Evaluation and comparison of Landsat 8, Sentinel-2 and Deimos-1 remote sensing indices for assessing burn severity in Mediterranean fire-prone ecosystems

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Abstract

The development of improved spatial and spectral resolution sensors provides new opportunities to assess burn severity more accurately. This study evaluates the ability of remote sensing indices derived from three remote sensing sensors (i.e., Landsat 8 OLI/TIRS, Sentinel-2 MSI and Deimos-1 SLIM-6-22) to assess burn severity (site, vegetation and soil burn severity). As a case study, we used a megafire (9,939 ha) that occurred in a Mediterranean ecosystem in northwestern Spain. Remote sensing indices included seven reflective, two thermal and four mixed indices, which were derived from each satellite and were validated with field burn severity metrics obtained from CBI index. Correlation patterns of field burn severity and remote sensing indices were relatively consistent across the different sensors. Additionally, regardless of the sensor, indices that incorporated SWIR bands (i.e., NBR-based indices), exceed those using red and NIR bands, and thermal and mixed indices. High resolution Sentinel-2 imagery only slightly improved the performance of indices based on NBR compared to Landsat 8. The dNDVI index from Landsat 8 and Sentinel-2 images showed relatively similar correlation values to NBR-based indices for site and soil burn severity, but showed limitations using Deimos-1. In general, mono-temporal and relativized indices better correlated with vegetation burn severity in heterogeneous systems than differenced indices. This study showed good potential for Landsat 8 OLI/TIRS and Sentinel-2 MSI for burn severity assessment in fire-prone heterogeneous ecosystems, although we highlight the need for further evaluation of Deimos-1 SLIM-6-22 in different fire scenarios, especially using bi-temporal indices.

Keywords: Composition Burn Index, remote sensing, thermal indices, spectral indices

1. Introduction

Burn severity, defined as the magnitude of the ecological change caused by fire (Lentile et al., 2006), has been identified as one of the most critical factors determining the ecological effect of fire on ecosystems (Tanase et al., 2011). It may affect post-fire plant regeneration dynamics, community composition and structure (Wang and Kemball 2003; Dzwonko et al., 2015), as well as increase degradation processes through the alteration of physical and chemical soil properties, microbial activity and soil erosion (Heydari et al., 2017). Consequently, the timely generation of reliable burn severity maps reflecting induced changes in vegetation and soil properties is of high priority for post-fire, short-term decision support (Miller et al., 2016).

Traditionally, burn severity evaluation has been conducted using field methods, such as the Composite Burn Index (CBI) and the GeoCBI index (Key and Benson 2006; De Santis and Chuvieco 2009). Nevertheless, field methods are usually costly and time-consuming, and provide limited spatial and temporal representation of post-fire ecological effects (Chuvieco et al., 2006). Fire causes substantial spectral and thermal changes on the land surface, associated with the consumption of vegetation and the exposure of soil and charred stems, which can be captured by remote sensing sensors (Epting et al., 2005; Mallinis et al., 2018). Based on these properties, remote sensing techniques provide a cost-effective alternative to field sampling to assess and quantify burn severity (Veraverbeke et al., 2011) over a wide range of temporal and spatial scales, and areas (Schepers et al., 2014).

Landsat multi-spectral sensors (30 m) provide one of the freely available, longest and most widely used collections of moderate spatial and spectral resolution imagery for monitoring burn severity (Eidenshink et al., 2007). Despite the widespread application of Landsat data, improved spatial, spectral and temporal resolution characteristics of recently available satellite sensors is attracting increasing interest among fire researchers (Mallinis et al., 2018). In this context, satellite sensors like Sentinel-2 MSI and Deimos-1 SLIM-6-22 have desirable characteristics, including a higher spatial (i.e., 10-20 m and 22 m, respectively vs 30 m) and temporal (i.e., 5 days and 2-3 days respectively vs 16 days) resolution than Landsat data, which may provide better information for burn severity assessment. Recent studies by Fernández-Manso et al. (2016) and Navarro et al. (2017) successfully assessed burn severity based on Sentinel-2 data. Similarly, Gómez-Sánchez et al. (2017) showed a relatively good performance of Deimos-1 to evaluate burn severity. To our knowledge, this is the only study that has analyzed the potential of Deimos-1 imagery for monitoring post-fire effects. Moreover, the number of studies using Sentinel-2 for burn severity assessment remains limited. Therefore, despite earlier promising results, evaluation of such sensors is still a relevant area of research to refine and improve the generalization of remotely sensed measures of post-fire effects.

Most of the satellite-based burn severity studies use methods based on remote sensing indices due to their computational simplicity and straightforward application (Veraverbeke et al., 2012). Nevertheless, differences in the sensitivity of each spectral region to changes in soil and vegetation may result in different capabilities of remote sensing indices to discriminate fire effects (Chuvieco et al., 2006; Veraverbeke et al., 2011). Spectral indices based on the Near Infrared (NIR) and Short Wave Infrared (SWIR) bands, specifically the Normalized Burn Ratio (NBR) and its bi-temporal approaches, such as the differenced Normalized Burn Ratio (dNBR) and the Relativized differenced Normalized Burn Ratio (RdNBR), have been identified as optimal burn severity measures (Miller et al., 2009; Veraverbeke et al., 2010). Nevertheless, some authors (Roy et al., 2006; Escuin et al., 2008) have found those indices suboptimal in describing burn severity. Other reflective indices like the Normalized Difference Vegetation Index (NDVI), the Soil Adjusted Vegetation Index (SAVI), the Enhanced Vegetation Index (EVI) and their bi-temporal counterparts have also shown good correlation with burn severity, even higher than NBR-based indices (Harris et al., 2011; Wu et al., 2015). Additionally, recent studies have begun to successfully incorporate thermal data for burn severity evaluation (Quintano et al., 2015, 2017) and for enhancing reflective indices' performance (Holden et al., 2005; Harris et al., 2011). Consequently, despite the numerous remote sensing indices developed in the literature to assess burn severity and the previous studies evaluating the potential of alternative sensors to Landsat for this purpose, there is no consensus about the optimal remote sensing indices and satellite sensor alternative (Mallinis et al., 2018). This fact highlights the need for further studies that evaluate the suitability of spectral indices and satellite sensors against field data for adequate burn severity assessment (Lentile et al., 2006).

The aim of this study was to evaluate the potential of Landsat 8 OLI/TIRS, Sentinel-2 MSI and Deimos-1 SLIM-6-22 imagery to quantitatively assess burn severity, using as a case study a megafire of 9,939 ha that occurred in a heterogeneous, forest-shrubland Mediterranean ecosystem in Spain. Specifically, we aimed: (i) to identify the most suitable sensor to assess site (vegetation plus soil), vegetation and soil burn severity; (ii) to detect the most capable remote sensing index from each sensor to discriminate site burn severity levels, as well as vegetation burn severity and soil burn severity individually, based on comparison with burn severity field measurements.

2. Material and methods

2.1. Study site

The study was conducted in the Cabrera mountain range (northwestern Spain; Figure 1) where 9,939 ha burned in August, 2017 (between 21th and 27th). This area is in the limit of the Mediterranean biogeographic region (Rivas-Martínez et al., 2011), with its climate classified as temperate, with maximum annual temperatures ranging from 8.7 to 29.4 ºC and a mean annual precipitation of 600-1500 mm. It has a rough and heterogeneous orography with altitudes ranging from 836 to 1,938 m.a.s.l. Soils are acidic, mainly originating from siliceous lithology such as slates. The area affected by the megafire was mainly covered by shrublands dominated by *Erica australis* and *Genista hystrix,* and forest dominated by *Quercus pyrenaica*. The fire occurred under relatively extreme weather conditions, with maximum temperatures of 35 ºC, low relative humidity values (35 %), and after a two-month drought episode. These extreme weather conditions increased the risk of fire and facilitated fire spread, resulting in large areas of high-severity effects.

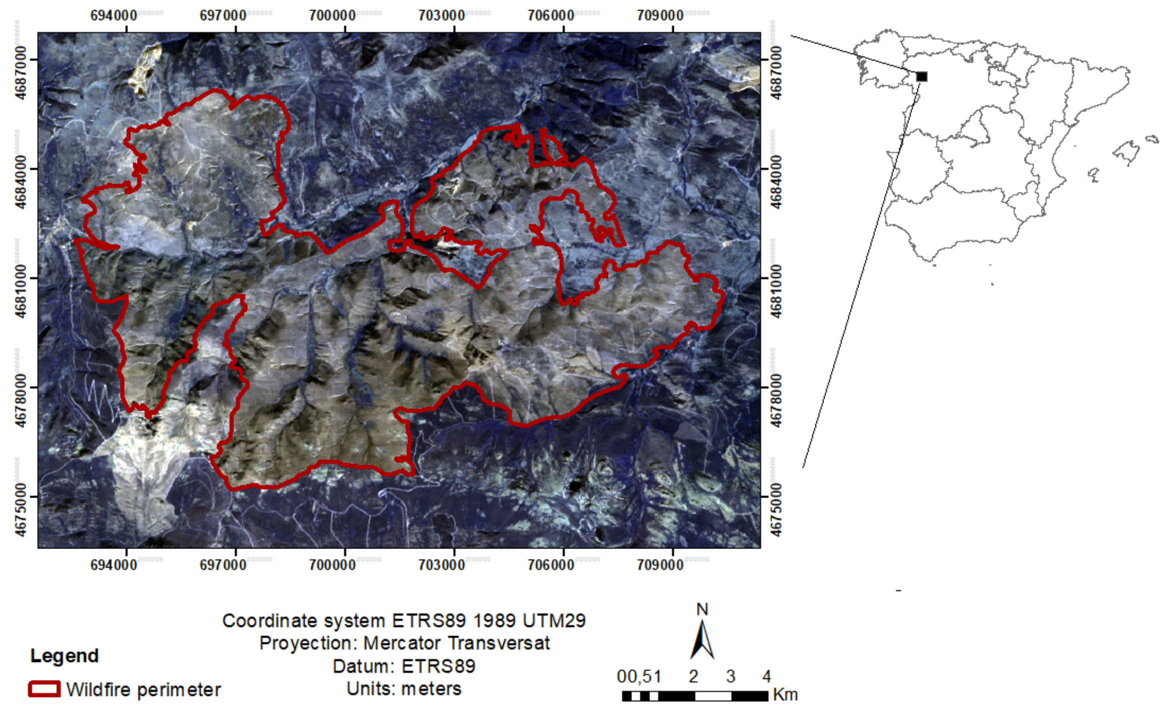

Figure 1. Location map of the study area (Sierra de la Cabrera, NW Spain) representing a false color composite post-fire image (10^{th} October, 2017) obtained from Landsat 8 OLI/TIRS.

2.2. Field estimation of burn severity

Field data to measure burn severity were collected three months after the fire event. Fifty-three field plots of 30 m x 30 m size were distributed in fairly homogeneous patches across the study area, following a stratified random sampling design by type of vegetation (i.e., heathlands, gorse shrub lands and oak forests) to encompass all types of vegetation affected by fire. The sampling size was proportional to the extent covered by each type of vegetation, resulting in 20 plots in heathlands, 11 plots in gorse shrublands and 23 plots in oak forest. We further established 19 plots in unburned areas, which were used as controls. Plot locations were georeferenced with a GPS receiver in post-processing mode (accuracy better than 0.50 m).

Assessment of site field burn severity was obtained following the protocol described by Fernández-García et al. (2018), which is an adaptation of the original CBI protocol developed by Key and Benson (2006). The procedure consisted on rating several variables from 0 (unburned) to 3 points (high severity) across five strata, to compute an average site burn severity using the average burn severity obtained per strata. Burn severity of vegetation and soil strata were also separately evaluated. See Fernández-García et al. (2018) for further details on the adapted CBI protocol.

2.3. *Remote sensing imagery and preprocessing*

Remote sensing information to estimate burn severity was obtained from three different data sources: the Landsat 8 OLI/TIRS, the Sentinel-2 MSI and the Deimos-1 SLIM-6-22 sensors. Landsat 8 OLI/TIRS imagery, at 30 m spatial resolution, includes nine reflective bands (i.e., three visible bands, two near-infrared [NIR] and short wave infrared bands [SWIR], one panchromatic band and two bands for describing aerosol, water vapor and cirrus clouds) and two thermal bands (United States Geological Survey 2015). Meanwhile, Sentinel-2 MSI has thirteen reflective bands (i.e., four 10 m visible and NIR bands; six 20 m red edge, NIR and SWIR bands; and three 60 m bands for characterizing aerosol, water vapor correction and cirrus clouds) (European Space Agency 2015). Deimos-1 SLIM-6-22 imagery is a 22 m spatial resolution product with three reflective bands (NIR, red, and green bands; https://earth.esa.int/documents/10174/2605161/DEIMOS-1-Imagery-User-Guide) (Figure 2).

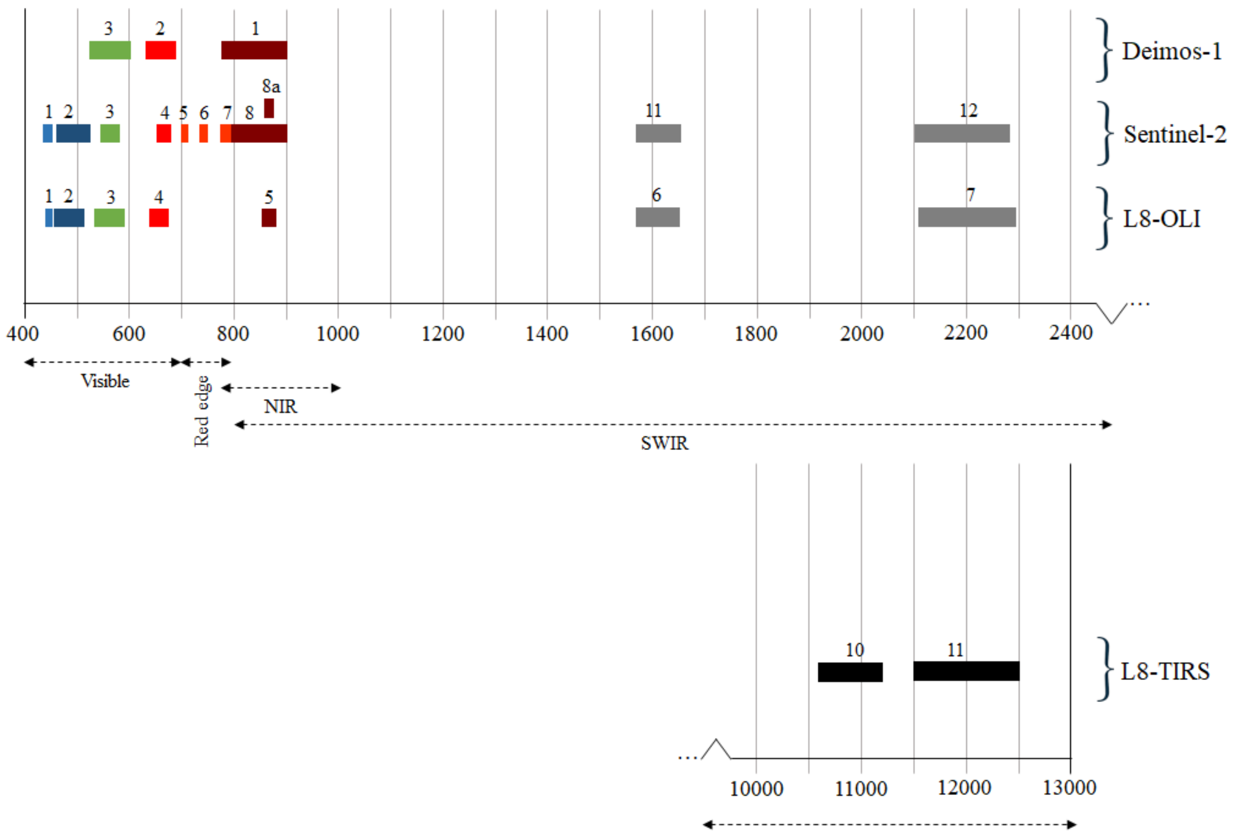

Figure 2. Comparison of spectral bands of Landsat 8 OLI/TIRS (L8-OLI and L8-TIRS), Sentinel-2 MSI and Deimos-1 SLIM-6-22 sensors.

Selected images to estimate burn severity included the available cloud-free pre- and post-fire images closest to the date of the fire, aiming to avoid phenological changes in the vegetation and to allow comparison among remote sensing products. Landsat 8 OLI/TIRS scenes were acquired on August 11th, 2017 (pre-fire image) and October 10th, 2017 (post-fire image) from the USG Earth Explorer server (United States Geological Survey, 1879); Sentinel 2 MSI scenes (C1-processing level) on August 13th, 2017 (pre-fire image) and September 2nd, 2017 (post-fire image) from the Copernicus server (European Space Agency 1975); and Deimos 1 SLIM-6-22 scenes on July 25th, 2017 (pre-fire image) and September 8th, 2017 (post-fire image).

The reflective bands of the three remote sensing products were atmospherically corrected and converted to at-surface reflectance using the ATCOR atmospheric correction model (Richter and Schläpfer 2018) included in the PCI GEOMATICS 2018 software. Furthermore, the thermal band (B10) of Landsat 8 was pre-processed and used to obtain the Land Surface Temperature (LST) product following the method described in Fernández-García et al. (2018).

2.4. *Burn severity spectral indices*

Among the wide range of existing remote sensing metrics described in the literature, we evaluated the performance of fourteen reflective, thermal and mixed (combining reflective and thermal bands) spectral indices (Table 1). Specifically, selected indices included: (i) seven reflective indices (NDVI, dNDVI, SAVI, NBR, dNBR, RdNBR, EVI and dEVI – difference Enhanced Vegetation Index-); (ii) two thermal indices (LST and dLST); and (iii) four mixed indices (NDVIT, SAVIT, (LST/EVI) and d(LST/EVI)).

NDVI, dNDVI and SAVI were calculated for Landsat 8 OLI/TIRS, Sentinel-2 MSI and Deimos-1 SLIM-6-22. Concerning the Sentinel-2 MSI sensor, these indices were created using the narrow NIR band (B8a) that has a high spectral correspondence with the NIR band of Landsat 8 OLI (Figure 2). The SAVI index adds a soil calibration constant (*L*) to the formula of NDVI to account for background effects (Schepers et al., 2014). In our case, we considered a *L* value of 0.5, as this value has been recommended for most environmental conditions (Epting et al., 2005).

The NBR, the dNBR and the RdNBR, as well as the EVI and the dEVI indices could not be calculated with the Deimos-1 sensor because it does not capture data over blue and SWIR regions (Figure 2). For the Sentinel-2 MSI sensor, these indices were derived using the narrow NIR band (B8a) and the longer SWIR band (B12) to facilitate direct comparison among sensors (i.e., Landsat 8 OLI and Sentinel-2; Figure 2). Moreover, the spatial resolution of Sentinel-2 bands was homogenized by rescaling the SWIR band from 20 m to 10 m spatial resolution using the Nearest Neighbor rule. Thermal information was only available using the Landsat 8 OLI/TIRS sensor (Figure 2).

With the aim of enabling comparative analyses among satellites, values of spectral indices corresponding to each CBI plot were obtained by averaging the values extracted from raster pixels using 900 sampling points systematically distributed within each 30 m x 30 m CBI plot, according to the procedure described in Picotte and Robertson (2011).

Table 1. Spectral indexes evaluated and calculation algorithms, using Landsat 8 OLI/TIRS, Sentinel-2 MSI and Deimos-1 SLIM-6-22 spectral bands.

Spectral Index	Landsat 8 OLI/TIRS formula	Sentinel-2 MSI formula	Deimos-1 SLIM-6-22 formula	Reference
NDVI	$(\rho_5 - \rho_4)/(\rho_5 + \rho_4)$	$(\rho_{8A} - \rho_4)/(\rho_{8A} + \rho_4)$	$(\rho_1 - \rho_2)/(\rho_1 + \rho_2)$	Rouse et al. (1973)
dNDVI	$(NDVI_{pre} - NDVI_{post})$	$(NDVI_{pre} - NDVI_{post})$	$(NDVI_{pre} - NDVI_{post})$	Zhu et al. (2006)
SAVI	$(1 + L)[(\rho_5 - \rho_4)/(\rho_5 + \rho_4 + L)]$ with L = 0.5	$(1 + L)[(\rho_{8A} - \rho_4)/(\rho_{8A} + \rho_4 + L)]$ with L = 0.5	$(1 + L)[(\rho_1 - \rho_2)/(\rho_1 + \rho_2 + L)]$ with L = 0.5	Huete (1988)
NBR	$(\rho_5 - \rho_7)/(\rho_5 + \rho_7)$	$(\rho_{8A} - \rho_{12})/(\rho_{8A} + \rho_{12})$		López-García and Caselles (1991)
dNBR	$1000\,(NBR_{pre} - NBR_{post})$	$1000\,(NBR_{pre} - NBR_{post})$		Key (2006)
RdNBR	$(dNBR/(\vert NBR_{pre}\vert^{0.5})$	$(dNBR/(\vert NBR_{pre}\vert^{0.5})$		Miller and Thode (2007)
EVI	$2.5[(\rho_5 - \rho_4)/(\rho_5 + 6\rho_4 - 7.5\rho_2 + 1)]$	$2.5[(\rho_{8A} - \rho_4)/(\rho_{8A} + 6\rho_4 - 7.5\rho_2 + 1)]$		Gao et al. (2000)
dEVI	$(EVI_{pre} - EVI_{post})$	$(EVI_{pre} - EVI_{post})$		Zhu et al. (2006)
LST	LST in Kelvin from B_{10}	-		Yu et al. (2014)
dLST	$(LST_{pre} - LST_{post})$	-		Zheng et al. (2016)
NDVIT	$(\rho_5 - \rho_4 * \rho_{10})/(\rho_5 + \rho_4 * \rho_{10})$	-		Smith et al. (2007)
SAVIT	$(1 + L)[(\rho_5 - \rho_4 * \rho_{10})/(\rho_5 + \rho_4 * \rho_{10} + L)]$ with L = 0.5	-		Smith et al. (2007)
LST/EVI	$(LST - 273.15)/EVI$	-		Zheng et al. (2016)
d(LST/EVI)	$(LST/EVI)_{post} - (LST/EVI)_{post}$	-		Zheng et al. (2016)

2.5. *Statistical analyses*

Statistical correlations between field burn severity (i.e., site, vegetation and soil burn severity) and remote sensing indices derived from each satellite (Table 1) were estimated by fitting separated Ordinary Least Squares (OLS) models, following the approaches of previous studies (Epting et al., 2005; Quintano et al., 2015; Fernández-García et al., 2018). This procedure resulted in twenty-five models per site, vegetation and soil burn severity. Residuals of OLS models were graphically checked to ensure the appropriateness of models (i.e., assumptions of normal residuals' distribution, independence and homoscedasticity). The coefficient of determination (R^2) and the statistical significance of OLS models were used to compare the performance of the different spectral indexes, as well as the performance of the different remote sensing satellites. OLS model were run using the statistical software R (R Core Team, 2017).

3. Results

Comparing remote sensing satellites, Sentinel-2 MSI data, with the highest spatial resolution, slightly improved the performance of Landsat 8 OLI/TIRS to assess site, vegetation and soil burn severity, although only for indices including the SWIR and NIR bands. The availability of Landsat 8 thermal bands did not contribute to improving burn severity evaluation. Deimos-1 imagery only enabled the assessment of spectral indices based on the NIR and red bands. Additionally, it showed some limitations using bi-temporal indices (Table 2, 3 and 4).

Table 2. Coefficients of determination (R^2) and significance (p) of linear regression models between remote sensing indices derived from Landsat 8 OLI/TIRS, Sentinel-2 MSI and Deimos-1 SLIM-6-22 sensors and site burn severity estimated as CBI values. Maximum R^2 values for each satellite are in bold.

Remote sensing indices		Site burn severity		
		Landsat 8	Sentinel-2	Deimos-1
Reflective	NDVI	0.556***	0.467***	**0.481*****
	dNDVI	**0.635*****	**0.674*****	0.420***
	SAVI	0.533***	0.520***	**0.517*****
	NBR	**0.640*****	**0.670*****	
	dNBR	**0.690*****	**0.767*****	
	RdNBR	**0.686*****	**0.762***	
	EVI	0.139**	0.005	
	dEVI	0.015	0.004	
Thermal	LST	0.119**		
	dLST	0.251***		
Mixed	NDVIT	0.406***		
	SAVIT	0.362***		
	dLST	0.251***		
	d(LST/EVI)	0.195***		

Significance of the correlations are represented as * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3. Coefficients of determination (R^2) and significance (p) of linear regression models between remote sensing indices derived from Landsat 8 OLI/TIRS, Sentinel-2 and Deimos-1 sensors and vegetation burn severity estimated as CBI values. Maximum R^2 values for each satellite are in bold.

Remote sensing indices		Vegetation burn severity		
		Landsat 8	Sentinel-2	Deimos-1
Reflective	NDVI	0.631***	0.548***	**0.560*****
	dNDVI	0.523**	0.569***	0.316**
	SAVI	0.589***	0.574***	**0.576*****
	NBR	**0.696*****	**0.721*****	
	dNBR	0.578***	0.658***	
	RdNBR	**0.693*****	**0.760*****	
	EVI	0.072*	0.000	
	dEVI	0.000	0.000	
Thermal	LST	0.159***		
	dLST	0.187***		
Mixed	NDVIT	0.453***		
	SAVIT	0.426***		
	d(LST/EVI)	0.139**		
	LST/EVI	0.169***		

Significance of the correlations are represented as * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 4. Coefficients of determination (R^2) and significance (p) of linear regression models between remote sensing indices derived from Landsat 8 OLI/TIRS, Sentinel-2 and Deimos-1 sensors and soil burn severity estimated as CBI values. Maximum R^2 values for each satellite are in bold

Remote sensing indices		Soil burn severity		
		Landsat 8	Sentinel-2	Deimos-1
Reflective	NDVI	0.347**	0.25***	0.275**
	dNDVI	**0.607*****	0.575***	**0.386*****
	SAVI	0.328**	0.304***	0.320***
	NBR	0.416**	0.452***	
	dNBR	**0.623*****	**0.686*****	
	RdNBR	0.515***	0.596***	
	EVI	0.185***	0.002	
	dEVI	0.044**	0.026	
Thermal	LST	0.054*		
	dLST	0.275***		
Mixed	NDVIT	0.253***		
	SAVIT	0.213***		
	d(LST/EVI)	0.193***		
	LST/EVI	0.238***		

Significance of the correlations are represented as * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Focusing on remote sensing metrics, reflective indices based on NBR (i.e., NBR, dNBR and RdNBR) derived from Landsat 8 OLI and Sentinel-2 MSI best fitted field burn severity (Tables 2, 3). Nevertheless, they showed relatively lower correlation values for soil burn severity (Table 4).

The use of Sentinel-2 MSI data slightly improved results of NBR-based indices compared to Landsat 8 OLI (Table 2, 3 and 4; Figure 3). Specifically, dNBR and RdNBR correlated the best with site burn severity ($R^2 = 0.69$ and $R^2 = 0.76$ for Landsat 8 OLI and Sentinel-2 MSI respectively; Table 2), and more weakly with soil burn severity ($R^2 > 0.515$ and $R^2 = 0.596$ for Landsat 8 OLI/ and Sentinel-2 MSI respectively; Table 4). However, considering vegetation burn severity, NBR and RdNBR outperformed the dNBR index (Table 3).

The use of reflective indices based on NIR and red wavelength bands, such as the post-fire NDVI and SAVI, resulted in weaker relationships with field burn severity compared to NBR-based indices (Table 2, 3 and 4). Furthermore, correlation values of mono-temporal NDVI and SAVI indices did not significantly differ among remote sensing data sources. In detail, both NDVI and SAVI obtained a similar moderate correlation with site and vegetation burn severity ($R^2 > 0.47$ and $R^2 > 0.55$ for site and vegetation burn severity, respectively; Table 2 and 3), but were not able to match soil burn severity ($R^2 < 0.35$; Table 4). The bi-temporal dNDVI index considerably outperformed the post-fire NDVI index for site and soil burn severity and showed relatively similar correlation values to NBR-based indices, except when using Deimos-1 imagery (Table 2 and 4; Figure 3).

The reflective index EVI and its bi-temporal counterpart dEVI poorly correlated with site, vegetation and soil burn severity, and especially using Sentinel-2 MSI data ($R^2 \leq 0.18$ and $R^2 \geq 0.02$ for Landsat 8 OLI and Serntinel-2, respectively; Table 2, 3 and 4).

The inclusion of thermal information did not improve correlations with field burn severity compared to reflective indices. Both thermal and mixed indices derived from Landsat 8 OLI/TIRS did not work well in any case (i.e., with site, vegetation and burn severity), with the variance explained by models lower than 0.45 (Table 2, 3 and 4).

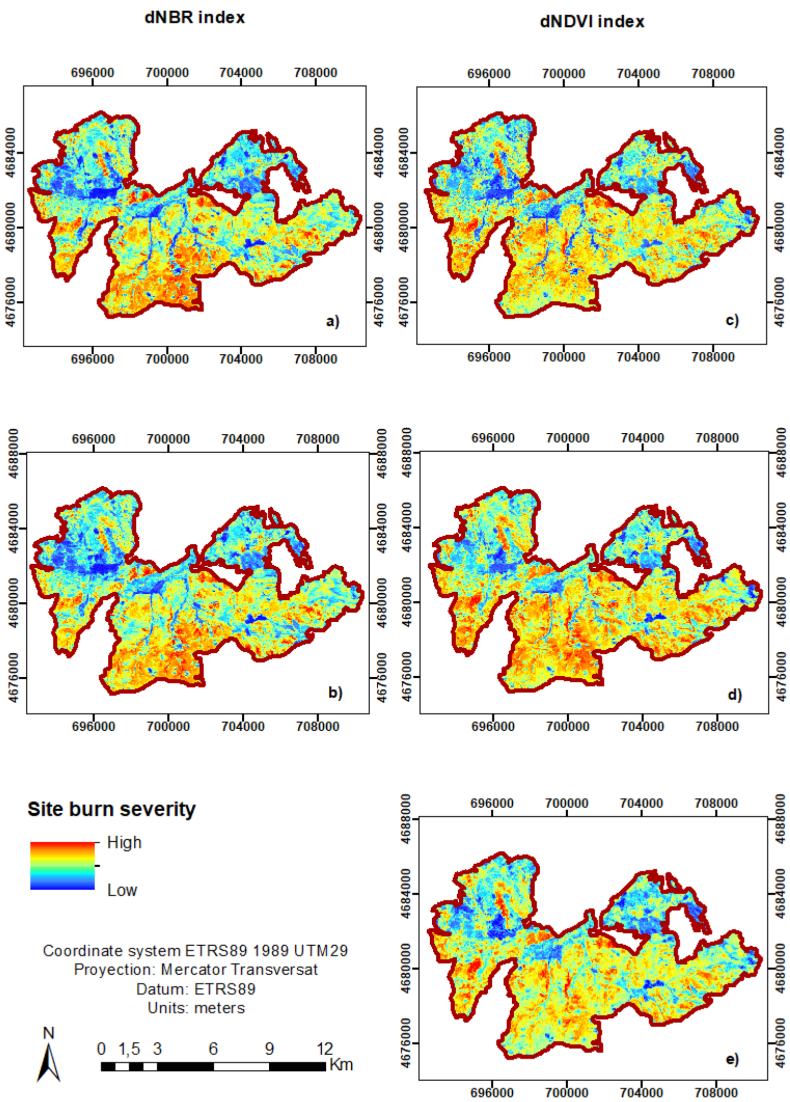

Figure 3. Site burn severity maps obtained using: a) dNBR index derived from Sentinel-2 MSI imagery; b) dNBR index derived from Landsat 8 OLI imagery; c) dNDVI index derived from Sentinel-2 MSI imagery; d) dNDVI index derived from Landsat 8 OLI imagery; e) dNDVI index derived from Deimos 1 SLIM-6-22.

4. Discussion

This study evaluates the suitability of individual Landsat 8 OLI/TIR, Sentinel-2 MSI and Deimos-1 SLIM-6-22 remote sensing indices in order to effectively assess fire severity in heterogeneous fire-prone Mediterranean ecosystems, dominated by shrublands and forest. Overall, correlation patterns of field burn severity (i.e., site, vegetation and soil burn severity) and remote sensing indices were consistent across different sensors. Furthermore, the results highlight that indices including NIR and SWIR bands better discriminated burn severity levels in heterogeneous landscapes, compared to indices based on NIR and red bands, and thermal and mixed metrics, as observed by Escuin et al. (2008) and Fernández-García et al. (2018).

Specifically, reflective indices based on NBR derived from both Landsat 8 OLI and Sentinel-2 MSI better correlated with field measurements of burn severity. The effectiveness of these indices to discriminate changes produced by fire is well established (Escuin et al., 2008; Veraverbeke et al., 2010, 2011), mainly due to the reduction of NIR reflectance, sensitive to chlorophyll content, and the increase in SWIR reflectance, related to a decrease in water content in vegetation and soil (Miller and Thode 2007). Indeed, in a study by Mallinis et al. (2018), comparing Landsat 8 and Sentinel-2, the most efficient in distinguishing fire effects was the NIR band of Landsat 8 and its corresponding wavelength band of Sentinel-2, the narrow NIR band (B8a), followed by the longer SWIR bands for both satellites. Similarly, Huang et al. (2016) also found that the narrow NIR band (B8a) and the longer SWIR band (B12) were the most suitable bands for detecting burned areas using a Sentinel-2 sensor.

Despite the overall good performance of NBR-based metrics, the response of individual indices differed among fire severities per strata. The dNBR and RdNBR strongly correlated with site burn severity, but more weakly with soil burn severity. Spectral indices correlated better with surface variables than with soil, likely because of the shielding effect of vegetation on the ground and the inadequacies of passive sensors to see under vegetation canopy (Tanase et al., 2011). Thefore, our results corroborate certain limitations of remote sensing data to analyze fire effects on soil (Fernández-García et al., 2018). Considering vegetation burn severity, the NBR and RdNBR indices outperformed the dNBR index. This could be explained by the heterogeneity of pre-fire vegetation types (i.e. *Erica australis, Genista hystrix* and *Quercus pyrenaica*), with different chlorophyll content and canopy cover, which may bias burn severity estimates using dNBR due to the strong influence of pre-fire vegetation on the magnitude of this index (Safford et al., 2008; Wulder et al., 2009). Thus, the relativized RdNBR index, which provides information on the changes induced by fire regardless of pre-fire land cover (Miller and Thode 2007), may more accurately predict burn severity in heterogeneous landscapes (Safford et al., 2008; Miller et al., 2009). Further, mono-temporal NBR may help provide a more accurate burn severity assessment in heterogeneous systems, likely due to an attenuation of errors associated with differences in vegetation phenology and cover (Epting et al., 2005; Lhermitte et al., 2011). Abovementioned correlation patterns of individual NBR-based indices were similar for both Landsat 8 OLI and Sentinel-2 MSI data. Moreover, the use of higher-resolution Sentinel-2 MSI only slightly improved correlations with field-based burn severity, compared to their counterparts derived from Landsat 8 OLI. These results support the findings of Mallinis et al. (2018) and could be attributed to the high correspondence between the spectral response function of NIR and the narrow NIR bands (B8a) of Landsat 8 OLI and Sentinel-2 MSI, and between the SWIR bands of both sensors (Skakun et al., 2017; Figure 2).

Reflective indices based on NIR and red bands derived from Landsat OLI, Sentinel-2 MSI and Deimos-1, (i.e., the post-fire NDVI and SAVI indices), were similarly correlated with field-based burn severity, but underperformed indices based on NBR. Epting et al. (2005) and Veraverbeke et al. (2011) reported that indices including information in the SWIR band (i.e., the NBR) were better suited than NDVI and SAVI for distinguishing burn severity levels. Such underperformance was mainly observed for soil burn severity. In this sense, the red band is strongly linked to vegetation chlorophyll content that decreases in burned areas, but presents limited sensitivity to spectral post-fire components of burned soil, such as black carbon or ash (Chuvieco et al., 2006; Rocha and Shaver 2009). Conversely, the association of the SWIR band to moisture content in vegetation and soil and charcoal variations would enhance sensitivity to changes in soil properties after fire, such as the charcoal signal, scorching and dry soil exposure, which would increase SWIR reflectance (Schepers et al., 2014).

The dNDVI index from Landsat 8 OLI and Sentinel-2 MSI data exceeded the NDVI index for site and soil burn severity and showed relatively similar correlation coefficients to NBR-based indices, contrary to studies by Chafer (2008) and Veraverbeke et al. (2010). Consequently, the dNDVI index may substitute NBR-based indices for assessing site and soil burn severity when imagery with a SWIR band is unavailable. Nevertheless, similar to dNBR patterns, the dNDVI index showed a weaker correlation with vegetation burn severity, probably due to the effect of the heterogeneity of pre-fire vegetation types in terms of chlorophyll content and canopy cover (Todd and Hoffer 1998; Lhermitte et al., 2011). Moreover, dNDVI from Deimos-1 data poorly correlated with field burn severity. This heterogeneous pre-fire environment may exhibit a complex spectrum signature difficult to discriminate with low spectral resolution sensors (Rocchini 2007). Consequently, coarse spectral resolution in the NIR and red bands of Deimos-1 could explain its reduced efficiency in evaluating burn severity based on the dNDVI index. To our knowledge, this is the second study that evaluates Deimos-1 imagery for burn severity assessment. Therefore, further research must be conducted under different fire scenarios aimed at determining the current potential of this sensor to detect burn severity, especially considering the unavailability of SWIR information.

The reflective post-EVI and dEVI indices seemed to be inefficient in assessing site, vegetation and soil burn severity, regardless of the sensor. There is still limited agreement on the functioning of those indices; while Schepers et al. (2014) noted a poor performance in ecosystems dominated by shrubs, Zheng et al. (2016) and Holden et al. (2010) found that correlations between the EVI and the dEVI and burn severity tended to increase in forest systems. These findings could suggest limitations of EVI and dEVI indices for assessing burn severity in shrubland ecosystems, likely because they are mostly tied to canopy structural characteristics, such as leaf area (Huete et al., 2002). Additionally, this poor performance may be associated with the inclusion of the blue band, which has less ability to discriminate burn areas, both with Landsat 8 OLI and Sentinel-2 MSI sensors (Mallinis et al., 2018).

Different studies support the utility of temperature data to assess burn severity (Veraverbeke et al., 2010; Quintano et al., 2017), likely because LST tends to increase after fire (Zheng et al., 2016). However, our study showed limitations of thermal data to determine field burn severity consistent with Harris et al. (2011) and Fernández-García et al. (2018). LST is strongly influenced by aspect and elevation (Vlassova et al., 2014; Quintano et al., 2015). Our study area is characterized by rough terrain and a wide altitudinal range that results in differences in insolation, moisture content, and vegetation type and cover, which ultimately affect LST (He et al., 2018). Therefore, inconsistencies in our results compared to previous studies could be attributed to the influence of topographic features on LST that lead to changes unassociated with burn severity (Fernández-García et al., 2018).

5. Conclusion

This study represents a novel approach comparing the performance of several Landsat 8 OLI/TIRS, Sentinel-2 MSI and Deimos-1 remote sensing indices as suitable tools to measure field burn severity in site, vegetation and soil in a very heterogeneous fire-prone Mediterranean ecosystem dominated by shrublands and forest. It confirms that, regardless of the sensor used, reflective NBR-based indices are more efficient in evaluating burn severity than indices based on the red and NIR bands, and thermal information. High resolution Sentinel-2 MSI imagery only slightly improved the performance of NBR-based indices compared to Landsat 8 OLI. The dNDVI index derived from Landsat 8 OLI and Sentinel-2 MSI correlated relatively well with site and soil burn severity, demonstrating its potential for assessing burn severity when remote-sensing imagery including SWIR information is unavailable. Moreover, mono-temporal and relativized indices, exhibited a better correlation with vegetation burn severity in heterogeneous systems compared to differenced indices. Results also highlighted the limitations of remotely sensed indices in determining soil burn severity.

Products derived from Sentinel 2 and Landsat 8 showed a good potential for detecting burn severity in a cost effective way, with minor differences between correlation patterns of field burn severity and remote sensing indices. Nevertheless, we highlight the need for further evaluation of the Deimos-1 sensor for different ecosystems, especially when applying bi-temporal indices.

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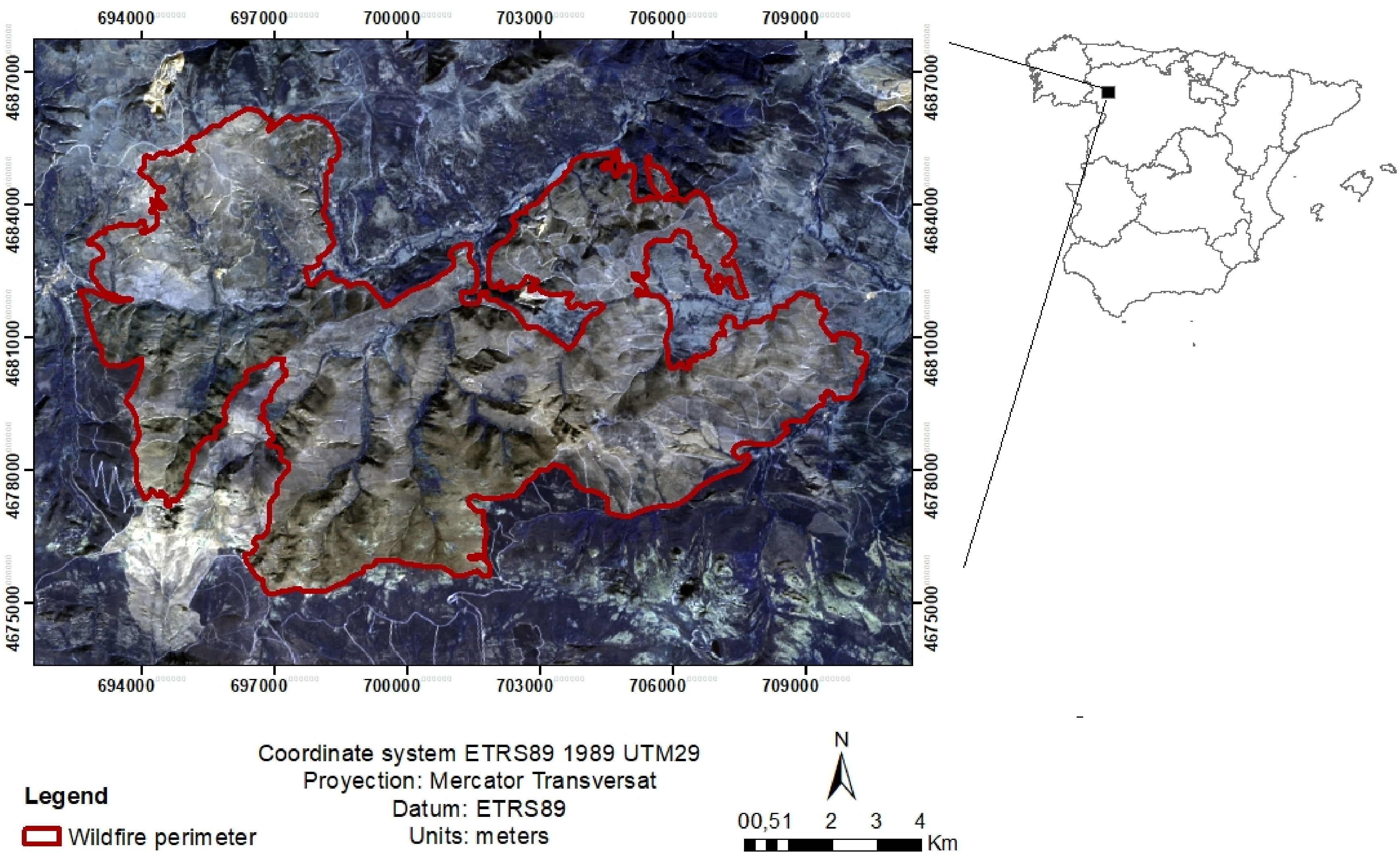

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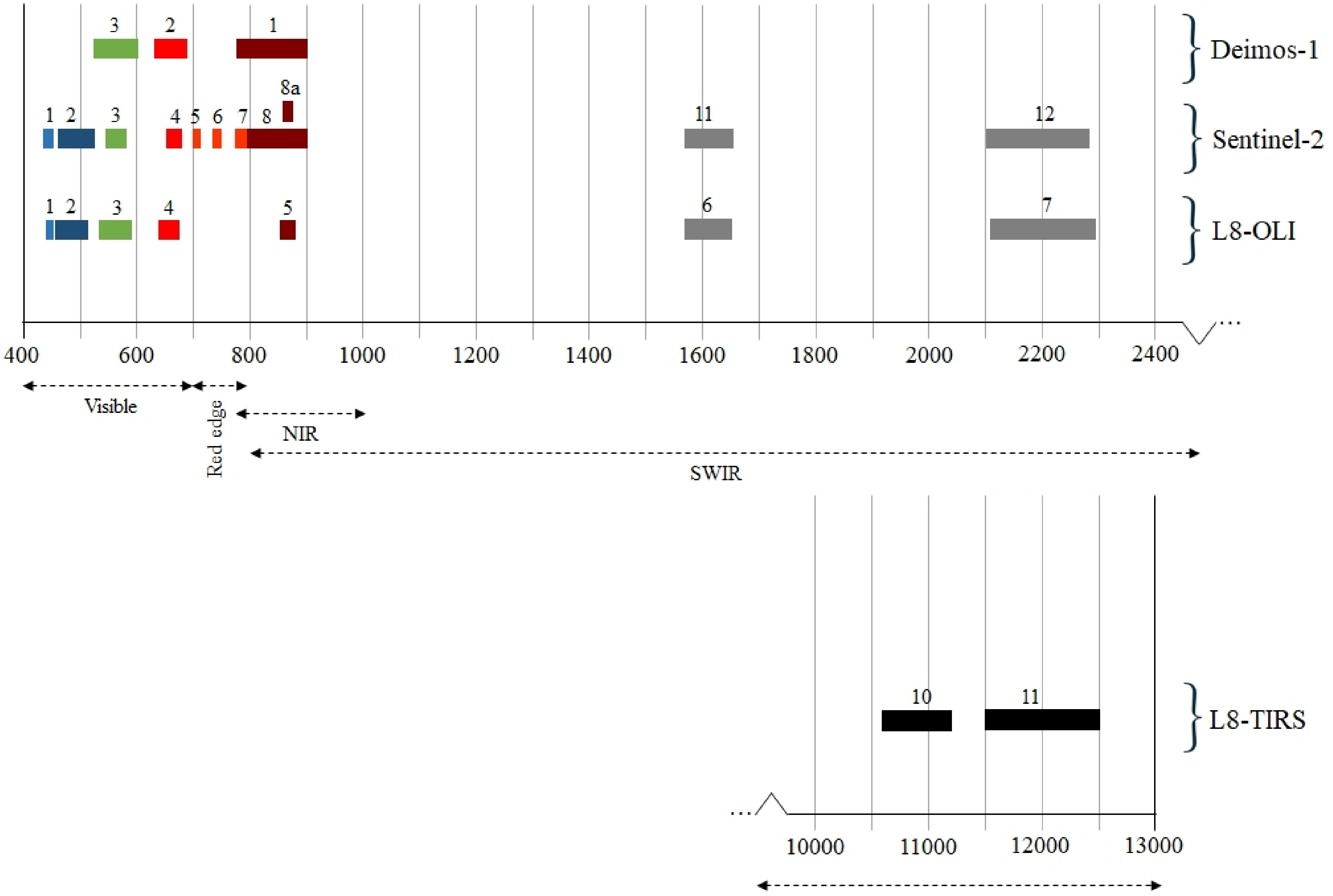
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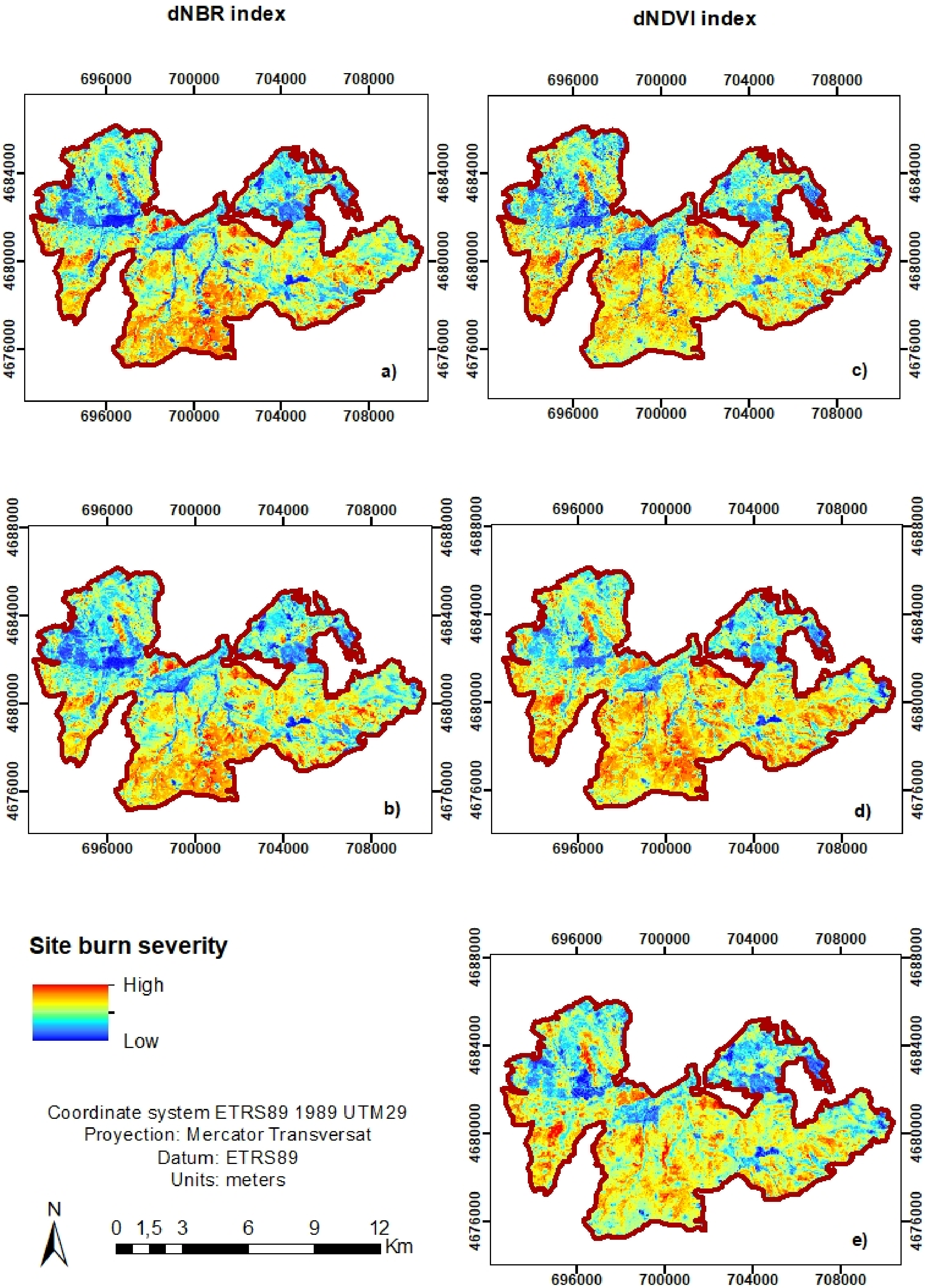
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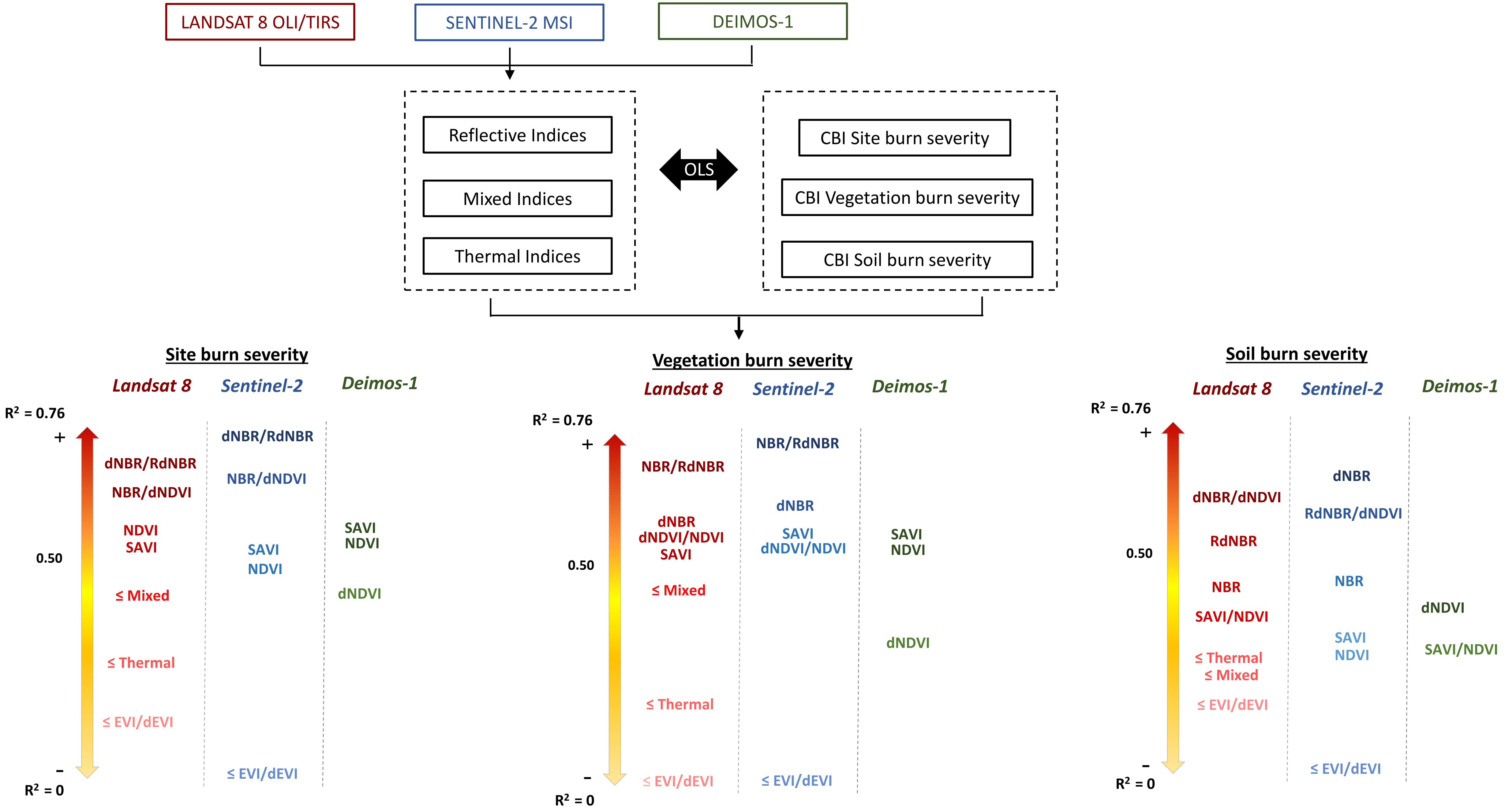

Figure1. Coefficients of determination (R^2) of OLS models between remote sensing índices from Landsat 8 OLI/TIRS, Sentinel-2 and Deimos-1; and site, vegetation and soil burn severity