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Assessing post-fire vegetation recovery using red-near infrared vegetation indices: accounting for background and vegetation variability

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Abstract

Post-fire vegetation cover is a crucial parameter in rangeland management. This study aims to assess the post-fire vegetation recovery three years after the large fires on the Peloponnese peninsula in southern Greece. In this context, thirteen red-near infrared (R-NIR) Vegetation

Indices (VIs) were evaluated. Some of these indices, the so called Soil Adjusted VIs (SAVIs), attempt to minimize the influence of background variability, however, so far the impact of the variability in spectral response between different vegetation species on index performance has not yet been rigorously assessed. Using a combination of field and simulation techniques this study accounts for the impact of both background and vegetation variability on index performance. The field data included a spectral library (59 vegetation and 29 substrate signals) and 78 line transect plots. One Landsat Thematic Mapper (TM) scene of July 2010, three years after the fire event, was employed in the study. Results based on simulated mixtures of in situ measured reflectance showed that (i) SAVIs outperformed the Normalized Difference Vegetation Index (NDVI) in environments with a single vegetation type, (ii) the NDVI more accurately estimated vegetation cover in environments with heterogeneous vegetation layers and a single soil type and (iii) overall, when both vegetation and background variability is incorporated in the model, the NDVI was the most optimal index. Findings from the simulation experiment corroborated with the results from the Landsat application. The Landsat NDVI showed the highest correlation with the line transect field data of recovery (R^2=0.68) and the rank in performance of the Landsat-based indices was similar to that of the simulation experiment in which both vegetation and substrate variability was introduced. Results depend on the initial variability present in the study area, however, some trends can be generalized. Firstly, results support the use of SAVIs in environments with a single vegetation type. Secondly, for applications in environments to which natural vegetation variability is inherent, such as the post-fire recovery landscape of this study, we, however, recommend the use of the NDVI because its strong normalizing capacity minimizes the impact of vegetation variability on fractional cover estimates.

Keywords: forestry; vegetation; forest fire; Landsat; spectral

1 Introduction

Wildfires have important biophysical and ecological consequences at multiple scale levels. At global scales, vegetation fires significantly contribute to the emission of trace gases in the atmosphere (Andreae and Crutzen 1997). As such they play an undeniable role in global climate cycles (Barbosa et al. 1999, Flannigan et al. 2000, Palacios-Orueta et al. 2005). At landscape levels, wildland fires partially or completely remove the vegetation layer and affect post-fire vegetation composition (Epting and Verbyla 2005, Lentile et al. 2005). Post-fire vegetation responses are highly dependent on vegetation type, soil, climate, scar patch size, fire severity, fire frequency etc. (Malanson and O'Leary 1985, Diaz-Delgado et al. 2002). These preconditions determine the potential regeneration pathways and the ecological functioning of plant communities with their inherent species composition and competition. In this respect, fire can be seen as a natural component in vegetation succession cycles (Capitaino and Carcaillet 2008, Roder et al. 2008a). For example Mediterranean-type shrublands are highly resilient to burning due to both obligate seeder and resprouter fire-adapted strategies. At the same time, other ecosystems with few fire-adapted species may be vulnerable to fire pressure. For example, recovery in some forested ecosystems can be very slow with risks of environmental degradation when the fire-return period is short (Nepstad et al. 1999). While Mediterranean-type shrublands can present relatively high regeneration rates (Capitaino and Carcaillet 2008), complete recovery in forested ecosystems can take several decades (Nepstad et al. 1999). This also shows that the relation between fire impact and ecosystem responses depends on ecotype (White et al. 1996). Thus, in contrast with the concept of fire as integral part of autosuccession (Hanes 1971), biomass burning also potentially increases degradation processes. Moreover, although ash increases the nutrient availability, the burned surface becomes more sensitive to nutrient leaching and soil erosion due to modified hydro-geomorphological processes (Kutiel and Inbar 1993, Thomas et al. 1999). These changes in soil hydrology and erodibility are closely connected to fire-induced changes at micro-scale level, such as increased post-fire soil water repellency (Doerr et al. 2006, Shakesby and Doerr 2006). The post-fire soil losses are dependent on topography, vegetation type, soil type, post-fire weather conditions and fire severity (Pausas et al. 2008). Vegetation fires thus have effects on a regional to global scale, which emphasizes the need for an improved knowledge on fire regimes and post-fire recovery trajectories (Chuvieco et al. 2008). As a result, the assessment of post-fire vegetation regeneration is of crucial importance for the understanding of the environmental impacts of fire and for supporting sustainable post-fire management (e.g. controlled grazing, Roder et al. 2008b). In comparison with labor-intensive field work, the synoptic nature of remote sensing systems offers a time-and cost-effective means to fulfill this duty (Lentile et al. 2006).

In the post-fire environment it is crucial to distinguish between the direct fire impact, generally referred to as fire severity, and subsequent post-fire recovery (Lentile et al. 2006, Veraverbeke et al. 2010a). The Normalized Burn Ratio (NBR), a near infrared-short wave infrared (NIR-SWIR) band combination (Key and Benson 2005), has become the standard spectral index to assess fire severity (a.o. Key and Benson 2005, French et al. 2008, Veraverbeke et al. 2010b, 2011a). In contrast, the remote sensing of post-fire vegetation recovery has a long tradition in the use of the Normalized Difference Vegetation Index (NDVI) (a.o. Viedma et al. 1997, Diaz-Delgado et al. 2003, van Leeuwen 2008, Clemente et al. 2009, Lhermitte et al. 2010) because of the strongly established relationship between the index and above-ground biomass in a wide range of ecosystems (Carlson and Ripley 1997, Henry and Hope 1998, Cuevas-Gonzalez et al. 2009). The NDVI combines the reflectance in the R (red) and NIR (near infrared) spectral region and is the most widely used vegetation greenness measure (a.o. Reed et al. 1994, DeFries et al. 1995, Myeni et al. 1997, Heumann et al. 2007). Some studies used low spatial resolution time series to monitor recovery processes. Cuevas-Gonzalez et al. (2009), for example, monitored post-fire forest recovery in Siberia using Moderate Resolution Imaging Spectroradiometer (MODIS)-derived NDVI data, while van Leeuwen et al. (2010) conducted a similar study in three different study areas (Spain, Israel and USA). In these studies, limitations due to low spatial resolution are compensated by the advantage of image acquisition with high temporal frequency (Veraverbeke et al. 2011b). The assessment timing of post-fire effects studies is, however, crucial to distinguish between fire-induced changes and seasonal dynamics (Lhermitte et al. 2011, Veraverbeke et al. 2010a). At moderate resolution scale the Landsat-derived NDVI is the most widely used method to assess post-fire vegetation recovery (a.o. Viedma et al. 1997, Diaz-Delgado et al. 2003, McMichael et al. 2004, Malak and Pausas 2006, Clemente et al. 2009).

The presence of char and ash in the post-fire environment is an ephemeral effect (Chuvieco et al. 2002, Pereira 2003). Once the char and ash have been removed due to weathering and erosion, the post-fire environment typically consists of a mixture of vegetation and substrate. In these mixed environments background and vegetation spectral properties result in mixed background-vegetation signals at the scale of moderate spatial resolution sensors. Numerous studies have denoted that the NDVI has higher values for a given amount of vegetation with a dark background than with a bright background (a.o. Huete 1998, Gao et al. 2000). Several modifications to the NDVI have been proposed in order to account for these background effects (Richardson and Wiegand 1977, Huete 1988, Baret and Guyot 1991, Qi et al. 1994, Rondeaux et al. 1996). The physical basis of these modifications relies on the fact that vegetation greenness isolines do not converge in the origin of the R-NIR bi-spectral space (Richardson and Wiegand 1997, Huete 1988). Soil-adjusted vegetation indices (SAVIs) were developed to account for the optical properties of the background in an attempt to align the index isolines with the isolines of the biophysical variables (e.g. fractional cover, leaf area index). Therefore SAVIs typically include an adjustment factor which is related to the direction of the soil line, i.e. the regression line of soil reflectance in the R-NIR space

(Richardson and Wiegand 1977, Huete 1988, Baret and Guyot 1991, Qi et al. 1994, Rondeaux et al. 1996). Although conceptually sound and backed with illustrative case studies, the theoretical improvements of the SAVIs do not consistently outperform the NDVI (Carreiras et al. 2006, Clemente et al. 2009). Several empirical studies indicated that the SAVIs did not result in more reliable estimates of vegetation cover compared to the NDVI (Leprieur et al. 1996, Purevdorj et al. 1998, Schmidt and Karnieli 2001, Diaz and Blackburn 2003, Baugh and Groeneveld 2006). Purevdorj et al. (1998) assessed the relationship between several R-NIR VIs over a wide range of grass densities in Mongolia and Japan. The grasslands consisted out of a plethora of species. Although they acknowledged the capability of the SAVIs to reduce the influence of soil variation, they concluded that overall the NDVI was best index, outperforming the SAVIs. Carreiras et al. (2006) aimed to estimate tree canopy cover in heterogeneous Mediterranean shrubland. They assumed that the partition between the tree overstorey and shrub understorey was constant over the full density range and as such they could use the mixed overstorey-understorey signal to estimate oak tree coverage. Regression equations between VIs and estimates of tree coverage retrieved from aerial photographs were calculated. Here, the NDVI also obtained higher R^2 values than the SAVIs. Clemente et al. (2009) and Vila and Barbosa (2010) represent two studies in a post-fire recovery environment. Clemente et al. (2009) contrasted the NDVI with the SAVIs for estimating post-fire vegetation regrowth 7 and 12 years after a fire in Spain. The vegetation layer was highly diverse and varied from shrublands to woodlands. The NDVI had higher correlations with field estimates of vegetation cover than any other index. Vila and Barbosa (2010) drew more or less the same conclusion. They also found that the NDVI was most accurately related to field data eight years after a fire in Italy.

Although there is a multitude of studies focusing on the elimination of background optical variation (Richardson and Wiegand 1977, Huete 1988, Baret and Guyot 1991, Qi et al. 1994, Rondeaux et al. 1996), to date, little work has been performed in assessing the impact of vegetation variability on the performance of existing Vegetation Indices (VIs). Canopy reflectance is highly variable and is not only governed by vegetation amount (Huemmrich and Goward 1997, Asner 1998, Asner et al. 2000). Yet, leaf optical properties (and thus foliar chemistry) and leaf angle distribution (LAD) also substantially affect canopy reflectance. Foliar chemistry and LAD can greatly vary between different vegetation species (Asner 1998) resulting in significantly different R and NIR reflectance. As a result, different canopy types can produce different VI values while having an identical fractional cover or Leaf Area Index (LAI) (Gao et al. 2000). Gao et al. (2000) demonstrated that NDVI values were fairly uniform across vegetation types, whereas the SAVI exhibited pronounced differences among canopy types. Our study aims to build on this knowledge by evaluating VIs in the R-NIR spectral domain for estimating fractional vegetation cover in mixed vegetation-background post-fire recovery landscape in which several vegetation species prevail. We aim to evaluate the potential of thirteen well-established spectral indices for monitoring post-fire vegetation regrowth three years after the large fires on the Peloponnese peninsula in Greece in 2007. Using a combination of field and simulation techniques we will account for both the effect of background and vegetation variability.

2 Methodology

2.1 Study area

This study focuses on the recovery of several large burned areas situated at the Peloponnese peninsula, in southern Greece (36°30’-38°30’ N, 21°-23° E) (Fig. 1). The first large burn initiated at July 26, 2007 and the burns prolonged till September 1, 2007. These fires were the worst natural disaster of the last decades in Greece. The fires consumed more than 175 000 ha, which merely consisted of shrub land and pine forest (Veraverbeke et al. 2010a) with Black pine (*Pinus nigra*) being the dominant conifer species. The shrub layer consists of a mixture of species and is mainly characterized by *Quercus ilex, Erica arborea* and *Arbutus unedo.*

FIGURE 1 HERE

Elevations in the study area range between 0 and 2404 m above sea level. Limestone sediments cover most of the mountainous inland. Also significant outcrops of flysch, sandstone with finer siltstone and clay, sediments occur (Institute of Geology and Mineral Exploration 1983, Higgins et al. 1996). The hilly and mountainous inland is covered with shallow and gravelly soils (European Commission 2005). The climate is typically Mediterranean with hot, dry summers and mild, wet winters. For the Kalamata meteorological station (37°4’ N, 22°1’ E) the average annual temperature is 17.8 °C and the mean annual precipitation is 780mm (Hellenic National Meteorological Service, www.hnms.gr, accessed 22 September, 2011).

2.2 Field data

2.2.1 Spectral library

In September 2010, field spectrometry measurements of the dominant background substrates and vegetation species were collected in the burned areas three years after the fire. Measurements were obtained within one hour before local solar noon on clear-sky days with a Unispec single channel spectroradiometer covering the 300-1100 nm spectral domain with a 3.7 nm resolution (PP Systems 2006). Fifty-nine top-of-canopy (TOC) measurements of regenerating vegetation were recorded: 23 of *Q. ilex* individuals, 16 of *A. unedo* individuals, 15 of *E. arborea* individuals and five of *P. nigra* individuals. Canopy height ranged between 0.5 and 2 m which made it possible to collect TOC signatures. Twenty-nine spectra of shallow and gravelly soils of both flysch and limestone sediments were also obtained: 15 above flysch substrate and 14 above limestone substrate. The spectra of each class collected were collected from various locations throughout the study area. More vegetation signals were measured compared to substrate measurements in order to incorporate the full inter-species vegetation variability. The collected spectra were resampled to the TM wavebands to facilitate further analysis. Fig. 2 shows the spectral signatures for each vegetation species and substrate class. Mean vegetation and background signals are equally presented. The TM red and near infrared band passes are indicated in the figure. In corroboration with Huete (1988) and Asner (1998) the background and vegetation variability are obvious in the figure.

FIGURE 2 HERE

2.2.2 Line transect data

Seventy-eight line transect plots were sampled to estimate the cover of regenerating vegetation in the burned areas three years post-fire, in September 2010. All plots were located in areas that burned with high severity (Veraverbeke et al. 2010ab, 2011ab). Sixty-three plots were measured in shrub land, whereas 15 plots were sampled in mixed pine forest-shrub land. The cover metric was chosen because of its high correlation with biomass and its relative ease to measure (Bonham 1989). This field metric has been proven to be a reliable means to assess remotely sensed post-fire vegetation cover estimates (Clemente et al. 2009, van Leeuwen et al. 2010, Vila and Barbosa 2010). The sample scheme was designed for the 30m Landsat resolution. The plots were selected during several one-day hikes based on a stratified sampling approach taking into account the constraints on mainly accessibility and time, while encompassing the range of variability in recovery rates in the study area. The plot's centre coordinates were recorded with a handheld Garmin eTrex Visa Global Positioning System (GPS, 15 m error in x and y, Garmin, 2005). To minimize the influence of spatial autocorrelation, plots were located at least 500m apart, although preferably more. They consist of two perpendicular 60m line transects, of which the first was directed north-south. The point-intercept method (Bonham 1989, Clemente et al. 2009, van Leeuwen et al. 2010, Vila and Barbosa 2010) was used at one meter interval along the line transects to verify the vegetation cover. Either the point contacts a part of the plant, or it does not. The fraction of vegetation cover equals the total number of vegetation interception points divided by the total number of interception points (Bonham 1989, Fig. 3). Linear transects of 60m were preferred to 30m transects to anticipate potential satellite misregistration. Moreover, samples were located in relatively homogeneous areas of regrowth. Fig. 4 shows example plot photographs of shrubland at different recovery rates.

FIGURE 3 HERE

FIGURE 4 HERE

2.3 Satellite data and preprocessing

One 30m resolution Landsat TM image (path/row 184/34, acquired on July 18, 2010) was used in this study. The image dates from the 2010 summer season which corresponds with the timing of the field work. Because of the focus on the R-NIR bi-spectral space of post-fire vegetation recovery studies (a.o. Viedma et al. 1997, Diaz-Delgado et al. 2003, McMichael et al. 2004, Malak and Pausas 2006, Clemente et al. 2009) and to retain consistency with the field spectral library, analysis was restricted to the R (TM3, 630-690 nm) and NIR (TM4, 760-900nm) wavebands. The image was subjected to geometric, radiometric, atmospheric and topographic correction.

The TM image was geometrically corrected using a set of homologous points of a previously georeferenced TM image of the study area (Veraverbeke et al. 2010ab, 2011ab). The resulting Root Mean Squared Error (RMSE) was lower than 0.5 pixels. The image was registered in Universal Transverse Mercator (UTM, 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). The radiance to reflectance conversion was performed using the COST method (Chavez 1996):

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

where r_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).

Additionally, it was necessary to correct for different illumination effects due to topography. This was done based on the modified c-correction method (Veraverbeke et al. 2010c), a modification of the original c-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 a 30m DEM (Hellenic Military Geographical Service, HMGS) resampled and co-registered with the TM images. The illumination is modeled as:

$$\cos\gamma_i = \cos\theta_p \cos\theta_z + \sin\theta_p \sin\theta_z \cos(\varphi_a - \phi_o) \tag{2}$$

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 r_t is defined as:

$$r_t = r_a\left(\frac{1 + c_k}{\cos\gamma_i + c_k}\right) \tag{3}$$

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 $r_a = b_k + m_k \cos \gamma_i$. Since topographic normalization works better when applied separately for specific land cover types (Bishop and Colby 2002) specific c-values for the recovering 2007 scars were calculated by masking the unburned areas using the burned area map of Veraverbeke et al. (2010c).

2.4 Vegetation indices

The formulas of vegetation indices evaluated in this study are listed in Table 1. The NDVI (Tucker 1979) probably is the most widely used index in ecological remote sensing (a.o. Reed et al. 1994, DeFries et al. 1995, Myeni et al. 1997, Heumann et al. 2007). It combines the advantages of its predecessors: the Difference VI (DVI, Jordan 1969) and the Ratio VI (RVI, Pearson and Miller 1972). The DVI was a first approach to extract vegetation structural information from R-NIR reflectance measurements, whereas the RVI has demonstrated to be robust for illumination effects because of its ratioing property. A defining characteristic of the NDVI is that it limits are bound from minus one to one. Haboudane et al. (2004) presented a relatively novel index, the Renormalized DVI (RDVI), based on a combination of DVI and NDVI data, whereas Payero et al. (2004) highlighted the potential of the Transformed VI (TVI) for estimating plant height. These two indices present relative simple adaptations to the NDVI in order to linearize their relationship with plant biophysical variables (Haboudane et al. 2004).

TABLE 1 HERE

The relationship between R and NIR reflectance of bare soils is generally linear because the R and NIR reflectance values are proportionally related to each other (Richardson and Wiegand 1977, Baret et al. 1991, Rondeaux et al. 1996). Based on the 29 pure substrate spectra acquired in the field (section 2.2.1), the linearity of the soil line is demonstrated in Fig. 5. In an attempt to reduce the influence of the background signal, several indices made use of the concept of the soil line. The simplest adaptation is the Weighted DVI (WDVI, Clevers 1991), in which the slope of the soil line regression is incorporated in the DVI. Similarly, Richardson and Wiegand (1977) presented the Perpendicular VI (PVI). The PVI is defined as the orthogonal distance between a point representing a fractional vegetation cover and the soil line. Although the PVI reduces background influences at low vegetative covers, high fractional covers are still affected by soil reflectance (Huete 1988). A significant improvement was achieved by Huete (1988) by presenting the SAVI. To reduce first-order soil background variations, Huete (1988) proposed the use of a soil-adjustment factor L. He found that any adjustment factor between 0.5 and one considerably eliminated background influences over a range of vegetation densities. SAVI is only an exact solution for bare soil if the soil line slope and intercept equal respectively one and zero (Baret et al. 1991). This causes problems when estimating the cover of low density biomass and gave birth to the Transformed SAVI (TSAVI, Baret et al. 1991) which incorporates the soil line parameters. Based on the fact that the soil-adjustment factor L varies with vegetation density (Huete et al. 1988), Qi et al. (1994) proposed the Modified SAVI (MSAVI). In the equation of MSAVI the adjustment factor L is replaced by a self-adaptable correction factor that changes with changing vegetation density. By doing so, MSAVI theoretically further reduces background noise and enhances vegetation sensitivity. After reexamining the SAVI-family of VIs, Rondeaux et al. (1996) proposed the Optimized SAVI (OSAVI). In this reexamination they demonstrated that the most optimal formula for the SAVI was the formula of the NDVI in which 0.16 was added to the denominator (Rondeaux et al. 1996).

2.5 Analysis

The analysis is twofold. Firstly, we used the spectral library with pure substrate (29) and vegetation signals (59) to create simulated mixed pixels. Although some authors recognize the occurrence of multiple photon scattering (Ray and Murray 1996, Somers et al. 2009), most vegetation monitoring studies consider a mixed pixel spectrum (r_m) as a linear combination of pure spectral signals of its constituents, weighted by their corresponding sub-pixel fractional covers (Adams et al. 1986):

$$r_m = f_v r_v + (1 - f_v) r_s + \varepsilon \qquad (4)$$

where r_v is a vegetation spectrum, r_s is a substrate spectrum, f_v is the fractional vegetation cover and ε represents residuals noise. A total of 1000 mixed vegetation-substrate spectra were calculated according to equation 1. Pure pixel spectra combinations and fractional covers were randomly assigned to each pixel. To account for ambient and instrumental error, normally distributed noise was added to the signal (with a mean of zero and standard deviation ranging from 0 % to 15 % of the mixed signal, Asner and Lobell 2000). For each mixed spectrum the R and NIR reflectance were extracted and VIs values were calculated according to the equations in Table 1. Simulated data supply a reliable means to evaluate the performance of the various indices as it inherently provides correct validation data (Rogge et al. 2006). To assess the influence of the variability in background and vegetation three different scenarios were performed:

- The first scenario only allows substrate variability. The vegetation spectrum (r_v in equation 4) is kept fixed and is defined by the mean vegetation spectrum of Fig. 2.
- In the second scenario the substrate spectrum (r_s in equation 4) is kept fixed and is defined by the mean substrate spectrum of Fig. 2. By doing so, substrate variability is eliminated and only vegetation variability is incorporated. Considering the mixed layer of regenerating shrubs r_v was modeled as a linear combination of the prevailing shrub species weighted by their corresponding fractional cover:

$$r_v = f_{qi} r_{qi} + f_{au} r_{au} + f_{ea} r_{ea} + f_{pn} r_{pn} \qquad (5)$$

where r_{qi} is a *Q. ilex* spectrum, r_{au} is a *A. unedo* spectrum, r_{ea} is a *E. arborea* spectrum and r_{pn} is a *P. nigra* spectrum. The cover fractions of the constituting vegetation species are bound to sum to unity and to be positive (Roberts et al. 1993).

- The third scenario allows both substrate and vegetation variability. Equation 5 was used to model the reflectance response of the heterogeneous shrub layer.

For each scenario, the performance of the VIs (Table 1) was expressed in the coefficient of determination (R^2) of the linear regression with the VI values as independent variable and the fractional vegetation covers a dependent variable.

In addition, we performed a sensitivity-to-variability analysis over the full fractional cover range (0-100 %, steps of 1 %) for each scenario. Therefore, we composed 29 (number limited by the number of substrate samples in the spectral library) random vegetation-substrate mixtures and their corresponding VI values were calculated for each fractional vegetation cover (steps of 1 %). For each fractional vegetation cover (steps of 1 %), the standard deviation of the 29 VI values of the 29 different mixtures is a measure for the sensitivity to variability in background and/or vegetation for this specific fractional cover. However, due to differences in index design (Table 1), the units of the different VIs are not directly comparable. To normalize for this, the obtained standard deviations were divided by the VI ranges. The VI ranges were defined as the absolute difference between the lowest VI value of the 29 mixtures at fractional vegetation cover of 0 % and the highest VI value of the 29 mixtures at a fractional vegetation cover of 100 %. The ratio between the standard deviation and the total index range represents the sensitivity-to-variability. For example, a ratio value of 0.10 for a certain fractional vegetation means that for that specific fractional cover 68 % of the corresponding VI values are within a range that equals 10 % of the total index range. The same three scenarios as above were performed (scenario one: only background variability, scenario 2: only vegetation variability, scenario 3: background and vegetation variability). The lower the ratio value is, the less sensitive the VI is for variability effects. The sensitivity-to-variability metric can be seen as an addition to the linear regression. It has the advantage that it, unlike the regression analysis, visualizes differences in sensitivity to variability over the whole fractional cover range

The second part of the analysis focused on the Landsat TM data. VI imagery was generated according to the formulas of Table 1. The index values of the line transect locations were extracted by calculating the mean index value of a 3-by-3 pixels matrix. It is widely accepted that using the mean of a pixel matrix minimizes the effect of potential misregistration (Ahern et al. 1991, Clemente et al. 2009). Linear regressions were performed to correlate the TM VIs (independent variables) and line transect field data of vegetation recovery (dependent variables). Regression model results were compared using the R^2 statistic. The best performing index was used to map the vegetation cover three years after the large 2007 Peloponnese wildfires.

3 Results

3.1 Simulation data

Table 2 lists the slope (a), intercept (b) and R^2 of the linear regression fits between modeled fraction of vegetation cover and 13 VIs for three scenarios based on 1000 random vegetation-substrate mixtures created from the spectral library. For each scenario both a noise-free and noise-added (Asner and Lobell 2000) model were performed. For all scenarios and all VIs the noise-added model generally resulted in a slightly lower R^2 compared to the noise-free model, however, the general trends and the ranking between the different indices did not depend on the incorporation of noise. For this reason and for clarity we will only consider the results of the no-noise model here:

- The first scenario only accounts for substrate variability while the vegetation spectrum was kept fixed. For all the indices that incorporate some kind of soil-adjusting parameter (WDVI, PVI, SAVI, TSAVI, MSAVI, OSAVI) the R^2 statistic (R^2 = 0.92-0.99) was clearly higher than the R^2 obtained from the NDVI model (R^2 = 0.88). The DVI and RDVI regression models also resulted in high R^2 values (respectively R^2 = 0.99 and R^2 = 0.97). The RVI model was markedly poorer (R^2 = 0.69), whereas the TVI model obtained a result similar to the NDVI (R^2 = 0.88).

- When the substrate spectrum was kept constant and only vegetation variability was allowed (second scenario), a totally different picture emerges. Only the NDVI and TVI model demonstrated a relatively strong performance (R^2 = 0.95). For the other models the performance markedly deteriorated by the inclusion of vegetation variability resulting in R^2 values between 0.61 and 0.92.
- The trends of the second scenario are similar to those of the third scenario, which combines both substrate and vegetation variability. Again the NDVI and TVI outperformed the other indices with a R^2 = 0.85. Results from the OSAVI and TSAVI were also reasonable with moderate-high R^2 statistics of respectively 0.81 and 0.80. The RDVI, SAVI and MSAVI models appear next in the rank with R^2 values between 0.69 and 0.74. Finally, the DVI, RVI, WVDVI and PVI achieved lower regression fits (R^2 = 0.51-0.59).

TABLE 2 HERE

The outcomes of Table 2 are clarified in Fig. 6, which visualizes the sensitivity-to-variability of the different VIs over the full range of vegetation cover (0-100 %). Again, the same three scenarios were considered:

- Fig. 6A (scenario 1) demonstrates the beneficial performance of the VIs with soil-adjusting parameters (WDVI, PVI, SAVI, TSAVI, MSAVI, OSAVI) in an environment with only substrate variability (fixed vegetation spectrum). Compared to the NDVI, all these indices revealed a lower sensitivity to the variation in background.

The NDVI, and also the TVI, were especially sensitive to background variability for intermediate vegetation cover (40-70 %). In contrast, the sensitivity to soil variability of the RVI progressively increased with increasing fractional vegetation cover, except for the abrupt drop for very high cover values (larger than 90 %).

- Fig. 6B (scenario 2) shows that for all VIs except the RVI the sensitivity to vegetation variability almost linearly increased with increasing vegetation coverage from 0 to 50 %. The NDVI's and TVI's sensitivity to variation in vegetation, however, stabilized for fractional covers larger than 50 %. In contrast, the sensitivity to variability in vegetation of the other indices kept increasing with increasing vegetation coverage over 50 %. The RVI showed a different behavior being very insensitive to vegetation variability between 0 and 75 % fractional vegetation cover. However, for a vegetation cover larger than 75 % vegetation cover the sensitivity of the RVI increased exponentially.
- Fig. 6C (scenario 3) combines substrate and vegetation variability. This graph merely is a combination of figures 6A and 6B, but the variability in vegetation seemed to be more dominant. For lower vegetation fractions (0-40 %) the NDVI and TVI performed poorer than the other indices, however, for moderate to high vegetation coverage (more than 40 %) the NDVI and TVI clearly outperformed the other indices. The RVI, conversed to 12 other indices, showed again a different behavior, similar to what was observed in scenario 2.

FIGURE 6 HERE

3.2 Landsat imagery

Table 3 summarizes slope, intercept and R^2 of the regression fits between the line transect points and VIs retrieved from the Landsat imagery. The goodness-of-fit ranking of the indices shows a very strong similarity with the ranking obtained from the third scenario (vegetation and substrate variability) based on simulated mixtures (Table 2, scenario 3). The NDVI and TVI demonstrated the best performance with R^2 values of respectively 0.68 and 0.67. OSAVI and TSAVI closely followed with model performance of R^2 = 0.64-0.66. The regression models of the other indices (DVI, RDVI, WDVI, PVI, SAVI, MSAVI) were clearly poorer as the R^2 dropped below 0.6. The only index that did not follow the trend of scenario 3 based on simulated data is the RVI. The correlation between the RVI and line transect data is relatively high (R^2 = 0.68), whereas its relationship with the modeled fractional vegetation cover in the simulation was markedly weaker. Fig. 7A displays the fractional vegetation cover map based on the relationship between the Landsat NDVI and the line transect field ratings (Fig. 7B).

TABLE 3 HERE

FIGURE 7 HERE

4 Discussion

4.1 Background variability

In line with the theoretical improvements of the SAVIs (Richardson and Wiegand 1977, Huete 1988, Baret and Guyot 1991, Qi et al. 1994, Rondeaux et al. 1996), these indices clearly outperformed the majority of VIs without a soil-adjustment factor when vegetation variability was not accounted for (i.e. only a single vegetation type occurs). The DVI also revealed a very strong performance. This can be explained by the fact that the soil line regression slope (1.05, Fig. 5) only slightly deviated from one which minimized the difference between the DVI and WDVI in this case study. The NDVI and its transformed variant (TVI) were more sensitive to variations in background brightness, especially for medium-to-high vegetation cover environments (Fig. 6A). For the first scenario with only background variability, the RVI revealed the lowest performance. This is due to very high sensitivity to background variation for high vegetation covers as illustrated in Fig. 6A. These outcomes support the well established idea that SAVIs are better suited for monitoring vegetation parameters in mixed vegetation-soil environments because their adjusted index design improves the alignment between the index isolines and the true vegetation isolines (a.o., Huete 1988, Rondeaux et al. 1996). However, it should be noted that this finding remains restricted to environments with one specific vegetation type, or at least environments in which the spectral signatures of the constituting vegetation species show only slight differences. Therefore, SAVIs are a significant improvement for precisions agriculture applications such as monitoring crop status or predicting crop yield (Haboudane et al. 2004). Agricultural applications generally contemplate only one crop in a controlled environment (Huete 1988, Clevers 1991, Payero et al. 2004). As a consequence, these studies inherently disregard natural variability in vegetation which is present in most (semi)natural landscapes.

4.2 Vegetation variability

Asner (1998) comprehensively demonstrated that leaf optical properties and LAD importantly govern canopy reflectance response and that these characteristics vary between vegetation species. Although this variation in canopy reflectance is well known (Huemmrich and Goward 1997, Asner et al. 2000), so far, few studies have assessed the impact of this vegetation variability on VI performance (Gao et al. 2000). Logically, the sensitivity to vegetation variability increased with increasing vegetation cover (Fig. 6B). However, this increase was clearly more explicit for the SAVIs compared to the NDVI (and the TVI). The NDVI managed to minimize the influence of vegetation variability thanks to its strong normalizing property. This normalizing feature consists of dividing the subtraction $NIR - R$ by the sum $NIR + R$. Illumination differences due to topography for example result in clearly different reflectance values for the same amount of vegetation, whereas the normalizing property of the NDVI is known to minimize the difference in index values along an illumination gradient (Song and Woodcock 2003). While some of the tested indices lack a similar normalization feature (DVI, WDVI, PVI and MSAVI), the index design of the others

(RVI, RDVI, TVI, SAVI, TSAVI, OSAVI) does consist of a quotient between reflectance values. Results from Table 2 scenario 2, however, show that the higher the relative importance of the soil-adjustment factor is in the equation, the lower the R^2 was. This is clearly demonstrated by the R^2 values of the SAVI with varying soil-adjustment factor L = 0.5, 0.75 and 1. The corresponding R^2 values were respectively 0.87, 0.85 and 0.83. In addition, the OSAVI, which has an soil-adjustment factor of 0.16, obtained a $R^2 = 0.92$. This also explains why the TVI, in which no soil-adjustment factor is used, performed as well as the NDVI. The beneficial behavior of the NDVI in accounting for vegetation variability was also demonstrated in Fig. 6B. This finding corroborates with Gao et al. (2002) who found that NDVI values for a given vegetation amount were fairly uniform across different canopy types, while SAVI values drastically varied among the different canopy types. The RVI again underperformed due to its very high sensitivity to variability for vegetation covers larger than 75 %. This phenomenon can be explained by the fact that simple ratioing ($RVI = \frac{NIR}{R}$) for these high vegetation covers implies a very low R reflectance due to the increased absorption by chlorophyll. When dividing by a R reflectance close to zero only a small amount of additional variability can cause considerable changes in the index outcome.

4.3 Background and vegetation variability

Most (semi)natural landscapes consist of a variety of vegetation species while several different lithologies generally occur over large areas. The results of the analysis which combined background and vegetation variability were more complex. For low vegetation cover environments (lower than 40 %), the SAVIs were less sensitive to variability than the NDVI (Fig. 6C). For these cases, the background signal dominates the mixed pixel spectrum. As a result, the insensitivity-to-background variability of the SAVIs outweighs their higher sensitivity to vegetation variability. However, for higher fractional vegetation covers (larger than 40 %) the overall sensitivity to variability of the SAVI became markedly higher than the

NDVI's sensitivity to variability. In the simulation experiment with both background and vegetation variability, the NDVI (and TVI) obtained the best scores (Table 2 scenario 3). This experiment mimicked the variability in substrates and vegetation as it occurs in natural environments. It is remarkable that the observed improvement of the SAVIs in reducing soil background influences is strongly diminished when vegetation variability was also allowed. The findings of the simulation experiment also corroborate with the rank in obtained R^2 values of the regression fits between the TM and line transect data. The only exception is the RVI, which, in contrast with its behavior in the simulation experiments, showed a very strong agreement with the field ratings of recovery. As discussed earlier, the RVI becomes very sensitive to variability for high vegetation cover (larger than 75 %). The highest fraction of vegetative cover observed in the field plots is 70 %. For the range between 0-70 %, the RVI proved to be a very consistent index (Fig. 6).

The obtained results, of course, depend on the initial spectral variability present in the study area. In our case study both the variation in substrate and vegetation were considerable (Fig. 2). It is likely that similar trends as those from our study will occur in environments with high vegetation variability. However, for environments with only slight differences in optical properties between vegetation types and significant soil color variation, SAVIs will potentially obtain the overall best results, especially for plots with low vegetation cover and thus relative high importance of the soil endmember.

Our findings in a mixed vegetation-substrate natural environment contribute to the many papers that compared several VIs and concluded that the SAVIs do not necessarily outperform the NDVI, despite of their theoretical improvements (a.o. Purevdorj et al. 1998, Carreiras et al. 2006, He et al. 2006, Clemente et al. 2009, Vila and Barbosa 2010). While those studies reported the beneficial performance of the NDVI over the SAVIs for estimating post-fire fractional vegetation cover, none of them elaborated on the reason why. Our study clearly demonstrated that, in line with Gao et al. (2000), the NDVI is more stable than SAVIs against the variability in spectral response of different vegetation types. This finding combined with the knowledge from Smith et al. (2010), in which the NDVI outperformed the NBR in terms of insensitivity to soil type in soil-char mixtures, support the use of the NDVI for short- to long-term post-fire monitoring across regions in which natural variability in soils and vegetation is present.

5. Conclusions

This paper demonstrated that (i) SAVIs outperformed the NDVI in environments with background variation and one single vegetation type, (ii) the NDVI revealed better results than SAVIs in mixed vegetation environments with a constant soil background, (iii) when both vegetation and background variability is present SAVIs outperformed the NDVI for low vegetation cover environment (lower than 40 %), (iv) for intermediate to high vegetated covers (larger than 40 %) in variable vegetation-background mixtures the NDVI is more optimal and (v) overall, the NDVI was the index that managed best to account for vegetation and background variability. These findings obtained from simulation experiments corroborate with the correlations retrieved between Landsat VIs and line transect field data of recovery. Findings also depend on the initial variability in both background and vegetation present in the study area, however, it is likely that these trends are more general. From a practical perspective, our results support the widely accepted idea of using SAVIs in controlled environments with a single vegetation type. The classic example of such monotonous environments are agricultural systems in which one generally focuses on a specific crop. For these applications, the use of SAVIs is recommended. However, for applications in which natural variability is important, we recommend the use of the NDVI. Due to its strong normalizing capacity this index effectively handles variability between vegetation species resulting in more reliable vegetation cover estimates. In this post-fire vegetation recovery case study, this is clearly demonstrated using both field and simulation techniques. Although we acknowledge the prospect of more innovative techniques such as Spectral Mixture Analysis (SMA) for estimating fractional cover of different vegetation types, especially with hyperspectral data (Somers et al. 2009ab), this paper is restricted to the utility of broadband vegetation indices for monitoring vegetation coverage without distinguishing between species. Total vegetation cover remains the most important parameter in rangeland management (Kutiel and Inbar 1993, Thomas et al. 1999) and the use of conceptually comprehensible VIs is aligned with the capabilities of current broadband satellite systems such as Landsat. Another possible amelioration could be the inclusion of the short-wave infrared (SWIR: 1300-2400 nm) spectral bands. This spectral region has proven to be very effective in discriminating soil and vegetation (Drake et al. 1999, Asner and Lobell 2000). Moreover, the SWIR spectrum is very sensitive to moisture content (Hunt and Rock 1989, Zarco-Tejada et al. 2003) and is consequently strongly related to plant water content. Carreiras et al. (2006) demonstrated that adding the SWIR Landsat bands resulted in better estimates of tree canopy cover in Mediterranean shrublands. To retain consistency with the field spectral library these wavebands were not included in our study.

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Figure 1. Location of the study area (the areas encircled with black represent the 2007 burned areas) and distribution of the field plots (marked with green dots) (Landsat Thematic Mapper image July 18, 2010 RGB-432).

Figure 2. Mean spectral signatures of the prevailing vegetation species and main substrate classes acquired in the field with a Unispec single channel field spectroradiometer (dashed lines). The overall mean vegetation and substrate signature are represented by full lines. The Thematic Mapper (TM) red (TM3) and near infrared (TM4) bandpasses are also indicated.

Figure 3. Line transect plot design (Bonham 1989)

Figure 4. Example plot photographs of shrubland with a high (A), moderate (B) and low (C) recovery rate.

Figure 5. Relationship between the red and near infrared reflectance of 29 substrate samples resulting in the soil line.

Figure 6. Sensitivity-to-variability over the full fractional vegetation range (0-100%) of the 13 Vegetation Indices (VIs) as listed in Table 1. Twenty-nine (number limited by the number of substrate samples in the spectral library) random mixtures and corresponding VI values were calculated for each fractional cover. Subsequently, the ratio between the standard deviation and the total index range represents the sensitivity-to-variability. Three scenarios were performed: (i) only substrate variability, (ii) only vegetation variability and (iii) both substrate and vegetation variability. The data shown in the figure refer to a noise-free model.

Figure 7. Fractional vegetation cover map (A) three years after the fires based on the regression fit between the Landsat Normalized Difference Vegetation Index (NDVI) and the line transect field ratings of vegetation cover (B).

Table 1. Red-near infrared (R-NIR) vegetation indices used in this study. The parameters a (1.05) and b (0.03) are retrieved from the soil line represented in figure 5.

Table 2. Slope (a), intercept (b) and coefficient of determination (R^2) of the linear regression fits between the modeled fraction of vegetation cover (FCOV) and the 13 Vegetation Indices (VIs) as listed in Table 1 ($FCOV = a \times VI + b$). The data consist of 1000 random mixtures created from the field spectral library. Three scenarios were performed: (i) only substrate variability, (ii) only vegetation variability and (iii) both substrate and vegetation variability. For each scenario, a, b and R^2 were retrieved from a no-noise and noise model (Asner and Lobell 2000).

Table 3. Slope (a), intercept (b) and coefficient of determination (R^2) of the linear regression fits between the line transect estimates of vegetation cover (FCOV) and the 13 Vegetation Indices (VIs) as listed in Table 1 calculated from Thematic Mapper imagery ($FCOV = a \times VI + b$).