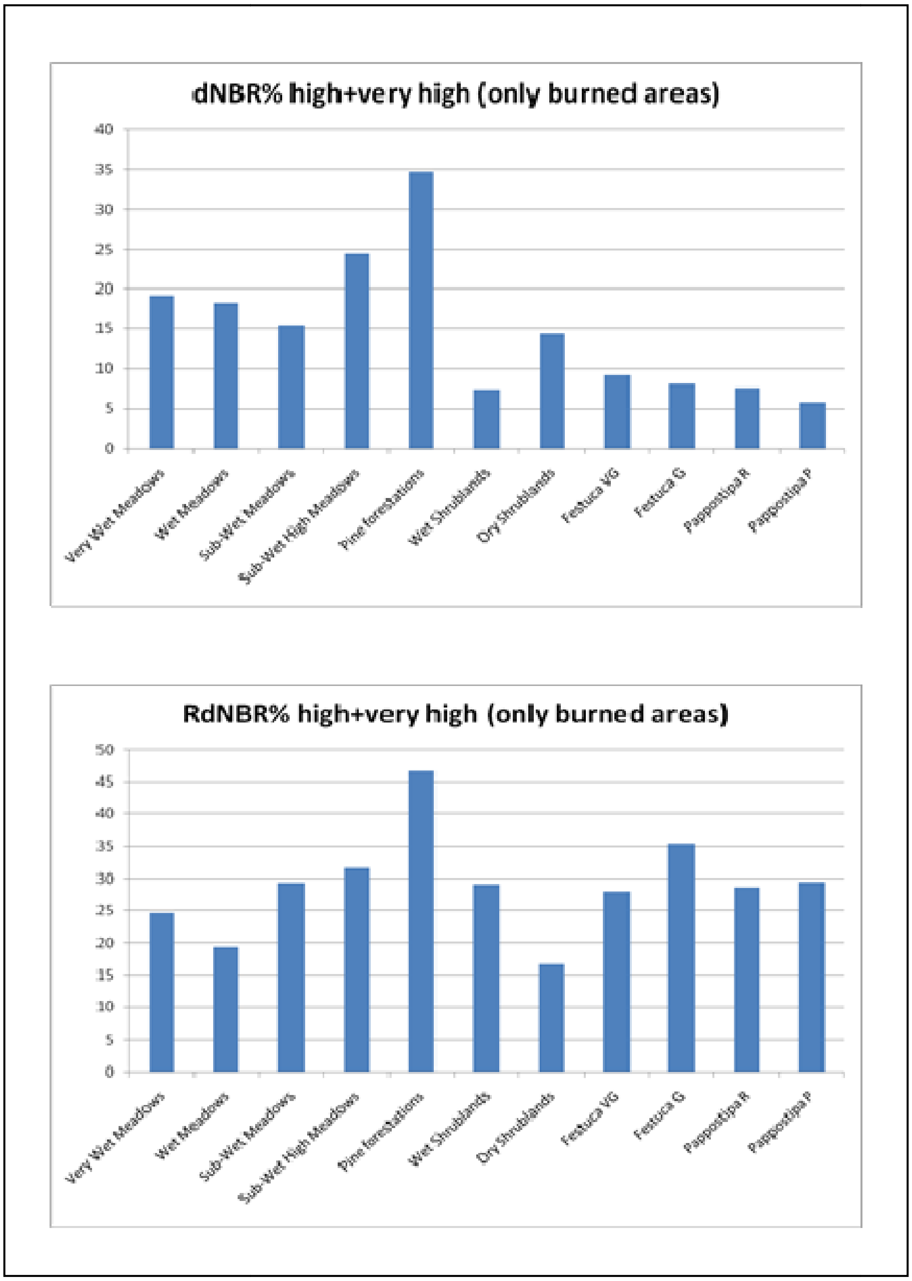


Figure 10: Percentage of dNBR and RdNBR burned areas g sub-wet meadow) had a rface with high and very high verywet severity

IV. Discussion

Fire severity remote sensing-based analysis is an essential tool for ecosystem assessments at large spatial scales that has prevalently been used in forests (Morgan et al., 2014). The dNBR and RdNBR indices show a low correlation within fire perimeter, which is an indication that they do not detect the same fire effects. Indeed, the analysis of the indices correlation indicated that fire acts as a decorrelation factor because in the unburned areas the correlation between dNBR and RdNBR is always higher than in burned surfaces for all the vegetation communities. This decorrelation effect varies greatly depending on the vegetation class and also between the different communities (in particular in grassland class). This result seems to justify attributing a different meaning to the two indices.

The fire residence time appears to be the variable to which dNBR index is more sensitive. In particular this is evident in the grassland class in which dNBR is always well below the overall average due to the low fire residence time. Furthermore, the fire behavior varies within each vegetation class. In particular the dNBR index in the four grassland communities seems to be conditioned by the fuel composition (abundance of shrubs intermingled with grasses) and total cover (which affects the horizontal continuity of fuel). In fact, the increase of shrubs and total vegetation cover provoke the increase of fire duration.

The results of RdNBR index in grassland shows that the lowest mean values correspond to the communities with highest fuel load (*Festuca* very good and *Pappostipa* regular). This can be associated with the greater fire rate spread generated by the high fine fuel load. When fire is relatively fast the damage to the vegetation is attenuated. Instead the *Pappostipa* poor community shows the lowest fuel load among grasslands. These features result in a low fire rate spread and in a high RdNBR mean (compared with *Festuca* very good and *Pappostipa* regular communities). However the highest RdNBR mean value corresponds to *Festuca* good community which has intermediate characteristics in terms of fuel load and vegetation continuity among the grassland communities. The impact of fire on the vegetation is determined by the interaction between fuel load, fuel composition and horizontal continuity and with other variables that characterize the sites in which the communities are present. *Festuca* good community is located in slopes and it is knows the relationship between the fire rate spread and the topography, being higher in slope than in flat.

In the burned grassland is remarkable the difference between the area affected by high and very high fire severity when we used the dNBR or the RdNBR indexes. A possible explication of this difference can be that the vegetation burned fast and, consequently, the heat transfer to the soil was poor. We agree with previous results in similar ecosystems that highlighted the NBR pre-fire very low values that generated relatively low dNBR values, regardless of the post-fire vegetation high impact (Roy et al., 2006; Parks et al., 2014).

In the meadow communities the fire effects were heavily affected by the water content: if it decreases, RdNBR increases because the minor resistance to fire of vegetation. The dNBR values are also determined by the water content but in two opposite aspects: the time of fire residence and the heat transfer to soil. In fact, with the increase in water content the fire duration increases whereas the amount of heat transferred to soil decreases.

Therefore the result of these contrasting factors is that the dNBR mean values of the meadows do not clearly distinguishes the four meadow communities (although the severity value in very-wet meadows is higher due probably to higher fire duration). However, it is interesting to note that in the sub-wet high meadows the percentage of area burned at highest severity was significantly major than in the other meadow communities probably because here heat transferred to soil is higher than in other meadows communities.

The two severity indices provide different information also by comparing the wet and dry shrublands that differ in the biomass amount of the herbaceous layer (wet shrublands are intermingled with meadows). This difference is crucial changing the fire behavior because the presence of the high herbaceous fuel load, summed to the shrubs load, increases the fire intensity and duration. Effectively both effects were visualized by the higher RdNBR mean (related to fire intensity) and the higher dNBR mean (related to fire duration) of wet shrublands. However, at the same time, the meadow layer increases the moisture rate and reduces the probability that in the wet shrublands the fire reach a high severity compared to the dry shrublands.

Contrary to expected, the forestation class had relatively low RdNBR values. The unexpected response of RdNBR probably was due to the presence of forestation sectors with green canopy (not burned or partially burned pines). This was confirmed by the analysis of photos taken in forested areas immediately post-fire. This could explain the relatively low average value even if the forestations were affected by high fire damage.

We compared the usefulness of the dNBR and RdNBR indices for mapping fire severity of a big wildfire that burned no woody vegetation in northwestern Patagonia steppe. In these ecosystems the sensibility of remote sensing products is lower than in woody communities because the spectral changes are small (Norton et al., 2009; Lu et al., 2016). Nevertheless fires in semiarid environments use to be huge due to vegetation flammability and wind exposition.

The results obtained show the possibility of discriminate different levels of fire severity in no woody or in poorly woody ecosystems, which was the principal objective of our study. Other important result was that the indices discriminated among categories of fuel load in the same ecosystem (e.i. grasslands, meadows and shrublands) showing an interesting sensibility and usefulness.

The principal economic activity of semiarid northwestern Patagonia is the extensive stockbreeding that is affected by post-fire vegetation changes, like shrub encroachments. In this context fire severity maps can be a useful tool for grassland managers and for political decision makers.

V. Conclusion

The main objective of this study was to evaluate the usefulness of the best known satellite-derived severity indices in the estimate of the fire induced effects in typical northern Patagonia ecosystems.

Specifically, the use of Landsat-TM historical images has allowed us to analyze the fire first order effects of a large wildfire occurred in January 1999 in a heterogeneous area characterized by the presence of typical species functional groups of semi-arid environments.

The comparison between the results obtained within each category and between the different categories of the vegetation (shrubland, meadow, grassland and forest) has provided a wealth of information about the behavior of fire in relation to the factors that influence the severity (fire intensity and duration; vegetation susceptibility to fire). In general we have shown that the interaction between fire and typology of vegetation modified the fire effects estimated by the severity indices, therefore from a methodological point of view is important, for a proper interpretation of the results, to analyze separately the different typologies and then compare them. In fact, this approach has provided the key to assess how the parameters (fuel load, moisture content, species composition, horizontal continuity) influenced the fire severity thorough the fire behavior.

The analysis carried out have also allowed to highlight a substantial difference in meaning of the two severity indices, confirming the thesis of according to which dNBR partially decouples plants mortality from severity because it is influenced by the pre-fire fuel load (Safford et al., 2008). Therefore dNBR would give an error in the severity estimation, useful, however, when one is interested in the potential heating effects on the soil, whereas RdNBR provides an estimate of the actual fire severity on the vegetation.

This thesis is confirmed, in our work, both on the basis of the comparison between the two indices in each vegetation typology that in the comparison among all typologies, but also on the base of the correlation analysis between the indices. The obtained results have allowed us to highlight that the fire, in the context of the four vegetation categories taken into consideration, has determined higher levels of severity in the forestation category both as regards the effects on vegetation that on the soil. From the plants mortality point of view, shrubland is the category that shows the greatest resistance to fire, in particular the dry shrubland community is absolutely the one that suffers less effects of fire on vegetation.

From the soil burn severity point of view, however, the grassland category is that presents the minor effects, but also the shrublands show relatively limited damages, in particular the wet shrubland typology.

Finally, it should be noted that in this work the contribution of remote sensing appears more essential than ever. In fact, without the aid of historical satellite images, it would not have been possible to estimate the fire severity, particularly for those ecosystems, such as grasslands, which require the availability of data as much as possible temporally close to fire event.

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