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Fire severity mapping in Garajonay National Park: comparison between spectral indices

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Abstract

A large wildfire in La Gomera (Canary Islands, Spain) burned more than 1,800 ha of Garajonay National Park in 2012. Landsat-7 images were used to calculate four spectral indices (dNBR, RdNBR, RBR and dBAIM) and generate fire severity maps according to threshold values defining discrete severity levels. The performance of the fire severity indices was assessed by comparing the agreement with a detailed reference map on fire severity classes: low, moderate and high severity. Results indicated that RdNBR and dBAIM had the best performance compared to reference data, with an overall accuracy of 78 % (Kappa = 0.589) and 80% (Kappa = 0.643) respectively. RBR and dNBR also had a high level of accuracy, but slightly lower than RdNBR and dBAIM, with 74% (Kappa = 0.557) and 70% (Kappa = 0.494) agreement. All the fire severity indices tested were useful to accurately classify the study area into the fire severity classes observed in the field. Better results were found when discriminating high severity than lower fire severity levels. In general terms, higher commission errors were observed in the intermediate severity class, whereas omission errors were higher in the low severity class. Significantly better results were obtained inside the National Park compared to the peripheral zone of protection in all cases, with an accuracy ranging from 78% to 85%. This result highlights an important effect of the vegetation type on fire severity metrics, which suggests that stratification of the burned area according to pre-fire ecosystems may be required in order to improve accuracy of fire severity estimation in large wildfires. Threshold levels for each spectral index should be carefully selected to identify fire severity classes as these spectral values are strongly site-dependent and temporarily variable.

1 INTRODUCTION

Laurel-evergreen forests, or *laurisilva*, are humid subtropical forests representing a relict vegetation of the Tertiary period, which have survived in the Macaronesian region because of its particular climatic conditions (Fernández et al. 2014). This endemic ecosystem is present in the Canary Islands (Spain), finding the best preserved examples in Garajonay National Park (La Gomera). Due to its humid environment, wildfires seldomly occur in this type of vegetation, except under extremely warm and dry weather and after long and severe droughts (Notario et al., 2015).

During the summer 2012, a large wildfire burned more than 3,600 ha in La Gomera Island, affecting 1,868 ha of the southern limits of Garajonay National Park and surrounding protected areas. More than 700 ha were burned inside the National Park, which represents 18% of its surface, whereas the rest affected the peripheral zone of protection. Because of the high environmental impact, this catastrophic event was considered the worse wildfire occurring in the Canary Islands in the last decades (Fernández et al. 2014). Consequently, National Park managers' efforts focused on detailed monitoring of the burned areas in order to detect possible problems that may hinder restoration of the high value ecosystems affected.

Fire severity, also referred to as 'burn severity' to avoid confusion with 'fire intensity', was a term that born out of the need to provide a description of how fire intensity affected ecosystems (Keeley, 2009). Spatial information on fire severity is essential in planning ecosystem restoration. However, despite being a critical parameter for fire assessment, fire severity is rarely evaluated, even from field data (Chuvieco & Kasischke, 2007). Measuring fire severity is difficult as it is commonly defined by general statements of broad impacts of fire on vegetation, e.g. the degree of environmental change caused by fire (Keeley, 2009). Some authors suggest that fire severity metric needs to consider the immediate effects aboveground (vegetation) and belowground (soil), which are directly related to fire intensity. These effects can be also simplified into categories of fire severity according to discrete values. Many factors such as pre-fire species composition, stand age, topography, substrate, and climate will all have some effect on how fire intensity translates into fire severity (Keeley, 2009).

Remote sensing provides a useful tool to assess the impacts of wildfire on ecosystems (Chuvieco & Kasischke, 2007). Several spectral indices are proposed in the literature to quantify fire severity from satellite imagery (Key & Benson, 2005; Miller & Thode, 2007; Parks et al., 2014). However, there is an active debate on the more suitable metric to identify the fire severity levels observed in the field (Escuin et al., 2008; Cansler & McKenzie, 2012; Parks et al., 2014). The purpose of this study was to compare the performance of different spectral indices to assess fire severity by evaluating their correspondence with fire severity classes defined according to field observations.

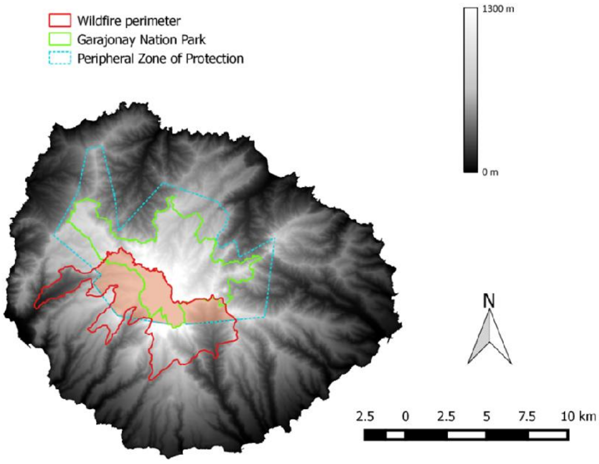

Figure 1. Location of the study area

2 METHODS

2.1 STUDY AREA

The study area comprised a total of 1,868 ha, with 743 ha burned inside the National Park and 1,125 ha in the peripheral zone of protection (Figure 1). The burned area covered a wide range of elevation and vegetation types, including grassland, shrubland and forests. Wind-driven fogs prevail in the highest elevation areas, which are located inside the National Park, reducing vegetation evapotranspiration and implying an additional source of precipitation (Ritter et al, 2008). Among the forest stands affected, the most representative species comprised *Erica arborea* L., *Myrica faya* Ait., *Laurus novocanariensis* Rivas Mart. *& al.*, and *Ilex canariensis* Poir. Some pine and hardwood plantations are also present in the study area. More xeric ecosystems, like *Cistus* shrubland, degraded heathland and endemic xerophytic vegetation, are restricted to lower elevation areas that are mainly located in the peripheral zone of protection. Soils are formed from volcanic parent materials in rugged terrain, with eptosols being the dominant soil type over steeper slopes and more developed soil types, predominantly Andosols, in areas with gentle slopes (Notario et al., 2015).

2.2 SPECTRAL INDICES AND IMAGE PROCESSING

We compared the performance of four fire severity indices proposed by several authors (Table 1) to generate fire severity maps. Key & Benson (2006) proposed a Landsat-based metrics called delta Normalized Burn Ratio (dNBR). This index is calculated as the difference between pre-fire and post-fire values of the normalized burn ratio (NBR) to quantify spectral change. This metric represents an absolute value, which means that it is highly dependent on pre-fire vegetation characteristics.

Several authors have proposed new versions of burn severity metrics derived from the original dNBR index. A commonly used spectral index is the Relativized Normalized Burn Ratio, RdNBR (Miller & Thode, 2007), which also relies on NBR values before and after the wildfire. This index emphasizes changes relative to the amount of pre-fire plant cover by including pre-fire NBR in the denominator (Table 1). More recently, a Relativized Burn Ratio (RBR) was proposed by (Parks et al., 2014). This is another Landsat-based fire severity metric that is an alternative to dNBR and RdNBR. Both RdNBR and RBR are relativized versions of dNBR, designed to detect changes even where pre-fire vegetation cover is low.

The Burn Area Index MODIS (BAIM) (Martín et al., 2006) was originally proposed to identify burn areas from MODIS-derived images. However, the difference between pre-fire and post-fire values of this index (difference Burn Area Index MODIS, dBAIM) can also be used to assess fire severity similarly to dNBR. We applied this index to Landsat-7 imagery using the corresponding spectral bands that were equivalent to near-infrared (NIR) and short-wave infrared (SWIR) from MODIS.

The available Landsat images corresponding to the dates of the wildfire event were Landsat-7 SLC-off (L7). Geometric and atmospheric corrections were applied to image data. A set of 20 ground control points identified from orthoimage were used as a reference for the geometric correction, resulting in a mean quadratic error of 15 m. Radiometric calibration and atmospheric correction were performed according to the methods proposed by Chander et al. (2009). Additional pre-processing was required in order to fill in bands of pixels without spectral information, which is a major constraint when using Landsat-7 imagery. A method for the combination of multitemporal images is proposed in order to avoid missing values (Figure 2). The images were selected from the available cloud free dates according to the closest pre-fire and post-fire images, respectively. Geospatial Data Abstraction Library (GDAL) was used in QGIS software for image processing and spectral indices calculations.

Table 1. Spectral indices derived from Landsat-7 images. NIR, reflectance in the near-infrared (band 4); SWIR, reflectance in the short-wave infrared (band 7).

Index	Equation	Reference
Normalized Burn Ratio	$NBR = \frac{NIR - SWIR}{NIR + SWIR}$	Key & Benson (2006)
Delta Normalized Burn Ratio	$dNBR = (NBR_{prefire} - NBR_{postfire}) \times 1000$	Key & Benson (2006)
Relativized Normalized Burn Ratio	$RdNBR = \frac{dNBR}{\lvert NBR_{prefire} \rvert^{0.5}}$	Miller & Thode (2007)
Relativized Burn Ratio	$RBR = \left(\frac{dNBR}{(NBR_{prefire} + 1.001)} \right)$	Parks et al. (2014)
Burn Area Index for MODIS	$BAIM = \frac{1}{(0.05 - NIR)^2 + (0.1 - SWIR)^2}$	Martín et al. (2006)
Difference Burn Area Index for MODIS	$dBAIM = BAIM_{prefire} - BAIM_{postfire}$	

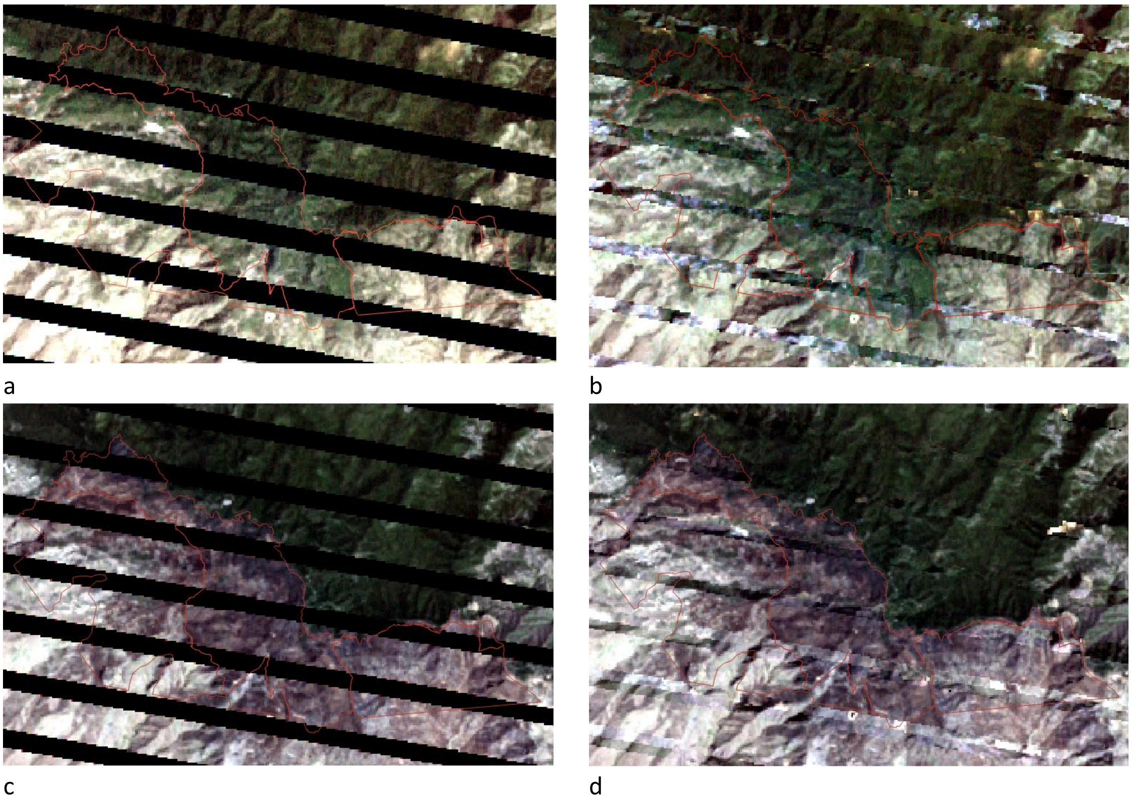

Figure 2. Landsat-7 images with missing pixels bands and resulting image mosaics after combination of multitemporal pre-fire (a, b) and post-fire images (c, d)

2.3 DATA ANALYSIS AND VALIDATION

A detailed fire severity map provided by the Nation Park Office was used as ground reference data. The burned area was classified within three fire severity classes according to detailed field observation and aerial photointerpretation: i) low severity, i.e. surface fire burning only the lower vegetation strata (litter, grass and shrub fuels), ii) moderate severity, i.e. surface fire burning understory and producing crown scorch in tree canopies, and iii) high severity, i.e.

crown fire burning both surface or understory fuels and tree canopies (Figure 3). The discrete values that best corresponded to each severity class (low, moderate and high) were calculated by comparing the spectral indices to the reference levels. Different threshold values for each fire severity index were obtained and used to generate fire severity maps by reclassifying the spectral values according to each severity level. Selecting these threshold values was not straightforward as slight variations resulted in abrupt changes in fire severity classes. Several trials were performed for each spectral index in order to choose the best threshold values. The agreement of the fire severity maps obtained for each spectral index was assessed by means of the accuracy derived from the confusion matrix and the Kappa statistic (Congalton, 1991). A total of 200 points were selected according to a stratified random sampling scheme, with a set of 125 points inside the National Park and a set of 75 in the peripheral zone of protection. Stratification was applied in order to get a higher number of validation points in the higher environmental value areas.

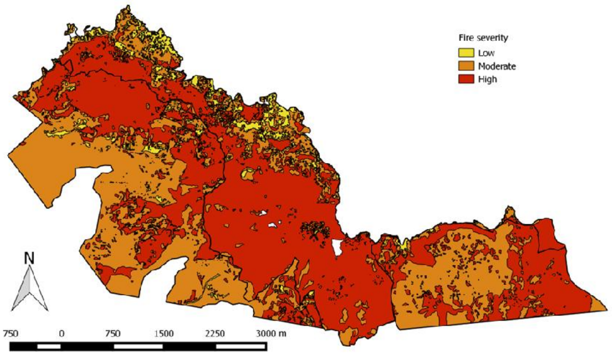

Figure 3. Fire severity levels used as reference data.

3 RESULTS AND DISCUSSION

Results indicated that RdNBR and dBAIM had the best performance compared to reference data, with an overall accuracy of 78% (Kappa = 0.589) and 80% (Kappa = 0.643) respectively. RBR also had a high level of agreement, being only slightly lower than RdNBR, with an overall accuracy of 74% (Kappa = 0.557). The worse performance was found for dNBR, although it was still acceptable, with an agreement of 70% (Kappa = 0.494). Despite some authors have pointed out the limitations of using dNBR (Parks et al., 2015; Veraverbeke et al., 2012), this index has become the standard spectral index for assessing fire severity. Our results are in agreement with previous studies reporting lower performance of dNBR, which is based on an absolute differencing value between pre-fire and post-fire images, compared to relative metrics such as RdNBR and RBR. In all cases, higher agreement was obtained inside the National Park compared to the peripheral zone of protection (Table 2).

Table 2. Classification accuracy (and Kappa statistic) in the study area.

Spectral index	Overall	National Park area	Peripheral zone of protection
dNBR	70.0 % (0,494)	77.6 % (0,595)	57.3 % (0,332)
RdNBR	78.0 % (0,589)	81.6 % (0,628)	72.0 % (0,525)
RBR	74.0 % (0,557)	79.2 % (0,618)	65.3 % (0,456)
dBAIM	80.5 % (0,643)	84.8 % (0,712)	72.0 % (0,516)

Again, RdNBR (82%, Kappa = 0,628) and dBAIM (84%, Kappa = 0,712) showed the best performance. A significant increase in accuracy was also found for RBR and dNBR inside the National Park area, with an agreement of 78% and 79%, respectively, in both spectral indices. This means that the threshold values used to define fire severity classes are more adequate for the laurel-evergreen forests, which are mostly located inside the National Park, than for the other types of ecosystems (pine and hardwood plantations, shrubland and grassland) included in the study area. This result highlights that fire severity indices are highly site-dependent, pointing out the need to account for the type of vegetation existing before the fire. Hence, in order to improve accuracy in large wildfires, previous stratification according to pre-fire ecosystems may be required, as threshold values of fire severity classes may differ across the burned area, even for a single severity index. Moreover, it should be kept in mind that despite fire severity is a readily measurable parameter, both on the field and with remote sensing, the precise metric varies with management needs (Keeley, 2009).

Focusing on the endemic laurel-evergreen ecosystem, i.e. excluding burned area outside the National Park, our results indicated that all the severity indices showed better correspondence with the high fire severity class (Table 3).Higher commission errors were found for lower severity levels, especially for the moderate severity class. Conversely, producer’s accuracy was generally higher for moderate fire severity compared to the low severity class, except for dNBR. These findings suggest the difficulty to discriminate between areas affected by surface fires, i.e. unburned tree crowns, with and without tree crown scorched. Confusion between low and moderate fire severity could be expected as some tree crowns may be only affected in the lower part of the canopy, and therefore be more difficult to detect from satellite imagery. This constraint is not expected to occur in the high severity areas where most of the canopy fuel was consumed by the fire. Higher spectral resolution may be required to improve discrimination among low and intermediate fire severity classes, which are generally more difficult to define. Veraverbeke et al. (2012) have developed an alternative index based on short-wave infrared (SWIR) and mid-infrared (MIR) reflectance, improving performance compared to NBR derived metrics. These authors illustrated the potential of SWIR-MIR band combination to detect fire effects, such as char fractional cover. The spectral information required by the proposed metric cannot still be retrieved from Landsat or other satellite imagery with adequate spatial resolution, but would likely become available in the future.

Previous studies demonstrate the difficulty of defining threshold values to classify fire severity into discrete severity classes (Cansler & McKenzie, 2012; Parks et al., 2014). Parks et al. (2014) evaluated the variability (i.e. the coefficient of variation) among a large number of fires from different fire regimes, finding a lower variability in threshold values for RBR compared to RdNBR and dNBR. Another potential strength of using RBR is that it avoids some of the mathematical difficulties associated with the RdNBR equation (Parks et al., 2014).

Our study shows that the combination of different temporal images proposed is useful to complete the pixel bands with missing values, but may only partially overcome the limitations of using Landsat-7 when fire severity mapping is required (Figure 4). The bitemporal image differencing used to calculate the spectral indices can be problematic due to image-to-image differences in illumination and phenology (Veraverveke et al., 2012) that can translate into inconsistent fire severity quantification in adjacent areas. However, these effects may be decreased by the use of relative version metrics compared to the absolute dNBR index (Figure 4). Another possible reason may be the limited availability of cloud free imagery in the study area, because of the particular climatic conditions of the island, which led to the use of multitemporal images with considerable time-lags compared to the reference pre-fire and post-fire images.

Table 3. Confusion matrices for each spectral index inside the National Park area. U.A., user's accuracy; P.A., producer's accuracy.

	dNBR	Reference				
		Low	Moderate	High	Total	U.A.
Landsat	Low	16	4	1	21	76,2%
	Moderate	4	15	12	31	48,4%
	High	0	7	66	73	90,4%
	Total	20	26	79	125	
	P.A.	80,0%	57,7%	83,5%		

	RdNBR	Reference				
		Low	Moderate	High	Total	U.A.
Landsat	Low	10	1	0	11	90,9%
	Moderate	10	14	1	25	56,0%
	High	0	11	78	89	87,6%
	Total	20	26	79	125	
	P.A.	50,0%	53,8%	98,7%		

	RBR	Reference				
		Low	Moderate	High	Total	U.A.
Landsat	Low	10	1	0	11	90,9%
	Moderate	10	20	10	40	50,0%
	High	0	5	69	74	93,2%
	Total	20	26	79	125	
	P.A.	50,0%	76,9%	87,3%		

	dBAIM	Reference				
		Low	Moderate	High	Total	U.A.
Landsat	Low	11	5	1	17	64,7%
	Moderate	9	18	1	28	64,3%
	High	0	3	77	80	96,3%
	Total	20	26	79	125	
	P.A.	55,0%	69,2%	97,5%		

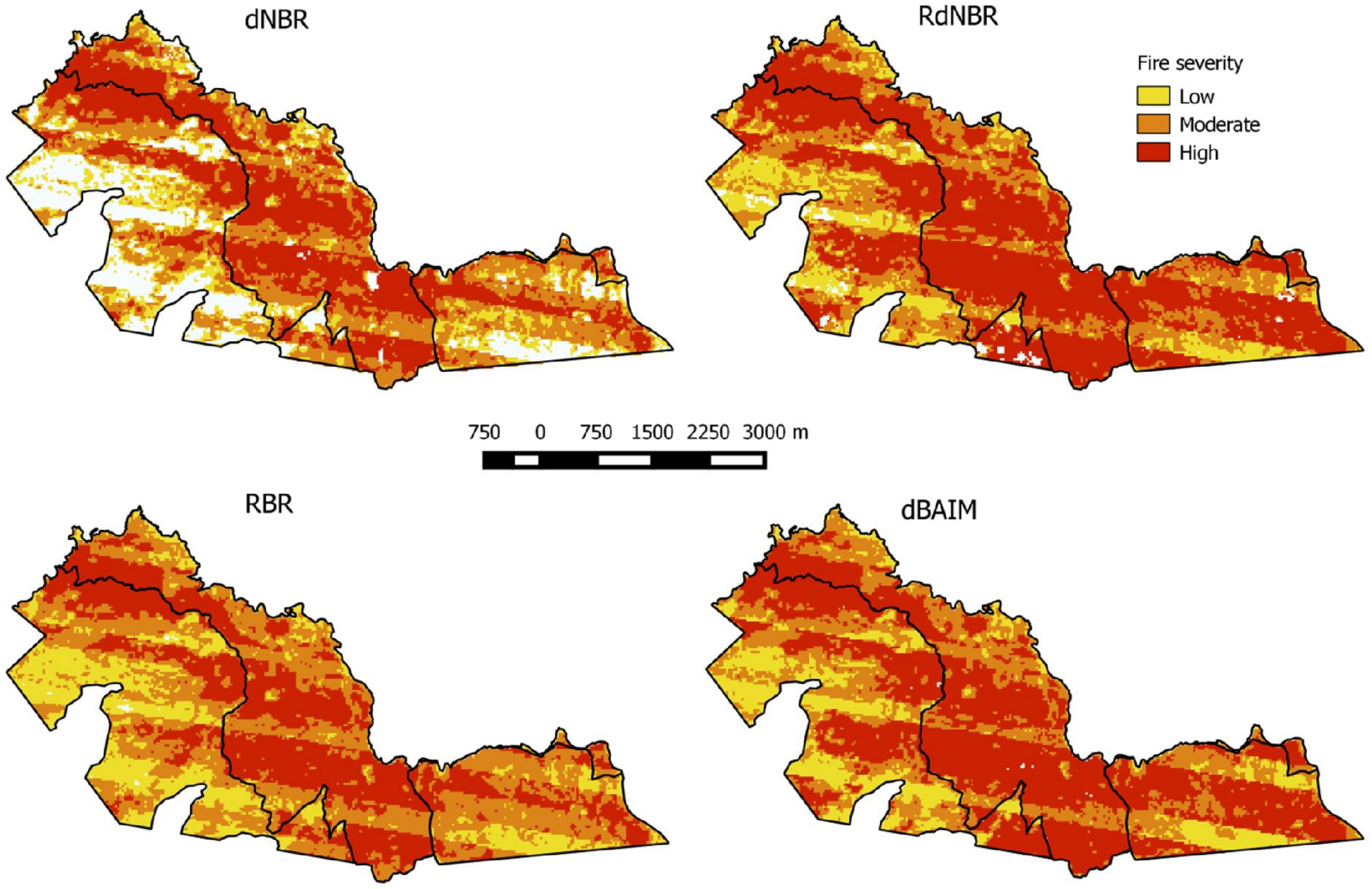

Figure 4. Fire severity levels obtained in the study area from the different spectral indices

4 CONCLUSIONS

Landsat-7 images were used to calculate four spectral indices (dNBR, RdNBR, RBR and dBAIM) in order to generate maps of fire severity of a large burned area in Garajonay National Park. A method is proposed to get a combination of images from different dates in order to fill in missing values from Landsat-7 imagery. The performance of the different spectral indices used to identify discrete fire severity levels were compared to a detailed fire severity map provided by the National Park Office. Our study suggests that:

i) All the spectral indices were useful to obtain sufficiently accurate classifications of fire severity in the study area. However, results pointed out the different performance of the fire severity indices tested.

ii) The worse results were obtained for the dNBR, which is still the most commonly spectral index used to assess fire severity. The alternative indices tested (RdNBR, RBR, and dBAIM) showed significantly better results.

iii) In general terms, better correspondence with reference data was observed for the high severity class, which suggests the need for higher spectral resolution data and more refined threshold values for the low and intermediate classes.

iv) An important effect of pre-fire vegetation on the fire severity metrics was observed, with a considerable increase in agreement for the laurel-evergreen ecosystems inside the National Park compared to the heterogeneous vegetation present in the peripheral zone of protection. This finding suggests the potential improvement in the performance of fire severity indices by including a stratified assessment according to vegetation types.

v) Caution should be taken when selecting the threshold values to identify discrete levels of fire severity for each spectral index as these metrics are highly dependent on reflectance of existing vegetation, which may also strongly vary between multitemporal images due to differing phenology and illumination conditions.

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