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Monitoring post-fire regeneration in Mediterranean ecosystems by employing multitemporal satellite imagery

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Abstract. Fire-damaged ecosystems have often been monitored by applying a combination of field survey information and vegetation indices derived from remotely sensed data. Furthermore, it has been demonstrated that remotely sensed data can be integrated as a useful tool in predicting the recovery of fire-damaged ecosystems over time. Using regression models, the present study analyzes the trend function described by the Normalized Difference Vegetation Index (NDVI) and Fractional Vegetation Cover (FVC) 7 and 12 years after the fire. The method was performed through (i) permanent plot collection per plant community type and data reduction; (ii) comparison of the correlation established between FVC with different vegetation index contrasted with the NDVI; (iii) monitoring vegetation recovery; and (iv) a supervised classification of FVC. The NDVI was the one that correlated most with the FVC. In both the seventh and twelfth year after fire, the linear regression model was used to accurately quantify FVC based on the NDVI. Results show that 12 years after the fire, the recovery rate of the FVC associated with scrub was higher than that of the FVC of other forest classes. Although vegetation recovery is taking place, the continuing increase in the FVC associated with shrub land classes could create a state of successional stagnation.

Additional keywords: dynamic modelling, Mediterranean communities, multitemporal analysis, NDVI, plant cover, regression model.

Introduction

Owing to various climatic and social factors, fire plays an integral role in Mediterranean ecosystems. However, the frequency and intensity of forest fires has increased considerably in recent decades (Piñol *et al*. 1998), resulting in biodiversity loss and soil erosion. Repeated fires change ecological community structure, turning potentially deciduous forests into evergreen shrublands with a marked dominance of taxa such as *Rhamnus*, *Juniperus*, *Cistus*, *Ulex*, *Lavandula*, *Thymus* and *Rosmarinus* (Trabaud 1987; Barbero *et al*. 1990). Various studies have been carried out on vegetation recovery processes. Short-term species regrowth has frequently been observed (Quintana *et al*. 2004; Keeley *et al.* 2005). Medium-term species recovery has rarely been monitored, but only predicted (Trabaud and Lepart 1981; Kazanis and Arianoutsou 2004; Rodrigo *et al*. 2004). Long-term effects of wildfire on species regeneration are difficult to predict in degraded Mediterranean communities (Terradas 2001). Yet, during recovery, there are some succession restraints caused by plant invasion that may result in a reinforcement of the fire regime itself. The long-term measurement and modeling of vegetation recovery is essential to the understanding of fire and its effects on the ecosystem. Traditionally, this monitoring has been done by time-consuming, arduous and expensive field surveys.

As an alternative, remote sensing methods could be used in order to develop mapping, monitoring and modeling techniques. A combined strategy results in an accurate long-term monitoring of wildfire effects. In these efforts, remote sensing has been used by various authors (Viedma *et al*. 1997; Riaño *et al*. 2002; Twele and Barbosa 2004) to evaluate regeneration patterns in Mediterranean ecosystems. Other authors (Hall *et al*. 1991; Gamon *et al*. 1995; Henry and Hope 1998) have also used this approach to study the relationships between vegetation indices and biophysical variables. Vegetation Indices (VIs) frequently represent different combinations between red and near-infrared channels in remote sensing imagery. These channels often contain over 90% of the information related to vegetation (Bannari *et al.* 1995). The Normalized Difference Vegetation Index (NDVI) has been widely applied in order to assess the post-fire recovery process (Viedma *et al*. 1997; Díaz-Delgado and Pons 1999; Riaño *et al*. 2002).

However, few studies integrate both remote sensing and field-based approaches (Hall *et al*. 1991). Multitemporal field surveys must be undertaken in order to support corresponding spectral data. Henry and Hope (1998) even question whether remote sensing can be used to study ecosystem recovery after fire. Based on the need to validate plant recovery models and vegetation index

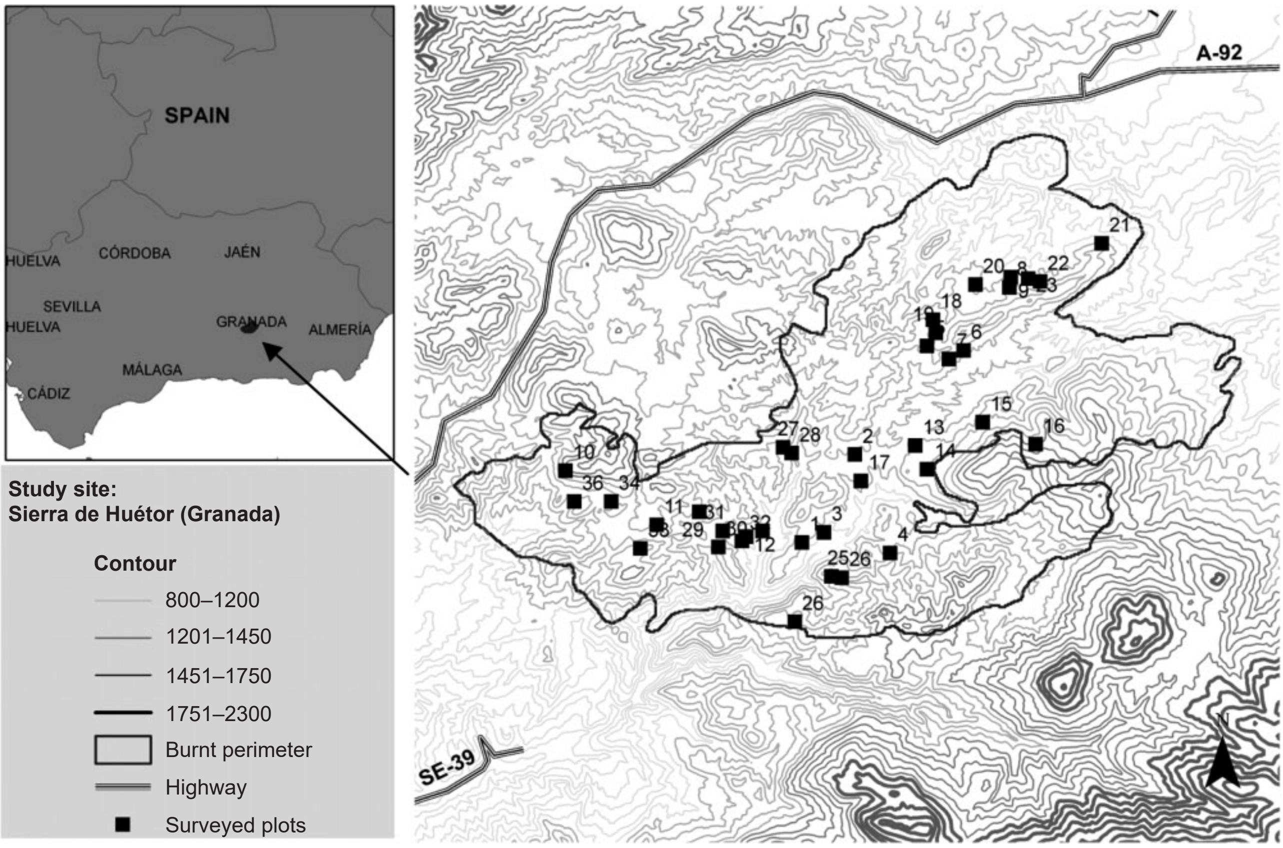


Fig. 1. Study site location, with latitude and longitude of $37^{\circ}15^{I}38.94^{II}$N, $3^{\circ}23^{I}45.51^{II}$W. Forest fire occurred in 1992 in Granada (Spain).

calibration, the current study focussed on regeneration patterns 12 years (1993–2005) after a wildfire in Sierra de Huétor. The aim of the present research was to evaluate the post-fire recovery trajectory of the vegetation based on the trend function described by the NDVI and the FVC (Fractional Vegetation Cover) over time. The objectives were to: (i) make a permanent plot collection per plant community type and data reduction; (ii) compare the correlation established between FVC and different VI contrasted with the NDVI; (iii) analyze regression models associated with FVC and VIs and select the model that most accurately tracked vegetation recovery; and (iv) carry out a supervised classification of FVC.

Study area

The study area (Fig. 1), Sierra de Huétor, located in Beas de Granada, southern Spain, has a central latitude of $37^{\circ}15^{I}38.94^{II}$N and longitude of $3^{\circ}23^{I}45.51^{II}$W and an area of 204 km^2. The climate is transitional, varying between Mediterranean semiarid and Mediterranean subhumid, and the average annual rainfall is 500 mm. According to Rivas-Martinez *et al*. (1997), the area belongs to the Malacitano–Almijarense sector, with meso- and supra-Mediterranean climates. It is characterized by typically continental variations, of over 15°C between winter and summer, and between maximum and minimum daily values. The lithology is homogeneous and chiefly composed of basic soils, such as carbonate stone, limestone and dolomites, which cover almost 80% of the study area. The remaining area is covered by acidic soils, such as mica-schists, gneisses (phyllites) and slates. According to the USDA Soil Taxonomy, the soils are classified as skeletal (Lithosols and Regosols) and are underdeveloped owing to the original hardness of the high, rocky (limestone) slopes on which they have evolved. Prefire vegetation types were defined based on the vegetation series given in Rivas Goday and Rivas-Martinez (1966), and from 1956 aerial photos (1 : 30 000). The vegetation in the area shows advanced degradation, altered by human activities. In the 1940s, an intense reforestation program was initiated in which *Pinus pinaster* Ait., *Pinus halepensis* Mill., *Pinus nigra* Arnold and, to a lesser extent, *Pinus sylvestris* L. and *Populus* sp. were planted.

A fire occurring between 23 and 26 August 1993 burned ~7000 ha. The fire severity level was ranked as extreme in 40% of the area, moderate in 47% and low for the remaining 13% of the area (Hernández-Clemente *et al*. 2006). The severity levels were estimated according to Escuin *et al*. (2008). The burned area was mainly covered by maritime pine (*Pinus pinaster*) and less so by Holm oak (*Quercus ilex* subsp. *ballota* (Desf.) Samp.), Mediterranean gorses (*Ulex* spp., *Genista* spp.) and Aleppo pine (*Pinus halepensis*). Although altitudes ranging from 1000 to 1700 m exist within the burned area, the topography is fairly uniform. After the 1993 wildfire, few reforestation efforts took place. The first such effort, in 1996, consisted of aerial sowing, which gave poor results even after spraying almost 78 million seeds of 16 species of pine tree and shrub. The next attempt,

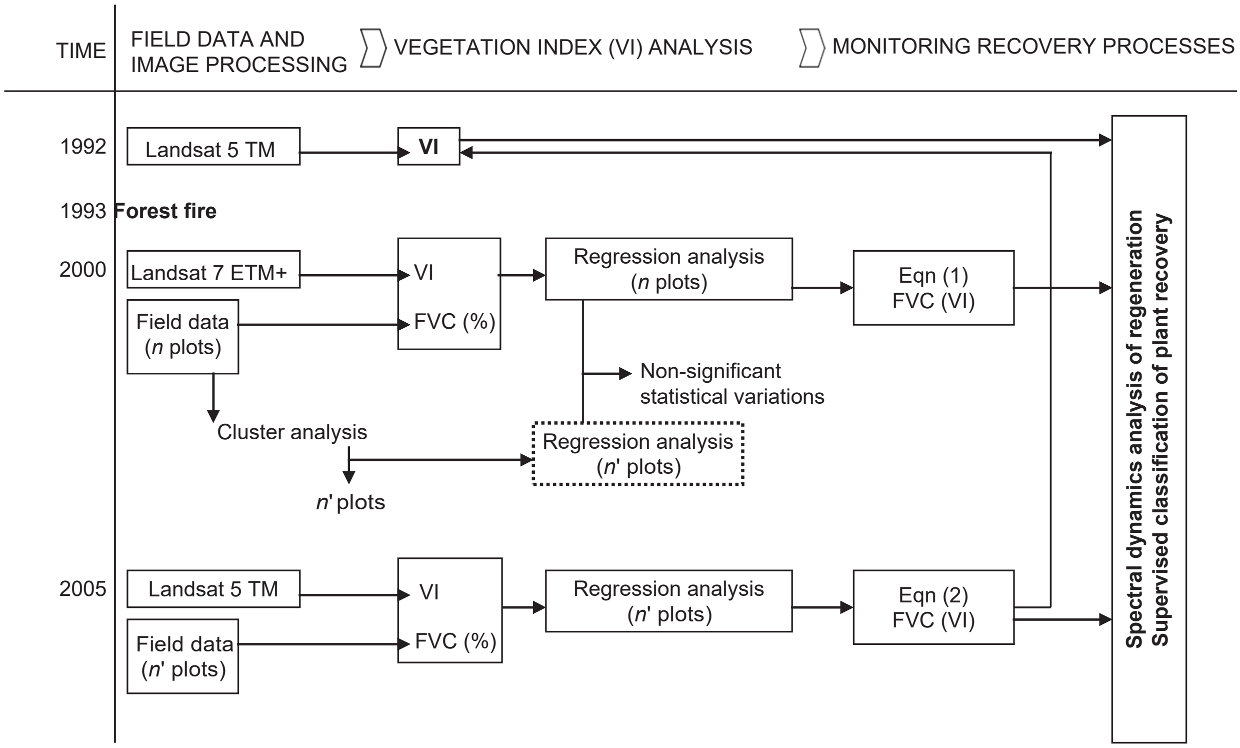


Fig. 2. Methodology flow chart for monitoring post-fire regeneration patterns using multitemporal satellite imagery.

direct machine planting in the field, was sporadic and not very effective. Fourteen years after the fire, dwarf gorse largely covers the burned area, but the presence of Holm oak, maritime pine and Aleppo pine has also been noted. However, the predominant type of ground cover is Mediterranean shrubland, mainly dominated by *Ulex parviflorus* Pourret, *Rosmarinus officinalis* L. and *Cistus clusii* Dunal, representing a fire-degraded stage of forest communities as they are fire-adapted species.

Material and methods

The methodology is presented in the following flow chart (Fig. 2). The analyses are divided into three categories: the field data and multitemporal image preprocessing, the comparison of VIs and the monitoring of the recovery processes. The final step was a supervised classification based on correlation model prediction of FVC.

Field data

Field surveys of the permanent plots took place in mid-August of 2000 (Escuin *et al*. 2006) and 2005. During both field inventories, identical methodology was used. Permanent plot selection (Fig. 1) was based on visual analysis of a 1998 Indian Remote Sensing Panchromatic (IRS-PAN) image and 1999 orthophotography (1-m resolution) provided by the Government of Andalusia. Plots with a homogeneous coverage, representing the various communities within the burned area, were selected. The total area sampled in 2000 (33 plots, each with a 25-m radius) was 66 759 m^2, representing 0.09% of the total burned area. In 2005, repeated measurements were taken on 15 plots. The selection of these plots was based on a hierarchical cluster analysis performed on the survey plots in 2000. Ward's method (Ward 1963) was used to evaluate the Euclidean distance between clusters. The results were interpreted and related to other types of variables (such as altitude or soil composition) that might influence the grouping criteria. Once the main vegetation classes were established, clusters were identified and related to each class. The aim of this last step was to optimize the number of permanent plots surveyed in 2000 in order to repeat measurements in following years.

On the ground, plot locations were identified using a handheld global positioning system (GPS) with an average error of <3–5 m. Two 50-m long perpendicular linear transects (one in the direction of the maximum slope) were defined for each plot and measured in both years (2000 and 2005) following the same methodology (linear interception method, Bonham 1989). The plants identified were registered with references COA00925 to COA00957 and then incorporated into the COA herbarium (Agricultural and Forest Sciences Resources Department, University of Córdoba). This incorporation served to aid the future identification of specimens from within the study area.

Ground data were used to calculate FVC in 2000 (FVC_{00}) and in 2005 (FVC_{05}) as the percentage of vegetation occupying a unit area. For each transect (t1 and t2), the sum of intercepted fraction (IF) per species was calculated as:

$$IF_{t1} = \Sigma l_k / d \tag{1}$$

$$IF_{t2} = \Sigma l_k / d \tag{2}$$

Table 1. Remote sensing data set used for multitemporal analysis of regeneration patterns

Period	Satellite	Band	Elevation angle (°)	Azimuth (°)
Pre-fire (1992)	Landsat 5	TM 17/08/92-200-34	53.27	122.96
Post-fire (1993)	Landsat 5	TM 05/09/93-200-34	49.26	130.97
Post-fire, field work (2000)	Landsat 7	ETM+ 31/08/00-200-34	54.29	138.56
Post-fire, field work (2005)	Landsat 5	TM 18/08/04-200-34	60.18	139.90

Table 2. Vegetation indices tested for post-fire Fractional Vegetation Cover (FVC) recovery monitoring
NIR, Infrared; MIR, Medium Infrared

Vegetation index	Algorithm	Reference
Class A: sensitive to soil optical properties		
Normalized Difference Infrared Index	NDII = (NIR − MIR)/(NIR + MIR)	Hardisky *et al.* (1983)
Ratio Vegetation Index	RVI = NIR/red	Pearson and Miller (1972)
Normalized Difference Vegetation Index	NDVI = (NIR − red)/(NIR + red)	Rouse *et al.* (1974)
Class B: consider soil effects introducing parameters such as the correction factor (L), the soil line intercept (a), the soil line slope (s) or the adjustment factor (X), L = 0.5, 0.8 and 1		
Soil Adjusted Vegetation Index	SAVI = (1 + L) + (NIR − red)/(NIR + red + L)	Huete (1988)
Transformed Soil Adjusted Vegetation Index	TSAVI = s × (NIR − s × red − a)/(a × NIR + red − a × s + X × (1 + s × s))	Baret and Guyot (1991) Modified
Soil Adjusted Vegetation Index	MSAVI2 = $1/2((2(\text{NIR}+1)) - (((2\text{NIR})+1)^2 - 8(\text{NIR}-\text{red}))^{1/2})$	Qi *et al.* (1994)
Enhanced Vegetation Index	EVI = G × ((NIR − red)/(NIR + (c1 × red) − (c2 × blue) + L))	Huete *et al.* (2002)

l_k being equal to the distance intercepted (l) for each species (k) and d, the length of each transect (50 m). By measuring two transects per sample, the FVC was obtained as

$$\text{FVC} = (\text{IF}_{t1} + \text{IF}_{t2}) \tag{3}$$

Multitemporal image data preprocessing

The images used in the present study are presented in Table 1. Standard gain and offset coefficients for each satellite and period were applied in order to transform digital numbers into radiance levels. Finally, a relative atmospheric correction was required to normalize remotely sensed images for a time-series analysis. The relative atmospheric correction was based on invariant targets following the methodology applied by Caselles and López (1989). Results obtained from the image normalization yielded a mean correlation coefficient (*r*) of 0.98 with a standard error of 0.029. The 2000 image was georectified using ground control points and high-resolution digital orthophoto quadraught (DOQ) of the study area obtained from the Regional Government of Andalusia in 2001. The remaining images were georeferenced to the 2000 image. Corrected images provided a maximum root mean square (RMS) error of less than one pixel. Finally, a multitemporal data set of NDVI was obtained from images acquired in 1992 (before the fire), and in 1993, 2000 and 2004 (after the fire).

Monitoring vegetation recovery

Vegetation recovery models were obtained by regression analysis. The variables intersected were FVC and the NDVI. The regression models tested were obtained from the 2000 data set and the 2005 data set:

$$\text{NDVI}_{00} = f(\text{FVC}_{00}) \tag{4}$$

$$\text{NDVI}_{05} = f(\text{FVC}_{05}) \tag{5}$$

The regression model applied for obtaining Eqns 4 and 5 was selected by comparing different regression models. The regression analysis was performed on the 2000 data set. The input data were the FVC of the 33 plots measured in 2000 and the NDVI related to them. The models tested were: linear, exponential, square-root-x and logistic. The regression model with the best fit to the data was applied to obtain Eqns 4 and 5. Both equations were compared in order to analyze the spectral dynamics of the vegetation recovery. Comparison of the models obtained for 2000 and 2005 could only be performed under the assumption of non-variance of the vegetation communities. A previous change analysis showed that plant-community types did not vary during the period 2000–05 (Hernández-Clemente *et al.* 2006).

Finally, a vegetation recovery assessment was performed. The analyses consisted of modifying the input parameters and comparing the precision of the models. In the first analysis, the NDVI was substituted by other VIs. The second analysis consisted of reducing the number of sample plots, introducing the plots selected for the 2005 survey.

The seven indices tested in the first analysis are included in Table 2. The FVC input data were those of the 33 sample plots measured in 2000. VIs were related to the FVC per plot and compared through a Pearson correlation matrix. The VIs selected (Table 2) can be divided into two different groups; the first group, composed of Normalized Difference Infrared Index (NDII), Ratio Vegetation Index (RVI) and NDVI, is sensitive to the optical properties of the soil. The second group (Soil Adjusted Vegetation Index, SAVI; Transformed Soil Adjusted Vegetation Index, TSAVI; Modified Soil Adjusted Vegetation Index, MSAVI; and Enhanced Vegetation Index, EVI) has a fit

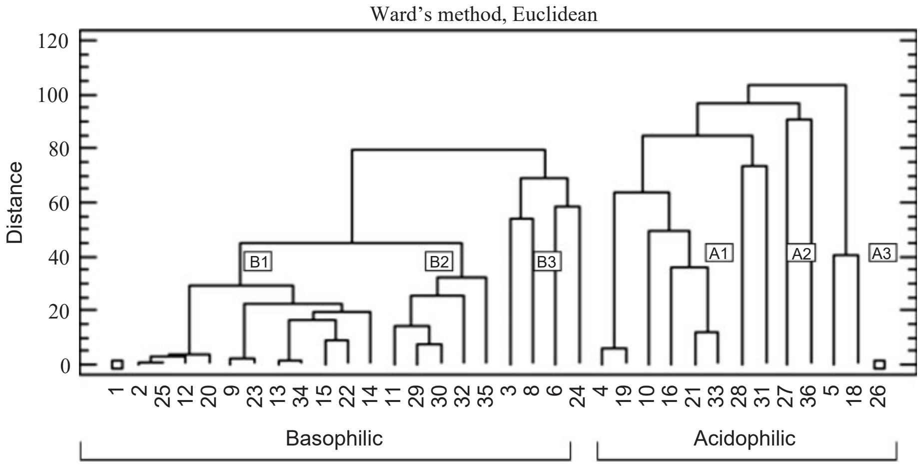


Fig. 3. Dendogram of plant communities obtained from the cluster analysis of the plant cover per species surveyed in the year 2000. The *x*-axis represents sample plot number identification and *y*-axis the distance between groups.

factor that minimizes soil background sensitivity (a value of 0.5 is considered to be appropriate for most soils). However, soil spectral deviations affect all spectral indices (Huete 1987). Spectral properties for ground survey location were extracted from the image by calculating the mean reflectance of a 3 × 3 matrix of pixels. It has been widely accepted that the approach of using a pixel matrix reduces potential geolocation errors (Ahern *et al.* 1991), which are difficult to avoid in time-series studies.

Finally, the regression model obtained from the 33 plots inventoried in 2000 (Eqn 4) was evaluated by reducing the number of plots to 15, selected from the cluster analysis. The objective of that reduction was to verify that the fit of the function did not significantly vary with the diminution of the number of plots introduced.

Supervised classification of vegetation cover

The final step involved the mapping of the vegetation cover obtained from regression model equations based on 2000 and 2005 data. This classification approach was used to define different FVC classes, and then compare the change in the FVC classes over time using a multitemporal data set. Owing to the lack of field data before the fire, 1992 ground data measurements were evaluated from the regression model obtained in 2005. This last criterion was accepted assuming the error associated with the differences in vegetation composition before the fire and 13 years later. However, in Mediterranean ecosystems, disturbances often modify the species' relative abundances rather than composition, and recovery only involves the return to initial abundances (Lavorel 1999).

Five plant-cover classes were defined based on the prefire vegetation cover types:

- 0–10%, barren land and herbaceous;
- 10–25%, herbaceous and shrub rangeland;
- 25–50%, brushland with dispersed trees;
- 50–80%, dispersed forest; and
- 80–100%, dense forest.

Threshold values of NDVI for each class were then calculated based on Eqns 4 and 5. Based on these FVC classes, the relative spectral response from the VI was calculated for each class. A supervised classification was then applied to 1992, 2000 and 2005 NDVI images using the previously defined FVC classes. Each unknown pixel was assigned to a class using the maximum likelihood method. The accuracy assessment of the classification was based on the Cohen Kappa coefficient. The kappa coefficient of agreement method is a simple cross-tabulation of the mapped class label against that observed on the ground or in reference data for a sample of cases at specified locations (Foody 2002). Next, an error matrix was created; both the global accuracy and the kappa coefficient of agreement were calculated for the supervised classifications.

Results and discussion

Plant community classification for test site selection

The hierarchical cluster analysis (Fig. 3) performed from FVC measurements of the 33 plots surveyed in 2000 permitted the description of the current main communities (Table 3) and the selection of the most representative sample plots. The results showed two well-differentiated groups with a Euclidian distance of 80. These classes are strongly influenced by the soil composition and topography of the plots. The dendrogram showed six subgroups, which were representative of the different plant communities found in the area. The clusters rightly show the floristic classification described in Rivas Goday and Rivas-Martinez (1966). Plant communities were distinguished in the cluster according to the presence of dominant plant species, soil type, or altitude. The cluster analysis enabled the distinction of different communities composed of *Ulex parviflorus*, *Rosmarinus officinalis* and *Cistus clusii*. This co-dominance reappears in a mosaic pattern in Sierra de Húetor.

The number of plots to be analyzed in 2005 was reduced, after classifying all plots in the hierarchical cluster analysis. This was done in order to develop permanent plots to be used in a field collection scheme compatible with remote sensing data for

Table 3. Cluster analysis of Fractional Vegetation Cover (FVC) per species surveyed in the year 2000
Soil types are A1–A3, Basophilic; B1–B3, Acidophilic

Clusters	Field survey parcel no.	Community type	Mean species	FVC Mean ± standard error	No. species Mean ± standard error	Altitude (m) Mean ± standard error
A		Gorse and rosemary thicket (G-R)				
A1	2, 25, 12, 20	Uniquely G-R	*Ulex parviflorus*	0.24 ±0.07	5.47 ±2.01	1264.32 ±40.21
			Rosmarinus officinalis	0.21 ±0.06		
			Cistus clusii	0.90 ±0.03		
A2	9, 23, 13, 34, 15, 22, 14	G-R with oak	*U. parviflorus*	0.26 ±0.09	5.32 ±2.11	1186.58 ±284.00
			R. officinalis	0.19 ±0.08		
			C. clusii	0.05 ±0.01		
A3	11, 29, 30, 32, 35, 3, 8, 6, 24	G-R + accompanying species	*U. parviflorus*	0.27 ±0.10	9.01 ±1.24	1291.02 ±79.47
			R. officinalis	0.16 ±0.05		
			C. clusii	0.06 ±0.04		
B		Pines, oaks or rose thicket				
B1	4, 19, 10, 16, 21, 33	Pine woods	*Pinus pinaster*	0.45 ±0.20	4.78 ±2.00	1417.22 ±99.10
B2	28, 31, 27, 36	Holm oak	*Quercus ilex*	0.22 ±0.14	6.10 ±1.45	1310.12 ±59.01
B3	5, 18	Laurel-leaved rock rose	*Cistus laurifolius*	0.35 ±0.06	7.01 ±2.33	1413.23 ±38.22
Residual	1, 26	Great diversity with no dominance		0.03 ±0.06	11 ±0.00	1305.34 ±7.23

Table 4. Pearson correlation matrix between vegetation indices (Normalized Difference Vegetation Index, NDVI; Soil Adjusted Vegetation Index, SAVI; Normalized Difference Infrared Index, NDII) and Fractional Vegetation Cover (FVC) (m^2/m^2) of year 2000-surveyed plots (n = 36)
SAVI index calculated for L = 0.5, 0.8 and 1. n = 39. Significant level: 0.05 (two-tailed)

	FVC	NDVI	SAVI			NDII
			L = 0.5	L = 0.8	L = 1	
FVC	1.00	0.92	0.89	0.88	0.86	0.84
	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

multitemporal analysis. The plot reduction was undertaken in a stepwise fashion based on the following plant community types defined by the hierarchical cluster analysis (see Table 3):

A1: Dwarf gorse (*Ulex parviflorus*)-dominated shrub land with *Rosmarinus officinalis* and *Cistus clusii.*
A2: Dwarf gorse with evergreen oaks (*Quercus ilex* and *Q. coccifera* L.).
A3: Shrubland composed of *Ulex parviflorus*, *Rosmarinus officinalis* and *Cistus clusii* with a large number of accompanying species.
B1: Pine forest chiefly composed of *Pinus pinaster* and *P. halepensis* and forest understorey.
B2: Holm oak forest composed of *Quercus ilex* mixed with forest understorey.
B3: Laurel-leaved rock rose mainly composed of *Cistus laurifolius* L.

Vegetation index analysis

All seven types of VIs calculated in the present study had a higher correlation coefficient than 0.68. In Table 4, a Pearson correlation matrix shows that the regression line of the VIs fitted the FVC surveyed per plot best. Judging from the results, NDVI presents the best goodness-of-fit with a correlation coefficient of 0.92. The suitability of this index in post-fire regeneration studies has been widely confirmed by various authors (Viedma *et al.* 1997; Díaz-Delgado and Pons 2001; Riaño *et al.* 2002). The SAVI, which might be expected to be more stable than the NDVI across the varying soil backgrounds (Huete 1988), showed the second best goodness-of-fit. Nevertheless, both indices showed similar correlations. This similarity is in agreement with the results obtained by Henry and Hope (1998), who monitored the post-burn recovery of chaparral vegetation in Southern California.

Changes in NDVI recorded among the four observation dates (1992, 1993, 2000 and 2005) for each permanent plot are displayed in Fig. 4. In order to visually assess the evolution of NDVI values, a normal curve was displayed. Except for the NDVI for 1993, taken some days after fire, the distribution of NDVI for 1992, 2000 and 2004 was normal (Table 5) with ($P > 0.05$) associated with the Kolmogorov–Smirnov statistics. The regeneration pattern effects on the spectral signature can be interpreted by examining the shapes of the histograms (Fig. 4) and the descriptive statistics of the variation in NDVI (Table 5). NDVI values showed an increasing trend since the fire event

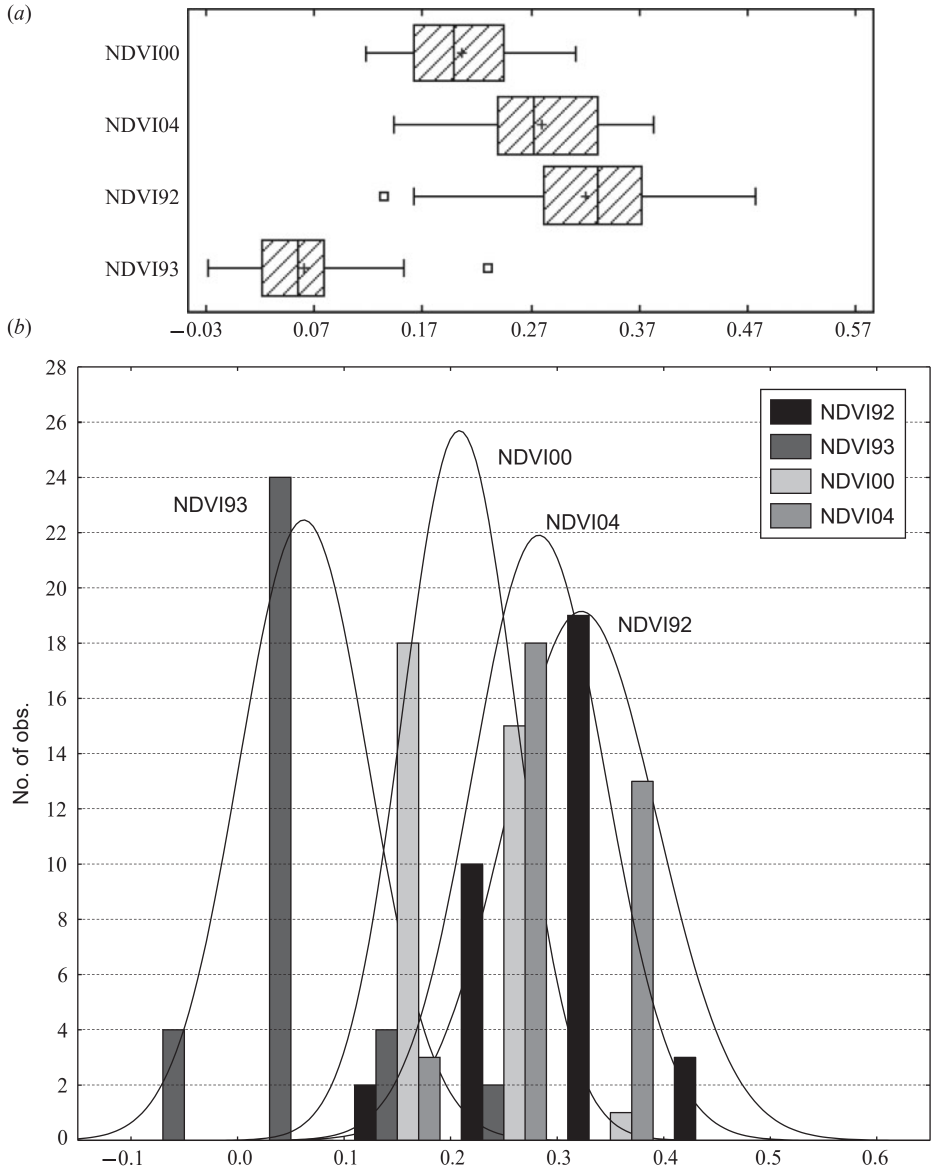


Fig. 4. Box-and-whisker plot (*a*); and histogram (*b*) obtained from the NDVI values extracted from the 34 plots (no. of obs.) monitored in 1992 (before forest fire); and 1993, 2000 and 2004 (after forest fire).

Table 5. Descriptive statistics obtained from Normalized Difference Vegetation Index (NDVI) values related to the field survey locations within the burned area in 2005, 2000 and 1992

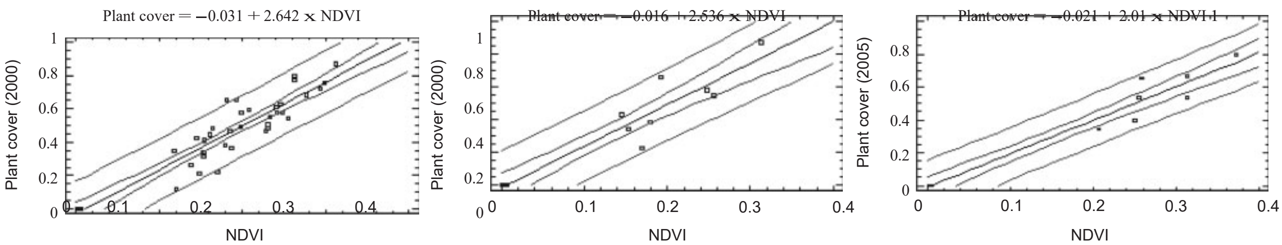
n = 34 plots

	Mean	Minimum	Maximum	Sum	Std error	Std deviation	Variance	Kolmogorov–Smirnov	Std error
NDVI92	0.320	0.135	0.477	10.891	0.012	0.071	0.005	0.200	0.403
NDVI93	0.061	−0.029	0.229	2.079	0.010	0.060	0.004	0.006	0.403
NDVI00	0.206	0.118	0.312	7.015	0.009	0.053	0.003	0.200	0.403
NDVI04	0.281	0.144	0.384	9.543	0.011	0.062	0.004	0.200	0.403

(1993), approaching the prefire values for 1992. The histogram derived from the first post-fire stage (barely 1 month after the fire) showed the lowest spectral values, responding to the strong decrease recorded in NDVI after the fire. However, there is recovery over time, with 2004 values close to those recorded in 1992. In fact, recovery tends to advance towards similar distribution patterns. These results imply that if vegetation remains undisturbed, post-fire spectral distribution may be similar to its

Table 6. Model regression comparison between Normalized Difference Vegetation Index (NDVI) and Fractional Vegetation Cover (FVC) recovery

	$Y = a + bX$	$Y = (a + bX)^2$	$Y = a + bsqrt(X)$	$Y = a + bln(X)$
r (correlation coefficient)	0.92	0.93	0.89	0.80
R^2	86.22	89.17	79.24	65.00
R^2 (adjusted)	85.84	88.87	78.68	64.06
Standard error	0.07	0.08	0.11	0.14
Durbin–Watson statistics	1.515	1.57	1.68	1.68
Significance (*P* value; *F*-test)	<0.001; 233.93	<0.001; 304.70	<0.001; 141.25	<0.001; 68.94



Correlation coefficient = 0.929	Correlation coefficient = 0.952	Correlation coefficient = 0.970
R^2 = 86.364%	R^2 = 90.772%	R^2 = 94.230%
R^2 = 85.977%	R^2 = 90.772%	R^2 = 93.705%
Standard error of est. = 0.089	Standard error of est. = 0.094	Standard error of est. = 0.076
Mean absolute error = 0.068 *n* = 36	Standard error of est. = 0.094 *n* = 18	Mean absolute error = 0.052 *n* = 18

Fig. 5. Linear regression models established between plant cover and NDVI value per plot. Models were obtained from 2000 and 2005 data sets. 2000 data were also tested to evaluate the effects of reducing the number of sample plots (from *n* = 33 to *n* = 15, adding in both cases three plots of bare soil).

prefire state. However, four plots influenced these results, as their spectral signatures remained invariant. These cases were related to grazing interactions that hindered vegetation regeneration.

Monitoring FVC recovery processes

Based on results derived from a regression analysis between NDVI and FVC, a linear regression model was selected. Table 6 shows the statistical results of different regression models established between the NDVI and the FVC. With correlations of 88.17 and 86.22, multiplicative and linear regression models had the best fit. However, the linear model had a lower standard error than that of the multiplicative model, so that the linear model ($NDVI_{00} = a + b(FVC_{00})$) was considered to be the best fit option. Estimation of the post-fire FVC had been evaluated through linear regression analysis previously (Twele and Barbosa 2004) based on a spectral mixture analysis.

In order to validate the reduction of invariant plots surveyed, the same regression type was calculated for 2000 data, at first considering all 33 plots. Plots were then removed using the stepwise method until reduced to 15. The reduction in the number of plots did not produce any significant variations in the regression model parameters, as shown in Fig. 5. Three bare-soil points were introduced into the regression model in order to fit the equations better.

A comparison of the results between the data set regression models ($NDVI_{00\text{–}05} = a + b(FVC_{00\text{–}05})$) ($n = 18$) indicated a slight statistical improvement for 2005, likely to be due to a decrease in the effect of soil reflectance on spectral data (Huete 1987). Nonetheless, FVC regeneration was related to NDVI values through a similar linear regression equation in the 7th and the 12th year after the fire. These results indicate that the regeneration trend of the main vegetation groups measured within the burned area remained constant. A detailed analysis of the post-fire ecological dynamics within the burned areas from 1992 to 2005 can be found in Hernández-Clemente *et al.* (2006).

Finally, the models obtained were used for performing a supervised classification of the plant recovery. Fig. 6 shows the results obtained from the time-series supervised classifications. The global accuracy of the FVC classification for the 2000 data was 80.5%, with a kappa coefficient of 0.74, whereas a global accuracy of 76.5% with a kappa coefficient of 0.71 was reached for the 2005 data. The FVC averages calculated for the entire burned area showed that the vegetation had already reached 38% ground coverage within 7 years, and 52% 12 years after the fire. Given that the prefire ground coverage was 63%, the results could be interpreted to indicate adequate recovery rates (Trabaud 1987). However, the recovery distribution area per class (Table 7) shows communities at ecological stages far removed from the prefire ecological stage. Areas with 50–100% FVC have yet to reclaim the prefire distribution. Although the tendency of these classes is to increase, the global FVC regenerated is still low considering that these FVC classes represent the recovered as well as the unburnt vegetation. Data show an

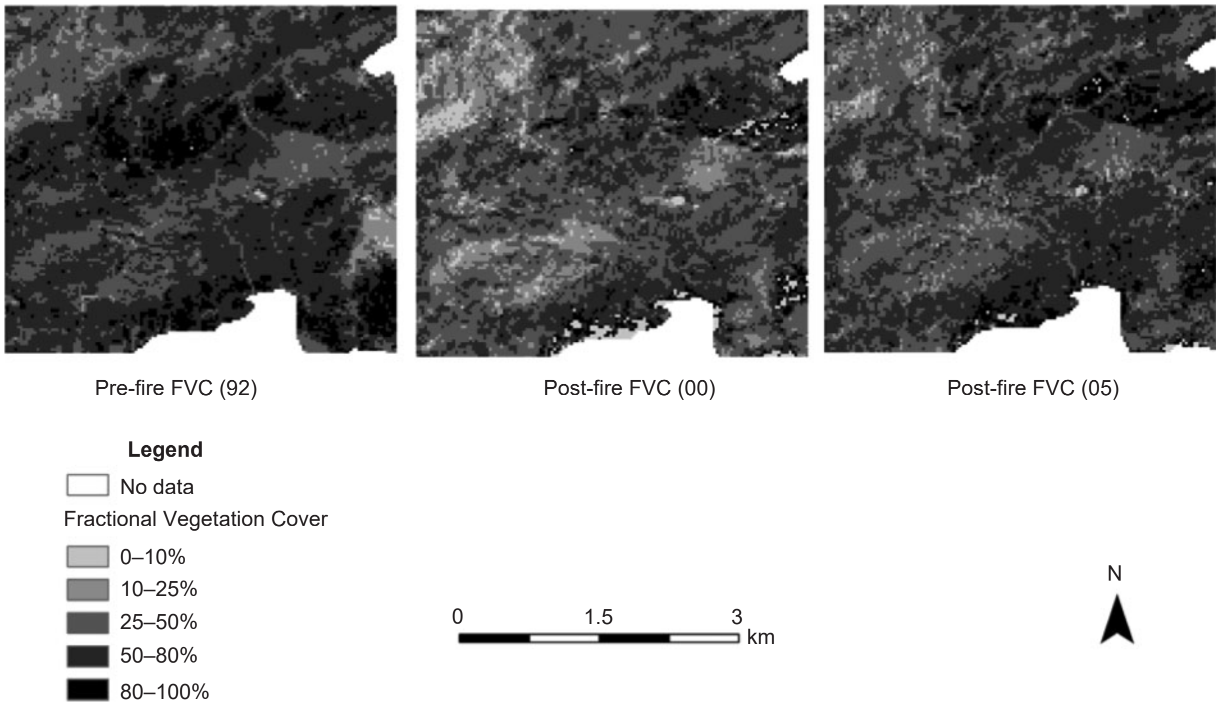


Fig. 6. Supervised classification obtained from the regression models established between FVC and NDVI value per plot within the burned area in 2000 and 2005. The prefire classification was calculated using the 2005 model.

Table 7. Percentage area of Fractional Vegetation Cover (FVC) classification derived from the multitemporal linear regression model obtained from 2005, 2000 and 1992 data sets

Classes	Vegetation classes	NDVI92 (%)	NDVI00 (%)	NDVI05 (%)
0–10%	Barren land	0.79	4.52	1.41
10–25%	Herbaceous	3.26	13.26	4.37
25–50%	Brushland	32.48	43.76	40.94
50–80%	Disperse canopy forest	51.38	32.25	46.85
80–100%	Dense canopy forest	12.09	6.20	6.43

initial strong increase in shrubland-associated classes (0–50% FVC), which, judging from 2005 data, have now decreased. This could serve as a strong indicator of succession evidenced by FVC recovery. Shrubland-associated coverage classes should be treated with caution, considering that from those in a previous study, it was observed that gorse–rosemary hindered Holm oak regeneration (Hernández-Clemente *et al*. 2006). Finally, barren land and grasses followed their expected post-fire regeneration, reaching a maximum during the first years and then decreasing in the long term (Trabaud and Lepart 1981).

Conclusions

The spectral post-fire analysis revealed that regeneration was related to gradual spectral changes over time within different communities. In this context, the proposed linear regression model showed itself to be capable of deriving accurate FVC estimates from NDVI data. Time-series analysis regression models indicated that, 7 years after the fire, the FVC regeneration was correlated with NDVI values. No significant differences were observed between regression equations for the 7th and the 12th year after the fire. This suggests that, during that period, the regeneration trend within the area remained constant. In this context, the proposed linear regression model proved to be capable of deriving accurate plant cover estimates from NDVI data over time. The sample plot selection method developed in the current study was essential in building a multitemporal regression model.

Results obtained from the present analysis indicate that the recovery of classes with the highest FVC, which are associated with woody species, is progressing at a slower rate than the change in FVC of the classes associated with shrubland. The reasons for this discrepancy in the recovery of vegetation types are two-fold: first, an increase in the FVC has been generated for shrubland classes, while, second, the accumulation of dry biomass from shrubland species perpetuates the fire risk. This process has arisen from the historical reforestation of the area and the loss of traditional uses (grazing) after fire. This final observation is indispensable for planning reforestation strategies in the area. In the future, the continuation of such a multitemporal study will be essential to evaluate the recovery pattern of these communities and to assess fire risk within the burned area.

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