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Evaluating Landsat Thematic Mapper spectral indices for estimating burn severity of the 2007 Peloponnese wildfires in Greece

Running head: Evaluating spectral indices for estimating burn severity

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Brief summary. This paper evaluates the performance of three different spectral indices for estimating burn severity. The indices were pre/post-fire differenced and correlated with field data of severity. In addition the burned pixels' bi-temporal shifts in the corresponding bi-spectral feature spaces were studied. Results reveal the importance of the short-wave and mid infrared spectral region in complement to the near infrared spectral region for assessing post-fire effects. Further research directions for estimating burn severity with remote sensing data are given.

Abstract. A vast area (more than 100 000 ha) of forest, shrubs and agricultural land burned down at the Peloponnese peninsula in Greece during the 2007 summer. Three pre/post-fire differenced Landsat Thematic Mapper (TM) derived spectral indices were correlated with field data of burn severity for these devastating fires. These spectral indices were the

Normalized Difference Vegetation Index (NDVI), the Normalized Difference Moisture Index (NDMI) and the Normalized Burn Ratio (NBR). The field data consists of 160 Geo Composite Burn Index (GeoCBI) plots. In addition, indices were evaluated in terms of optimality. The optimality statistic is a measure for the index's sensitivity to fire-induced vegetation depletion. Results show that the GeoCBI-dNBR (differenced NBR) approach yields a moderate-high $R^2 = 0.65$ whereas the correlation between field data and the differenced NDMI (dNDMI) and the differenced NDVI (dNDVI) was clearly lower (respectively $R^2 = 0.50$ and $R^2 = 0.46$). The dNBR also outperformed the dNDMI and dNDVI in terms of optimality. The resulting median dNBR optimality equalled 0.51 while the median dNDMI and dNDVI optimality values were respectively 0.50 and 0.40 (differences significant for $p<0.001$). However, inaccuracies observed in the spectral indices approach indicate that there is room for improvement. This could imply improved preprocessing, revised index design or alternative methods.

Additional Keywords: fire severity; Normalized Burn Ratio, Normalized Difference Vegetation Index, spectral index, wildfires, Geo Composite Burn Index, optimality.

Introduction

Wildfires play a major role in Mediterranean Type Ecosystems (MTEs) (Vazquez and Moreno 2001; Diaz-Delgado et al. 2004; Pausas 2004; Pausas et al. 2008) as they partially or completely remove the vegetation layer and affect post-fire vegetation composition, water and sediment regimes, and nutrient cycling (Kutiel and Inbar 1993). As such they act as a natural component in vegetation succession cycles (Trabaud 1981; Capitaino and Carcaillet 2008; Roder et al. 2008) but also potentially increase degradation processes, such as soil erosion (Thomas et al. 1999; Chafer 2008; Fox et al. 2008). Assessment of the fire impact is thus a major challenge to understand the potential degradation after fire (Kutiel and Inbar 1993; Fox et al. 2008) and to comprehend ecosystem's post-fire resilience (Epting and Verbyla 2005; Lentile et al. 2007).

The terms fire severity and burn severity are often interchangeably used (Keeley 2009) describing the amount of damage (Hammill and Bradstock 2006; Gonzalez-Alonso et al. 2007; Chafer 2008) the physical, chemical and biological changes (Landmann 2003; Chafer et al. 2004; Cocke et al. 2005; Stow et al. 2007; Lee et al. 2008) or the degree of alteration (Brewer et al. 2005; Eidenshink et al. 2007) that fire causes to an ecosystem. Some authors, however, suggest a clear distinction between both terms by considering the fire disturbance continuum (Jain et al. 2004), which addresses three different temporal fire effects phases: before, during and after the fire. In this context, fire severity quantifies the short-term fire effects in the immediate post-fire environment (Lentile et al. 2006) and is usually measured in an initial assessment scheme (Key and Benson 2005). As such, it mainly quantifies vegetation consumption and soil alteration. Burn severity, on the other hand, quantifies both the short- and long-term impact as it includes response processes (e.g. resprouting, delayed mortality), which is evaluated in an extended assessment (EA) that incorporates both first- and second-order effects (Lentile et al. 2006; Key 2006). In this study burn severity, defined as the absolute magnitude of environmental change caused by a fire (Key and Benson 2005), is estimated one year post-fire.

Several remote sensing studies have discussed the potential of satellite imagery as an alternative for extensive field sampling to quantify burn severity over large areas. These studies evaluated the use of spectral unmixing, simulation techniques and spectral indices to assess burn severity (for a comprehensive review of remote sensing techniques for burn severity assessment, see Kasischke et al. 2007; French et al. 2008). Spectral mixture analysis (Rogan and Yool 2001; Lewis et al. 2007; Robichaud et al. 2007) and simulation models (Chuvieco et al. 2006; De Santis and Chuvieco 2007; De Santis et al. 2009) have proven to provide valuable information with regards to burn severity. Spectral indices, however, are a more popular approach, mainly because of their computational and conceptual simplicity. These spectral indices are typically based on Normalized Difference Spectral Indices (NDSIs), such as the Normalized Difference Vegetation Index (NDVI) (Isaev et al. 2002; Chafer et al. 2004; Diaz-Delgado et al. 2004; Ruiz-Gallardo et al. 2004; Hammill and Bradstock 2006; Hudak et al. 2007) or the widely used Normalized Burn Ratio (NBR) (e.g. Lopez-Garcia and Caselles; Epting et al. 2005; Key and Benson 2005; Miller and Thode 2007). The NDVI combines the reflectance in the R (red) and NIR (near infrared) spectral region and is a measure for the amount of green vegetation, whereas the NBR relates to vegetation moisture by combining the NIR with MIR (mid infrared) reflectance. Since fire effects on vegetation produce a reflectance increase in the R and MIR spectral regions and a NIR reflectance drop (Pereira et aL. 1999), bi-temporal image differencing is frequently applied on pre- and post-fire NDVI or NBR images. This results respectively in the differenced Normalized Difference Vegetation Index (dNDVI) (Chafer et al. 2004; Hammill and Bradstock 2006) and the differenced Normalized Burn Ratio (dNBR) (Key and Benson 2005). The advantage of these pre/post-fire differenced indices is that they permit a clear discrimination between unburned sparsely vegetated areas and burned areas, which is difficult in mono-temporal imagery (Key and Benson 2005).

A wide range of field data has been considered to validate the remotely sensed indices for estimating burn severity: % live trees (Lopez-Garcia and Caselles 1991; Alleaume et al. 2005; Smith et al. 2007) or % tree mortality (Kushla and Ripple 1998; Isaev et al. 2002), basal area mortality (Chappell and Agee 1996), combustion completeness (Alleaume et al. 2005), changes in Leaf Area Index (LAI) (Boer et al. 2007) and fractional cover of several components (Kokaly et al. 2007; Lewis et al. 2007; Robichaud et al. 2007). However, by far the most widely used field measurement is the Composite Burn Index (CBI) (Key and Benson

2005). The CBI is a semi-quantitative field sampling approach based on an expert judgement procedure, developed as an operational methodology for validating remotely sensed assessments of burn severity on a national scale in the USA as part of the FIREMON (Fire Effects Monitoring and Inventory Protocol) project. The CBI is fundamentally different to the above-mentioned field approaches because in the CBI the sample plot is considered in a holistic way. Several attributes (e.g. char height, % LAI change…) of the plot are visually examined and numerically rated per ecosystem stratum (substrates, low shrubs, tall shrubs, intermediate trees and high trees). The total plot score, which is an average of the average stratum ratings, expresses the plot's burn severity. Recently, GeoCBI, a modified version of the CBI, has been developed (De Santis and Chuvieco 2009). The main modification of the GeoCBI consists of the consideration of the fraction of coverage (FCOV, the percentage of cover with respect to the total extension of the plot) of the different vegetation strata, which resulted in a more consistent relation between the GeoCBI and the remotely sensed burn severity measure (De Santis and Chuvieco 2009). The GeoCBI-dNBR relationship recently experienced a knowledge gain for the North American boreal region (Epting et al. 2005, Allen and Sorbel 2008; Hall et al. 2008; Hoy et al. 2008; Murphy et al. 2008). However, studies that assessed the empirical relationship between vegetation indices and field data in the fire-prone Mediterranean biome (De Santis and Chuvieco 2007) are underrepresented in literature.

The dNBR approach has been questioned (Roy et al. 2006) as it was initially developed for detecting burned areas (Lopez-Garcia and Caselles 1991) rather than evaluating within-burn differences in combustion completeness. To evaluate dNBR index performance, a pixel-based optimality measure originating from the spectral index theory (Verstraete and Pinty 1996), which varies between zero (not at all optimal) and one (fully optimal), has been developed (Roy et al. 2006). An optimal burn severity spectral index needs to be very sensitive to fire-induced vegetation changes and insensitive to perturbing factors such as atmospheric and illumination effects. Very low mean optimality values were reported using in situ reflectance, Landsat Enhanced Thematic Mapper plus (ETM+) and Moderate Resolution Imaging Spectroradiometer (MODIS) sensed data, suggesting that the dNBR approach is incapable of retrieving reliable information with regards to burn severity (Roy et al. 2006). However, markedly higher mean optimality measures were found for six burns in Alaska, USA (Murphy et al. 2008). Also, the dNBR optimality statistics were found to outperform the dNDVI optimality measures (Escuin et al. 2008) suggesting that the dNBR remains the most optimal NDSI for estimating burn severity.

Several authors highlight the need for an independent validation of burn severity assessments based on spectral indices for specific regions and vegetation types (Cocke et al. 2005; Key et al. 2005; Lentile et al. 2006 ; Chuvieco and Kasischke 2007; Fox et al. 2008). As the technique is conceptually and computationally easy, burn severity maps based on spectral indices could form an important instrument for post-fire management practices in the fire-prone Mediterranean ecoregion. It is therefore our objective to evaluate different spectral indices derived from Landsat TM imagery for assessing burn severity of the large 2007 Peloponnese wildfires in Greece. This general objective is fulfilled (i) by evaluating the relationship between field data and several pre/post-fire differenced vegetation indices and (ii) by comparing optimality statistics of those indices.

Study area

The area of interest is located at the Peloponnese, Greece (36°30'-38°30' N, 21°-23° E) (see figure 1). Elevations range between 0 and 2404 m above sea level. Hot, dry summers alternate with mild, wet winters resulting in a typical Mediterranean climate. For the Kalamata meteorological station (37°4' N, 22°1' E) the mean annual precipitation equals 780 mm and the average annual temperature is 17.8 °C (Hellenic National Meteorological Service, www.hnms.gr).

Large wildfires struck the area (Gitas et al. 2008) in the 2007 summer. The first large burn initiated on 26/07/2007 and lasted until 01/09/2007. The fires devastated a large amount (more than 100 000 ha) of coniferous forest, broadleaved forest, shrub lands (phrygana and maquis communities) and olive groves. Black pine (*Pinus nigra*) is the dominant conifer species. Phrygana is dwarf scrub vegetation (< 1 m), which prevails on dry landforms (Polunin 1980). Maquis communities consist of sclerophyllous evergreen shrubs of 2-3 m high. The shrub layer is characterised by e.g. Kermes oak (*Quercus coccifera*), Hungarian oak (*Q. frainetto*), mastic tree (*Pistacia lentiscus*), sageleaf rockrose (*Cistus salvifolius*), hairy rockrose (*C. incanus*), tree heath (*Erica arborea*), and thorny burnet (*Sarcopoterum spinosum*). The olive groves consist of *Olea europaea* trees whereas oaks are the dominant broadleaved species.

Methods

Data and preprocessing

For assessing burn severity of the summer 2007 Peloponnese fires two anniversary date Landsat TM images (path/row 184/34) were used (23/07/2006 and 13/08/2008) (step 1 in figure 2). The images were acquired in the summer, minimizing effects of vegetation phenology and differing solar zenith angles. The images were subjected to geometric, radiometric, atmospheric and topographic correction (step 2 in figure 2).

The 2008 image was geometrically corrected using 34 ground control points (GCPs), recorded in the field with a Garmin eTrex Vista GPS (Global Positioning System) (15 m error in x and y under ideal condition (Garmin 2005), but up to 35.5 m under closed canopy (Chamberlain 2002)). The resulting Root Mean Squared Error (RMSE) was lower than 0.5

pixels. The 2006 and 2008 images were co-registered within 0.5 pixels accuracy. All images were registered in Universal Transverse Mercator (zone 34S), with ED 50 (European Datum 1950) as geodetic datum.

Raw digital numbers (DNs) were scaled to at-sensor radiance values (L_s) (Chander et al. 2007) but with band-specific parameters proposed for Landsat TM data processed and distributed by the ESA (European Space Agency) (Arino et al. s.d.). The radiance to reflectance conversion was performed using the COST method (Chavez 1996):

$$\rho_a = \frac{\pi(L_s - L_d)}{(E_o / d^2)(\cos\theta_z)^2} \qquad (1)$$

where ρ_a is the atmospherically corrected reflectance at the surface; L_s is the at-sensor radiance ($Wm^{-2}sr^{-1}$); L_d is the path radiance ($Wm^{-2}sr^{-1}$); E_o is the solar spectral irradiance (Wm^{-2}); d is the earth-sun distance (astronomical units); and θ_z is the solar zenith angle. The COST method is a dark object subtraction (DOS) approach that assumes 1 % surface reflectance for dark objects (e.g. deep water). After applying the COST atmospheric correction, pseudo-invariant features (PIFs) such as deep water and bare soil pixels, were examined in the images. No further relative normalization between the images was required.

It was necessary to correct for different illumination effects due to topography. This was done based on the C correction method, an empirical modification of the cosine correction approach (Teillet et al. 1982), using a digital elevation model (DEM) and knowledge of the solar zenith and azimuth angle at the moment of image acquisition. Topographical slope and aspect data were derived from 90 m SRTM (Shuttle Radar Topography Mission) elevation data (Jarvis et al. 2006) resampled and coregistered with the Landsat images. The illumination is modeled as:

$$\cos\gamma_i = \cos\theta_p \cos\theta_z + \sin\theta_p \sin\theta_z \cos(\phi_a - \phi_o) \qquad (2)$$

where γ_i is the incident angle (angle between the normal to the ground and the sun rays); θ_p is the slope angle; θ_z is the solar zenith angle; ϕ_a is the solar azimuth angle; and ϕ_o is the aspect angle. Then terrain corrected reflectance ρ_t is defined as:

$$\rho_t = \rho_a \left(\frac{\cos\theta_z + c_k}{\cos\gamma_i + c_k} \right) \quad (3)$$

where c_k is a band specific parameter $c_k = b_k / m_k$ where b_k and m_k are the respective intercept and slope of the regression equation $\rho_a = b_k + m_k \cos\gamma_i$. Since topographic normalization works better when applied separately for specific land cover types (Bishop and Colby 2002) burned area specific c-values were calculated by masking the unburned areas using a two-phase threshold method (Veraverbeke et al. in press).

To assess burn severity in the field, 160 GeoCBI plots were collected one year post-fire, in September 2008. The GeoCBI is a modified version of the Composite Burn Index (CBI) (De Santis and Chuvieco 2009). The (Geo)CBI is an operational tool used in conjunction with the Landsat dNBR approach to assess burn severity in the field (Key and Benson 2005). The GeoCBI divides the ecosystem into five different strata, one for the substrates and four vegetation layers. These strata are: (i) substrates, (ii) herbs, low shrubs and trees less than 1 m, (iii) tall shrubs and trees of 1 to 5 m, (iv) intermediate trees of 5 to 20 m and (v) big trees higher than 20 m. The strata are grouped in the understorey (i-iii) and the overstorey (iv-v). In the field form, 20 different factors can be rated (e.g. soil and rock cover/colour change, % LAI change, char height) (see table 1) but only those factors present and reliably rateable, are considered. The rates are given on a continuous scale between zero and three and the resulting factor ratings are averaged per stratum. Based on these stratum averages, the GeoCBI is calculated in proportion to their corresponding fraction of cover, resulting in a weighted average between zero and three that expresses burn severity.

The 160 sample points were selected based on a stratified sampling approach, taking into account the constraints on mainly accessibility and time, which encompasses the whole range of variation found within the burns. Contributing to this objective 10 out of the 160 plots were measured in unburned land, with a consequent GeoCBI value of zero. The field plots consist of 30 by 30 m squares, analogous to the Landsat pixel size. The pixel centre coordinates were recorded based on one measurement with a handheld Garmin eTrex Vista GPS device. To minimize the effect of potential misregistration plots were at least 90 m apart and chosen in relatively homogeneous areas of at least 60 by 60 m, although preferably more (Key and Benson 2005). This homogeneity refers both to the fuel type and the fire effects. Of the 160 field plots 67 plots were measured in shrub land, 58 in coniferous forest, 17 in broadleaved forest and 18 in olive groves. Figure 3 shows example low, moderate and high severity plot photographs for the coniferous forest fuel type.

Spectral indices and optimality

In this study the potential of three Normalized Difference Spectral Indices (NDSIs) for assessing fire-induced vegetation change is evaluated using TM bands most sensitive to post-fire reflectance changes: TM3 (630-690 nm), TM4 (760-900 nm), TM5 (1550-1750 nm) and TM7 (2080-2350 nm). Reflectance in the visual (TM3) and mid infrared (TM5 and TM7) regions increases after fire, while the NIR region (TM4) is characterised by a reflectance drop (Pereira et al. 1999). To capture this information, The Normalized Difference Vegetation Index (NDVI) combines R (TM3) band with NIR (TM4) band information whereas the Normalized Difference Moisture Index (NDMI) (Wilson and Sader 2002) and the Normalized Burn Ratio (NBR) combine the NIR (TM4) band with a MIR (TM5 and TM7, respectively) band. The NBR has become the standard spectral index for assessing fire/burn severity, especially in North American regions, whereas the NDMI has not been evaluated before for fire/burn severity applications. Nevertheless, it has been suggested that TM5 is well suited for remote sensing of canopy water content (Tucker 1980). Consequently it might also reflect post-fire reflectance changes and was included in this study. These are the formulas of the spectral indices used (steps 3 and 4 in figure 2):

$$NDVI = \frac{TM4 - TM3}{TM4 + TM3} \qquad dNDVI = NDVI_{pre} - NDVI_{post} \tag{4}$$

$$NDMI = \frac{TM4 - TM5}{TM4 + TM5} \qquad dNDMI = NDMI_{pre} - NDMI_{post} \tag{5}$$

$$NBR = \frac{TM4 - TM7}{TM4 + TM7} \qquad dNBR = NBR_{pre} - NBR_{post} \tag{6}$$

For evaluating the optimality of the bi-temporal change detection, the TM4-TM3, TM4-TM5 and TM4-TM7 bi-spectral spaces were considered (see figure 4). If a spectral index is appropriate to the physical change of interest, in this case fire-induced vegetation depletion, there exists a clear relationship between the change and the direction of the displacement in the bi-spectral feature space (Verstraete and Pinty 2006). In an ideal scenario a pixel's bi-temporal trajectory is perpendicular to the first bisector of the Cartesian coordinate system. This is illustrated in figure 4 for the displacement from unburned (U) to optimally (O) sensed burned. However, in practice perturbing factors such as atmosphere and illumination decrease the index performance. For example, in figure 4, a pixel displaces from unburned (U) to burned (B) after fire. Here, the magnitude of change to which the index is insensitive is equal to the Euclidian distance $|OB|$. Thus the observed displacement vector UB can be decomposed in the sum of the vectors UO and OB, hence, the index optimality is defined as (Roy et al. 2006):

$$optimality = 1 - \frac{|OB|}{|UB|} \tag{7}$$

As $|OB|$ can never be larger than $|UB|$, the optimality measure varies between zero and one. If the optimality measure equals zero, then the index is completely insensitive to the change of interest. An optimality score of one means that the index performs ideal for monitoring the change of interest.

Due to the non-linearity of the relationship between field and spectral indices estimates of burn severity (Zhu et al. 2006, Hall et al. 2008), second-degree polynomial regressions were performed to correlate the spectral indices (independent variables) and GeoCBI field data of burn severity (dependent variables). Regression model results were compared using two goodness-of-fit measures: the coefficient of determination R^2 and the Root Mean Squared Error (RMSE). The coefficient of determination is an estimate of the proportion of the total variation in the data that is explained by the model. The RMSE is a measure of how much a response variable varies from the model predictions, expressed in the same units as the dependent data. The RMSE describes how far points diverge from the regression line. In addition, optimality statistics of all burned pixels were compared for the different indices. The median statistic was used for this purpose because of its robustness to outlier values and because the optimality distribution functions appeared to be non-normal.

Results

Correlation with field data

The distribution plots and regression lines of the GeoCBI and pre/post-fire differenced spectral indices are displayed in figures 5D, 6E and 6F. Comparison of the R^2 statistics shows that the GeoCBI-dNBR relationship proved to be the strongest. This relationship yielded a moderate-high $R^2 = 0.65$ for a polynomial fitting model. This was followed by the GeoCBI-dNDMI correlation which had an $R^2 = 0.50$. The GeoCBI-dNDVI relationship was the weakest ($R^2 = 0.46$). The decreasing trend in R^2 statistic is at the same time associated with an increasing RMSE (0.35, 0.42 and 0.44 for the relationships between the GeoCBI and respectively dNBR, dNDMI and dNDVI data). The spectral index values of the dNBR approach clearly range more than those of the dNDMI and dNDVI approaches. The within-burn dNBR range almost doubles the within-burn dNDVI range. Most field plots have dNBR values ranging from 0 and 0.8 (see figure 5F) and dNDMI and dNDVI between 0 and 0.5 (see figures 5D and 5E). Figures 5A, 5B and 5C depict respectively the dNDVI, dNDMI and dNBR maps. The dNBR map clearly reveals more contrast in the burnt areas than the other maps.

Index optimality

Figures 6A-C depict the dNDVI, dNDMI and dNBR optimality maps of the burned areas. The dNBR index (median = 0.51) outperformed the dNDMI and dNDVI indices (medians of respectively 0.50 and 0.40), whereas the dNDMI provided better results than the dNDVI. The performance differences are also reflected when the respective histograms are inspected (see figures 6D-F). A large number of pixels have a dNDVI optimality lower than 0.1 and the number of pixels steadily decreased with increasing dNDVI optimality. The dNDMI histogram is more equally distributed. Although many pixels have dNBR optimality scores above between 0.2 and 0.4 we can observe a slightly increasing trend in terms of number of pixels when dNBR optimality increases. According to the non-parametric Wilcoxon test (Hollander and Wolfe 1999) differences in median optimality and distribution functions are statistically significant ($p<0.001$).

Discussion

The dNBR approach gave the overall best correlation with GeoCBI field data followed by the dNDMI and the dNDVI approach. Indices with a mid infrared spectral band yielded better results than indices lacking a MIR band. This corroborates with earlier research findings:

AVHRR (Advanced Very High Resolution Radiometer) spectral indices based on the NIR and MIR channels had a higher discriminatory potential for burned surface mapping than indices based on the NIR and red channels (Pereira 1999), the importance of the MIR region for burned shrub-savannah discrimination with MODIS (Moderate Resolution Imaging Spectroradiometer) data has been demonstrated (Trigg and Flasse 2001) and significant post-fire spectral changes occurred in the 1500-2500 nm region using hyperspectral AVIRIS (Airborne Visible and Infrared Imaging Spectroradiometer) data (van Wagtendonk et al. 2004). In previous studies assessing the correlation between several spectral indices and CBI field data the NBR was ranked as the first index in pre/post-burn approaches (Epting et al. 2005). For fires in several regions in the USA dNBR yielded higher correlations than dNDVI (Zhu et al. 2006). In this report the within-burn range of dNDVI values was about half the within-burn range of dNBR values, which is similar to our results. They also concluded that dNDVI was more influenced by hazy remote sensing conditions due to the elevated potential of atmospheric scattering in the red spectral region. Overall results show a moderate-high correlation between GeoCBI field data and dNBR for this case study in a Mediterranean environment. Polynomial fitting models resulted in $R^2 = 0.65$. These outcome falls within the range of results of previous studies (French et al. 2008).

In studies based on the spectral index theory the dNBR had a higher mean optimality (0.49) than the dNDVI (0.18) based on Landsat TM/ETM+ images (Escuin et al. 2008). Our results approximate to the values reported in similar studies of 0.49 (Escuin et al. 2008) and ranging from 0.26 to 0.8 for six burns in Alaska, USA (Murphy et al. 2008). However, results contrast with the very low mean dNBR optimality scores (0.1) based on Landsat ETM+ imagery for African savannah burns (Roy et al. 2006). These authors also report low dNBR optimality values for MODIS sensed fires in other ecosystems (Russia, Australia and South America). These results suggest that the dNBR index is to a high degree suboptimal for assessing burn severity. These poor optimality results, however, can possibly be explained by the fact that Roy et al. (2006) included unburned pixels in their optimality analysis. Unaffected pixels are generally associated with low optimality scores as a pixel's displacement in the bi-spectral space is only due to the noise (Escuin et al. 2008). This explains the low optimality values reported (Roy et al. 2006).

The NDMI based approach, which had not been evaluated before for estimating burn severity, performed better than the NDVI based approach. However, the NBR outperformed the NDMI. This can be explained by the typically lower pre-fire reflectances in Landsat TM band 7 (2080-2350 nm) than in Landsat TM band 5 (1550-1750 nm) due to a higher degree of water absorption by vegetation at longer wavelengths. Therefore fire-induced reflectance increase is likely to be more explicit in TM7 than in TM5. As a result, an index with TM7 instead of TM5 is able to capture a larger range of variation in post-fire effects.

Apart from the fact that the dNBR outperformed the dNDMI and dNDVI, use of the dNBR to indicate burn severity is still problematic. When the GeoCBI-dNBR scatter plot and regression line (see figure 5F) are examined, three points of defectiveness attract attention: (i) the insensitivity of the regression model to unburned pixels, (ii) the saturation of the model for GeoCBI values higher than approximately 2.5, and (iii) the moderately high dispersion of the point cloud around the fitting line. First, the regression line crosses the x-axis at dNBR = -0.23 while the unburned reference plots are situated closer to dNBR = 0. According to the regression equation (see figure 5F) an unburned plot with a dNBR value of zero would be associated with a GeoCBI value of 0.91, which is a clear overestimation of severity. Secondly, the regression model reveals asymptotic behaviour for GeoCBI values higher than 2.5. As a consequence the empirical model potentially underestimates high severity plots and is not able to differentiate between them. This phenomenon was also reported in previous studies (e.g. van Wagtendonk et al. 2004; Epting et al. 2005). As a solution for the insensitivity to unburned pixels and the saturation problem, a non-linear model based on a saturated growth model was proposed (Hall et al. 2008). This model effectively handled the insensitivity and saturation problems, however, at the expense of a lower R^2 and a higher RMSE. Thirdly, the GeoCBI-dNBR model has a RMSE of 0.35, which is about one ninth of the total GeoCBI variation. The observed GeoCBI values thus substantially diverge from the model predictions.

Potential sources of inaccuracy arise from both the field and satellite levels. For example, 67 GeoCBI plots were measured in shrub land to fulfill the need for a stratified sampling approach that requests that the number of plots of each fuel type is in proportion to the total area burned of each pre-fire land cover type. However, as is known (e.g. van Wagtendonk et al. 2004; Epting et al. 2005), the CBI approach underperforms in non-forested areas. Part of the observed inaccuracy can also be explained by the fact that that both field and satellite data are imperfect proxies of burn severity. The CBI is based on semi-quantitative judgement procedure and therefore possibly lacks absoluteness, while several noise factors hamper satellite image analysis.

The amount of noise in the dNBR approach appeared to be fairly high as the median dNBR optimality of 0.51 is considerably lower than the optimality of 1. An important part of the spectral change in the TM4-TM7 bi-spectral space occurs parallel to the NBR isolines (confer distance $|OB|$ in figure 4). Deficient preprocessing (no or unsatisfactory atmospheric correction, topographic correction, image-to-image normalization…) can introduce noise in a remote sensing analysis. The application of these procedures in burn severity applications is sometimes blurred (French et al. 2008), although its importance has already been demonstrated for example by revealing the effect of illumination on index values (Verbyla et al. 2008).

These findings can direct the burn severity research in different directions. First, a thorough review of the influence of preprocessing steps (especially atmospheric and topographic correction) on dNBR performance is suggested. Secondly, it is desired to improve the index design towards an index whose isolines are oriented to realize a higher degree of sensitivity to burn severity while providing insensitivity to other sources of spectral variation. These first two research directions retain the conceptual ease of the spectral indices approach. A third alternative could focus on the further development of more advanced remote sensing techniques into operational use. In this context, radiative transfer models (Chuvieco et al. 2006; De Santis and Chuvieco 2007; De Santis et al. 2009) and spectral mixture analysis (Lewis et al. 2007) have already proven to have big potential.

Conclusions

Results of the field data and optimality based analyses confirm one another, demonstrating that the dNBR approach was the best index of the three spectral indices tested for estimating burn severity in this case study in a Mediterranean environment. Results, however, also indicate that the dNBR approach suffers from some striking inaccuracies. The empirical fit between field and remotely sensed data is subject for improvement while the mean dNBR optimality score was markedly lower than the ideal scenario with optimality values of one. Further research in burn severity mapping should therefore focus on (i) noise removal (e.g. by improved preprocessing), (ii) improved index design and (iii) alternative methods such as radiative transfer models and spectral unmixing.

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Fig. 1. Location of the study area and distribution of the field plots (Landsat TM image 13/08/2008, UTM 34S ED50).

Fig. 2. Methodological workflow.

Fig. 3. Example photographs of a high, moderate and low severity plot in coniferous forest.

Fig. 4. Example pre/post-fire trajectory of a pixel in the TM4-TM3, TM4-TM5 or TM4-TM7 feature space. A pixel displaces from unburned (U) to burned (B). The index (NDVI, NDMI or NBR) is sensitive to the displacement $|UO|$ and insensitive to the displacement $|OB|$.

Fig. 5. dNDVI, dNDMI and dNBR maps (a,b and c) and scatter plots and regression lines for the GeoCBI-dNDVI (d), GeoCBI-dNDMI (e) and GeoCBI-dNBR (f) relationships.

Fig. 6. dNDVI (a and d), dNDMI (b and e) and dNBR (c and f) optimality maps and histograms.

Table 1. GeoCBI criteria used to estimate fire/burn severity in the field (after De Santis and Chuvieco 2009).