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Advances in Remote Sensing of Post-Fire Vegetation Recovery Monitoring – A Review

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1. Introduction

Accurate information relating to the impact of fire on the environment and the way it is distributed throughout the burned area is a key factor in quantifying the impact of fires on landscapes (van Wagtendonk et al. 2004), selecting and prioritizing treatments applied on site (Patterson and Yool 1998), planning and monitoring restoration and recovery activities (Jakubauskas 1988; Jakubauskas et al. 1990; Gitas 1999) and, finally, providing baseline information for future monitoring (Brewer et al. 2005).

In order to assess economic losses and ecological effects, post-fire impact assessment requires precise information on extent, type and severity of fire (short-term impact assessment) as well as on forest regeneration and vegetation recovery (long-term impact assessment). Assessing the short-term impact is related to the study of fire behaviour, fire suppression and fire effects while the long-term impact assessment of fires is needed in order to establish post-fire monitoring management and introduce restoration and recovery activities.

As fire sizes increase and time becomes a constraining factor, traditional methods to assess post-fire impact on vegetation have become costly and labour-intensive (Bertolette and Spotskey 2001; Mitri and Gitas 2008). Given the extremely broad spatial expanse and often limited accessibility of the areas affected by fire, satellite remote sensing is an essential technology for gathering post-fire related information in a cost-effective and time-saving manner (Smith and Woodgate 1985; Chuvieco and Congalton 1988; Jakubauskas et al. 1990; White et al. 1996; Patterson and Yool 1998; Beaty and Taylor 2001; Escuin et al. 2002).

In addition, the development of high spatial and spectral resolution remote sensing instruments, both airborne and spaceborne, as well as advanced image analysis techniques have provided an opportunity to evaluate patterns of forest regeneration and vegetation recovery after wildfire.

The aim of this chapter is to review the role of Remote Sensing (RS) in post-fire monitoring of vegetation recovery. More specifically, traditional and advanced methods and techniques that have been so far employed to monitor vegetation regrowth after fire by RS will be reviewed and future trends will be identified.

More specifically, Part 2 deals with the ecological framework of the effects of fire on the ecosystem, Part 3 describes the methods and techniques that have so far been employed to estimate forest regeneration and vegetation recovery by means of field survey and by RS, Part 4 focuses on the advances in RS of post-fire vegetation monitoring, Part 5 emphasises on future trends in RS of post-fire monitoring, and Part 6 outlines the main conclusions of the chapter.

2. Ecological framework

Fire is an integral part of many ecosystems (Trabaud 1994). However, in recent decades the general trend in the number of fires and in the surface burned has increased spectacularly. This increase can be attributed to: (a) land-use changes (Rego 1992; García-Ruiz et al. 1996), and (b) climatic warming (Maheras 1988; Torn and Fried 1992; Amanatidis et al. 1993; Piñol et al. 1998; EPA 2001).

The **ecological effects** of forest fires are very diverse. This is not only because of the complexity of plant communities and the interface of disturbances such as grazing and cutting with burning, but also because of the different responses to the type, duration and intensity of fire, the season in which it occurs and its frequency (Le Houerou 1987).

The effect of fire on forested ecosystems can range from disastrous to beneficial. Harmful effects include changes in the physical, chemical and biological properties of soils; benefits are the removal of accumulated fuels, an increase in water yield, the control of insects and diseases, the preparation of seedbeds, and the release of seeds from serotinous cones (Kozlowski 2002).

Specifically, the main effects of fire on soils are the loss of nutrients during burning and the increased risk of erosion after burning. The latter is in fact related to the regeneration traits of the previous vegetation and to environmental conditions (Pausas et al. 1999). Large fires that produce a greater number of intensely burned patches can favour the colonization of invasive, fire tolerant species at the expense of rare/endemic species that are less tolerant to post-fire conditions. Thus biodiversity is also affected by fire (Dafis 1990). Climate change predictions and repercussions of forest fires on erosion, water yield and desertification further add to these threats (Moreno et al. 1990).

The effects of forest fires on vegetation are the most evident due to plants vulnerability to burning leading to permanent changes in the composition of the vegetation community, decreased vegetation cover, biomass loss and the alteration of landscape patterns (Perez-Cabello et al. 2009). However, forest fire is the major force in the biological evolution of biota such as in the Mediterranean (Naveh 1991). For instance, most Mediterranean plant species exhibit effective regeneration mechanisms for overcoming the immediate effects of fire (Mooney and Hobbs 1986). Plant species mechanisms can be passive (e.g. thick insulating bark), or active (e.g. re-sprouting from underground storage organs and seedlings from fire

protected seeds), which may lead to a rapid process of vegetation cover with similar characteristics to the previous communities (Perez-Cabello et al. 2009). However, the response of vegetation to fire is very complex and it is not easy to generalize because of the large number of factors that can affect the regeneration process (e.g. topographic-climatic influences, plant composition, topographic parameters, soil characteristics, etc.).

Natural regeneration (the regrowth of lost or destroyed parts or organs) of disturbed mature forests to a pre-disturbance condition is often slow, unpredictable, and fraught with difficulties (Kozlowski 2002). The natural regeneration of disturbed forest stands typically occurs in four sequential stages:

1. A stand initiation and regeneration stage: interactions among propagules (including seeds in seed banks and those dispersed into a site as well as sprouting or layering of residual trees) and soil and climatic conditions.
2. A thinning or stem exclusion stage: canopy closes and mortality of trees accelerates, competition for resources (light, water, mineral nutrients), leaf area index reaches its maximum.
3. A transition or understory regeneration stage: death of some overstorey trees, resulting in the formation of gaps in the canopy and the reintroduction of understorey vegetation.
4. A steady-state or old-growth stage: the continuation of a series of successional stages beginning in the previous stage and which may culminate in an old-growth climax forest (Oliver 1981; Oliver and Larson 1996; Kozlowski 2002).

Plant species react to fire through different morphological and physiological traits (Perez-Cabello et al. 2009). Some can survive fires due to protected plant tissues sprouting (e.g. underground storage organs) and high growth rates after fire and others can rapidly establish seedlings (Buhk et al. 2007). Resprouting ability is a very common survival strategy. Post-fire buds respond by producing new shoots (Miller 2000) and this engenders a rapid return to pre-fire conditions. Differently, seedling establishment may originate from on-site seeds or from off-site seed sources if favourable environmental conditions appear following fire (Baeza and Roy 2008).

The total recovery of a burned area includes different aspects such as revegetation, fauna recuperation, biodiversity, landscape aesthetics, 'natural' runoff rates and sediment yield (Inbar et al. 1998). Opinions about the natural state (the target value of post-fire recovery) differ among disciplines. Seen from a soil and water conservation point of view, a return to the original vegetation cover is sufficient, while ecologists consider recovery as a return in the richness of the original species. From a silvicultural perspective, it is important to consider both the quantity and quality of fire-induced tree regeneration (Gould et al. 2002).

The assessment of the ecological effects of fires on biodiversity, soil degradation and on the cycling of carbon and nitrogen requires not only a detailed and accurate mapping of the burned areas but also an accurate mapping of the type and severity of fire and of post-fire forest regeneration (for example pine regeneration) and vegetation recovery (for example shrub recovery) (Le Houerou 1987; Jabukauskas et al. 1990; Naveh 1991).

3. Post-fire monitoring using remote sensing

This part of the chapter consists of three different sections. Section (3.1) provides information on field based post-fire vegetation monitoring, section (3.2) discusses the airborne and spaceborne sensors used in post-fire monitoring, and section (3.3) introduces

the relative satellite image analysis techniques. The latter, provides a thoroughly description of well-known methods employed in post-fire monitoring and discuses studies related to the estimation of post-fire albedo and Land Surface Temperature. Subsection (3.3.6) deals with the use of SAR data to monitor the post-fire impact on forests. A summary table (Table 2) is also included.

3.1 Field based post-fire monitoring

Traditional methods of recording post-fire impact on vegetation include extensive field work or observations from an airborne platform, followed by the initial mapping (manually) of resource damage into predetermined classes (Bertolette and Spotskey 2001). As fire sizes increase and time becomes a constraining factor, traditional methods have become costly and labour-intensive.

Most studies are carried out in the first years after fire, and are mainly focused on seedling germination and on the survival and the restoration of plant cover (Table 1). Several years after the fire, measurements usually focus more on the characteristics of, for example, the trees, namely height, canopy width, basal diameter and volume. It has been realised that long-term monitoring is often required in order to evaluate the resilience of the different ecosystems towards forest fires. Normally, in long-term post-fire vegetation monitoring sampling units are established right after the fire event and the studied variables are monitored for several consecutive years (Calvo et al. 1998; Tarrega et al. 2001).

The most common sampling technique for monitoring plant populations is the use of permanent square plots. Taking into account both species characteristics and the extent of the study area, the size, the shape and the number of different plots are determined (Arianoutsou 1984; Clemente et al. 1996; Calvo et al. 2002; Cruz et al. 2003; Mitri and Gitas 2010). Accordingly, and in order to facilitate the objective collection of data on the ground, a number of field variables have been measured. In addition, there is a wide variety of sampling protocols depending on the type of survey (Daskalakou and Thanos 2004) that have been developed.

The analysis of post-fire vegetation recovery and monitoring can be either structural (involving variables such as cover and spatial heterogeneity), which is based on visual or floristic assessments (species composition, richness, community diversity, etc.), or a combination of the above (Pausas et al. 1999; Eshel et al. 2000; Kazanis and Arianoutsou 2004). In addition, protocols used can be distinguished into two general categories, that of plots (Thanos et al. 1996; Daskalakou and Thanos 1997; Tsitsoni 1997; Martínez-Sánchez et al. 1999; De Luis et al. 2001; Bailey and Covington 2002; Kennard et al. 2002) and that of transects (Ne'eman et al. 1999; Pausas et al. 1999; Caturla et al. 2000; Wahren et al. 2001; Gould et al. 2002).

Pausas et al. (1999) investigated the effect of different environmental conditions (climatic zones, aspect, and lithology) on the recovery process. They found large spatial variation in plant recovery in different localities with the same aspect, and for different aspects in the same locality. The recovery rate was different for different years due to changing climatic conditions and was higher on north-facing slopes, which are wetter than south-facing slopes. Belda and Meliá (2000) investigated the influence of climate on the natural post-fire regeneration of the burned area and found that regeneration followed an exponential curve, which was stronger in wet zones and had high correlation coefficients. Tsitsoni (1997) found that a high value of organic matter of the burned soil was a favourable factor for natural regeneration, as well as the position on the hillside, with lower regeneration indice values

for the upper position and increasing values when descending the slope. De Luís et al. (2001) investigated the combined effect of fire and rainstorm on short-term ecosystem response by simulating high intensity rainfall on burned field plots in a Mediterranean shrubland. They found that one-year seedling survival was lower in the plots affected by rainfall simulation than in the control plots. A higher mortality rate, as a consequence of rainfall, was observed in the most abundant species. Pre-fire conditions may also affect the heterogeneity of burn severity, creating a wide range of local and landscape effects (Ne'eman et al. 1999). The propagation of fires and recolonisation processes are events that depend on the spatial organization of vegetation (Mouillet et al. 2001).

Variables assessed in the field	Reference
Different environmental conditions (climatic zones, high intensity rainfall, aspect, and lithology)	(Pausas et al. 1999; Belda and Meliá 2000; De Luis et al. 2001)
Organic matter of the burned soil	(Tsitsoni 1997)
Pre-fire conditions (i.e. spatial organisation of vegetation)	(Calvo et al. 1994; Ne'eman et al. 1999; Mouillet et al. 2001)
Resprouting vigour (plant's anatomical features, and the characteristics of the individual before disturbance), intensity of disturbance, and the environmental conditions after disturbance	(Lloret and Vilà 1997; Díaz-Delgado and Pons 2001)
Seed banks and germination - Seed number contained in soil samples - Cone opening and seed dispersal	(Thanos and Georghiou 1988; Skordilis and Thanos 1995; Daskalakou and Thanos 1996; Ferrandis et al. 1996; Herranz et al. 1999; Keeley 2000)
Seedling germination, survival and growth in a plot and along a transect on which samples are taken of plant cover, tree cover, tree characteristics or the floristic composition and cover per species	(Thanos et al. 1996; Daskalakou and Thanos 1997; Tsitsoni 1997; Martínez-Sánchez et al. 1999; Ne'eman et al. 1999; Pausas et al. 1999; Caturla et al. 2000; De Luis et al. 2001; Wahren et al. 2001; Bailey and Covington 2002; Gould et al. 2002; Kennard et al. 2002)
Post-fire structural dynamics	(Calvo et al. 1991)
Species richness patterns and vegetation diversity -density of seedlings – abundance of different age classes	(Pausas et al. 2003; Perula et al. 2003; Kavgaci et al. 2010)
Permanent plot collection per plant community type and data reduction - Visual cover of the plant species	(Santalla et al. 2002; Clemente et al. 2009)
Non-native species cover correlated with high native species richness	(Hunter et al. 2006)
Field spectrometry	(Broge and Leblanc 2000; Thenkabail et al. 2000; Thenkabail et al. 2002; Mitri and Gitas 2010)

Table 1. Field variables assessed to determine post-fire monitoring

Vegetative resprouting is possible when buds survive the fire to resprout. Some species regenerate by both sexual and vegetative reproduction. Resprouting vigour depends upon the plant's anatomical features, the characteristics of the individual before disturbance (plant size, number of shoots and physiological status of the plant), intensity of disturbance, and the environmental conditions after disturbance (Lloret and Vilà 1997). Areas where sprouting species are available usually show higher recovery rates than areas with mainly obligated seeders (Díaz-Delgado and Pons 2001). Seed banks are important in the dynamics of many plant communities as they provide an immediate source of propagules for recruitment after disturbance.

Measurements may be focused on the monitoring of seedling germination, survival and growth (height) in a plot (Tsitsoni 1997; Martínez-Sánchez et al. 1999; De Luis et al. 2001; Bailey and Covington 2002; Kennard et al. 2002), or may be along a transect on which samples are taken of plant cover (Caturla et al. 2000), tree cover (Ne'eman et al. 1999), tree characteristics (Ne'eman et al. 1999; Gould et al. 2002) or the floristic composition and cover per species (Pausas et al. 1999; Wahren et al. 2001).

Field spectrometry measurements were employed to investigate the spectral properties of plants, vegetation recovery, and naturally regenerating forest (Broge and Leblanc 2000; Thenkabail et al. 2000; Thenkabail et al. 2002; Mitri and Gitas 2010). More general methods to estimate vegetation abundance (Bonham 1989), recovery and forest regeneration in the field were adopted.

3.2 Airborne and spaceborne sensors

In comparison with extensive and labour-intensive field campaigns, remote sensing offers a time- and cost-effective alternative for mapping post-fire vegetation over large areas. Ground truthing based on limited sample sets is, however, always suggested for calibration and validation purposes (Shaw et al. 1998; Mitri and Gitas 2010). Airborne platforms provide a first option to acquire remotely sensed imagery. Stueve et al. (2009) used aerial photography in combination with KH-4B (Key Hole 4B) imagery from the CORONA mission to detect post-fire tree establishment at an alpine treeline ecotone, whereas Amiro et al. (1999) employed airborne measurements to monitor the post-fire energy balance of boreal forest. Peterson and Stow (2003) applied Spectral Mixture Analysis on Airborne Data and Acquisition and Registration (ADAR) data for the mapping of post-fire chaparral regrowth in Southern California. Airborne imagery allows detailed spatial information (Bobbe et al. 2001). However, despite the increasing availability of digital aerial images, these data are rather seldom used. This is explained by the fact that airborne measurements usually cover relatively small areas. As a result, many photographs are required to cover large burned areas, which subsequently require correction and mosaicking (Gitas et al. 2009).

In addition to aerial photographs, spaceborne sensors have shown big potential for assessing post-fire regrowth effects. Table 2 lists a multitude of studies focusing on the use of remote sensing for assessing post-fire vegetation recovery. Satellite sensors are characterized by their technical specifications. These technical specifications determine the sensor's capabilities with regards to the monitoring of post-fire recovery trajectories. In this context, the term resolution is of paramount importance. Resolution is the character of data that limits the user's ability to detect and identify an object of feature within the data (Bobbe et al. 2001). Resolution is fourfold; difference is made between spatial, temporal, spectral and radiometric resolution:

- Spatial resolution is a measure of fineness of spatial detail and it determines the smallest object that can be identified in the data. For digital sensors, spatial resolution is expressed as pixel size.
- Temporal resolution refers to the sensor's revisiting time, i.e. the time period in which the same area is successively sensed. Temporal resolution depends upon orbital characteristics.
- Spectral resolution is a measure of the specific wavelength intervals in which the sensor records. It is important to distinguish between broadband sensors, in which reflectance values are averaged over relatively wide bandpasses, and hyperspectral sensors, which are characterized by the acquisition over many fine wavebands.
- Radiometric resolution is a measure of the sensor's ability to distinguish between two features of similar reflectance.

Sensor design is a determinant factor when choosing the appropriate image analysis technique. In this context, it is important to trade-off between spatial and temporal resolution. High to moderate spatial resolution (e.g. smaller than 30 m) acquire only a few images a year, while low spatial resolution sensors (e.g. larger than 250 m) are characterized by daily image acquisition (Veraverbeke et al. 2011a).

Most studies listed in Table 2 are based on optical satellite sensors. These images generally are subject to preprocessing prior to the analysis. In order to obtain geometrically registered top-of-canopy (TOC) reflectance values the imagery usually requires geometric, radiometric, atmospheric and topographic corrections (e.g. Veraverbeke et al. 2010a). After the abrupt changes caused by the fire, the more gradual vegetation recovery leads to alterations in radiometric response at landscape scale. These changes are governed by: (i) disappearance of the charcoal/ash, (ii) changes in the proportion of bare soils and (iii) an increase in vegetative cover. So far, many studies focused on the red-near infrared (R-NIR) bi-spectral space to discriminate between bare soils and vegetated areas because vegetation recovery results in higher NIR reflectance values and lower R reflectance values due to augmented chlorophyll absorption.

According to the references included in Table 2, applications conducted for post-fire monitoring can be sorted based on the characteristics of the sensor that was used:

- High resolution sensors: 6 studies were based on airborne imagery, 1 on Quickbird imagery and one on KH-4B imagery.
- Moderate resolutions sensors: the majority of the studies applied Landsat sensors: 27 studies used Thematic Mapper (TM) images, 10 Enhanced Thematic Mapper plus (ETM+) images and 5 Multispectral Scanner images (MSS). In addition, 3 authors applied Satellite Pour l'Observation de la Terra (SPOT) Multispectral (XS) data, 2 Synthetic Aperture Radar (SAR), 1 Earth Observing-1 (EO1) Hyperion and 1 ICESAT Geoscience Laser Altimeter System (GLAS).
- Low resolution sensors: although these sensors are characterized by their low spatial resolution, they have the advantage of repeated temporal sampling with high temporal frequency. Nine studies used Terra Moderate Resolution Imaging Spectroradiometer (MODIS) time series, 5 SPOT Vegetation (VGT) and 5 National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution (AVHRR) Data.
- SAR: three studies used multi-temporal ERS images (C band), in one study the potential of ALOS PALSAR (L band) was investigated for post-fire monitoring, while multiple-polarization aircraft L-band was used to monitor burn recovery in a coastal marsh.

Reference	Ecological parameter(s) measured	Technique	Ecosystem	Field data	Remotely sensed data
Alcaraz-Segura et al. 2010	Greening	NDVI	Boreal forest	/	AVHRR
Amiro et al. 1999	Sensible heat (H), latent heat (LE), CO_2 flux, surface radiometric temperature net radiation	Surface energy balance	Boreal forest	/	BOREAS Twin Otter airborne data
Belda and Melia 2000	/	NDVI	Mediterranean ecosystem	/	TM
Bisson et al. 2008	/	NDVI	Mediterranean ecosystem	Selected plots	TM, ETM+
Bourgeau-Chavez et al 2007	Soil moisture variations in fire disturbed areas	Regression models	Boreal forest	5 10X10 sample plots, randomly selected along 200m long transcects	ERS 2
Carranza et al. 2001	/	NDVI and landscape structure	Mediterranean ecosystem	33 line transect plots	TM
Clemente et al. 2009	Fractional vegetation cover	NDVI and other indices	Mediterranean ecosystem	/	TM, ETM+
Cuevas-Gonzalez et al. 2008	fAPAR	NDVI transformation	Boreal forest	/	MODIS
Cuevas-Gonzalez et al. 2009	/	NDVI and other indices	Boreal forest	/	MODIS
Diaz-Delgado and Pons 2001	/	NDVI and control plot selection	Mediterranean ecosystem	/	MSS
Diaz-Delgado et al. 2002	/	NDVI and control plot selection	Mediterranean ecosystem	/	MSS
Diaz-Delgado et al. 2003	/	NDVI and control plot selection	Mediterranean ecosystem	/	MSS, TM

Reference	Ecological parameter(s) measured	Technique	Ecosystem	Field data	Remotely sensed data
Goetz et al. 2006	/	NDVI	Boreal forest	11 sites	AVHRR
Goetz et al. 2010	Tree height	LIDAR	Boreal forest	/	GLAS, TM, MODIS
Gouveia et al. 2010	/	NDVI	Mediterranean ecosystem	/	VGT
Hall et al. 1991	Land cover classification including regeneration classes	Supervised classification	Boreal forest	/	MSS
Henry and Hope 1998	/	NDVI and other indices	Mediterranean ecosystem	36 line transect plots with plant community statistics	XS
Hernandez-Clemente et al. 2009	/	NDVI	Mediterranean ecosystem	/	TM, ETM+
Hicke et al. 2003	NPP	NDVI transformation	Boreal forest	/	AVHRR
Hope et al. 2007	/	NDVI	Mediterranean ecosystem	/	TM, ETM+
Idris et al. 2005	/	NDVI and control plot selection	Tropical and boreal forest	/	AVHRR
Jabukauskas et al. 1990	Land cover classification including regeneration classes	Supervised minimum distance-to-mean classification	Temperate coniferous forest	32 linguistic sample points	TM
Jacobson 2010	/	NDVI and other indices	Woodland community	/	XS
Kasischke et al 2007	Relations between soil moisture patterns and post-fire tree recruitment	Empirical relations	Boreal forest	2 test sites	ERS 1 and 2

Reference	Ecological parameter(s) measured	Technique	Ecosystem	Field data	Remotely sensed data
Kasischke et al 2011	Biomass estimation of regenerating forests	Empirical relations	Boreal forest	/	ALOS PALSAR
Lhermitte et al. 2010	/	NDVI and control plot selection	Savannah ecosystem	/	VGT
Lhermitte et al. 2011	/	NDVI and control plot selection	Savannah ecosystem	/	VGT
Li et al. 2008	/	NDVI, EVI and control plot selection	Temperate forest	/	MODIS
Lozano et al. 2010	/	NDVI and other indices, landscape structure	Mediterranean ecosystem	/	TM, ETM+
Lyons et al. 2008	/	Albedo	Boreal forest	/	MODIS
Malak and Pausas 2006	/	NDVI	Mediterranean ecosystem	/	TM
Marchetti et al. 1995	/	Infrared index	Mediterranean ecosystem	/	TM
McMichael et al. 2004	LAI	NDVI transformation	Mediterranean ecosystem	62 sample points and field spectroscopy	TM, ETM+
Minchella et al. 2009	Vegetation recovery	Simulations with scattering model	Mediterranean ecosystem	/	ERS
Mitchell and Yuan 2010	/	NDVI	Temperate forest	/	TM
Mitri and Gitas 2010	Land cover classification including regeneration classes	Object-based classification	Mediterranean ecosystem	/	Hyperion
Palandjian et al. 2009	Classification of 4 regeneration classes	Density slicing on NDVI data	Mediterranean ecosystem	Flux tower	Quickbird

Reference	Ecological parameter(s) measured	Technique	Ecosystem	Field data	Remotely sensed data
Peterson and Stow 2003	Fractional vegetation cover	SMA	Mediterranean ecosystem	/	TM, ADAR
Ramsey et al. 1999	Time-since-burn	Regression analysis	Marsh ecosystem	/	Aircraft SAR
Randerson et al. 2006	/	Albedo	Boreal forest	93 line transect points and field spectroscopy	MODIS
Riaño et al. 2002	/	NDVI and control plot selection	Mediterranean ecosystem	/	AVIRIS
Ricotta et al. 1998	/	NDVI and landscape structure	Mediterranean ecosystem	/	TM
Roder et al. 2008	Fractional vegetation cover	SMA	Mediterranean ecosystem	Ground-based NDVI	MSS, TM, ETM+
Sankey et al. 2008	Fractional vegetation cover	SMA	Sagebrush community	Field spectroscopy	XS, aerial photographs
Schroeder and Pereira 2002	/	Landscape structure	Boreal forest	/	TM
Segah et al. 2010	/	NDVI	Tropical forest	60 sample points	TM, VGT
Shaw et al. 1998	/	NDVI and other indices	Boreal forest	/	Field spectroscopy
Steyaert et al. 1997	Land cover classification including regeneration classes	Unsupervised cluster classification	Boreal forest	/	AVHRR, TM
Stueve et al. 2009	Tree establishment classification	Supervised minimum distance-to-mean binary classification	Alpine treeline border	Line transect plots	Airborne and KH-4B imagery

Reference	Ecological parameter(s) measured	Technique	Ecosystem	Field data	Remotely sensed data
Telesca and Lasaponara 2006	/	Detrended fluctuation analysis on NDVI time series	Mediterranean ecosystem	78 line transect plots and field spectroscopy	VGT
Van Leeuwen 2008	Phenological metrics	NDVI	Temperate ecosystem	/	MODIS
Van Leeuwen et al. 2010	Phenological metrics	NDVI and control plot selection	Temperate and Mediterranean ecosystems	78 line transect plots and field spectroscopy	MODIS
Veraverbeke et al. 2012	Fractional vegetation cover	NDVI and other indices	Mediterranean ecosystem	/	TM
Veraverbeke et al. 2012	/	NDVI, albedo, LST and control plot selection	Mediterranean ecosystem	/	MODIS
Veraverbeke et al. 2012	Fractional vegetation cover	SMA	Mediterranean ecosystem	19 line transect points	TM
Vicente-Serrano et al. 2008	/	NDVI and other indices	Mediterranean ecosystem	/	TM/ETM+
Viedma et al. 1997	Regeneration rate	NDVI	Mediterranean ecosystem	/	TM
Vila and Barbosa 2010	Fractional vegetation cover	NDVI and other indices, SMA	Mediterranean ecosystem	Field data	TM, ETM+
White et al. 1996	/	NDVI	Boreal forest	/	TM
Wittenberg et al. 2007	/	EVI	Mediterranean ecosystem	/	TM, ETM+

(ADAR: Airborne Data and Acquisition and Registration, AVHRR: Advanced Very High Resolution Radiometer, AVIRIS: Airborne Visible/Infrared Imaging Spectroradiometer, ETM+: Enhanced Thematic Mapper plus, EVI: Enhanced Vegetation Index, fAPAR: fraction of Absorbed Photosynthetically Active Radiation, GLAS: Geoscience Laser Altimeter System, KH: Key Hole, LAI: Leaf Area Index, LST: Land Surface Temperature, LIDAR, Light Detection and Ranging)MSS: Multispectral Scanner, MODIS: Moderate Resolution Imaging Spectroradiometer, NDVI: Normalized Difference Vegetation Index, NPP: Net Primary Productivity, RADAR: Radio Detection and Ranging, SAR: Synthetic Aperture Radar, SMA: Spectral Mixture Analysis, TM: Thematic Mapper, XS: Multispectral VGT: Vegetation

Table 2. Examples of post-fire vegetation recovery studies using remotely sensed data

A review of the studies presented in Table 2, shows that current research mainly focused on multispectral Landsat, MODIS, VGT and AVHRR data. The moderate and low resolution scales are relatively well documented. For the coarse spatial resolution this usually goes hand in hand with time series analysis. The overview also highlights a need for further exploration of high spatial resolution and high spectral resolution, i.e. hyperspectral, data. High resolution data (e.g. Quickbird, IKONOS) could help in the recognition of individual plants, whereas hyperspectral data have the potential to discriminate between different vegetation species (Asner and Lobell 2000; Mitri and Gitas 2010; Somers et al. 2010). Besides optical imagery, Synthetic Aperture Radar (SAR) data is also worth a more in-depth evaluation.
From Table 2 it can also be concluded that vegetation recovery studies have been carried out in a number of different ecosystems including:

- Mediterranean ecosystems: 26 studies were conducted in the Mediterranean basin, whereas 5 papers concentrate on the Mediterranean ecozone of California (USA).
- Boreal forests: 20 study areas were carried out in boreal forests of North American and the Eurasian boreal zone.
- Temperate forests: 5 studies focused on temperate forests..
- Other types of forests: 2 studies were conducted in tropical forests, 2 in savannah ecosystems, 1 along an alpine treeline border, 1 in a sagebrush community and 1 in a marsh ecosystem.

Post-fire recovery rates depend on fire severity (Diaz-Delgado et al. 2003), soil properties (Bisson et al. 2008), post-fire meteorological conditions (Henry and Hope 1998; van Leeuwen et al. 2010) and ecotype (Viedma et al. 1997; Veraverbeke et al. 2010b; Lhermitte et al. 2011; Veraverbeke et al. 2011b). In fire-adapted sclerophyllous shrub lands, for example, recovery only takes a few years (Viedma et al. 1997; Pausas and Verdu 2005) whereas in boreal forests recovery lasts several decades (Nepstad et al. 1999). The summary above clearly shows that recovery research so far focused on boreal and Mediterranean ecosystems. Table 2 also reveals that only 26 % of the papers included in the list were supported by ground truth. This highlights a need to conduct research on the remote sensing of post-fire vegetation recovery supported by field campaigns, while other ecosystems such as tropical forest and savannah ecosystems urgently require a knowledge gain.

3.3 Image analysis techniques

Several image analysis techniques are employed in the remote sensing of post-fire recovery. Most of the traditional approaches have an origin outside fire applications but their methodology is easily adjustable for recovery studies. The most important traditional methods are image classification, Vegetation Indices (VIs) and Spectral Mixture Analysis (SMA). They are thoroughly discussed below. In addition, one specific technique applicable for ecological disturbances, i.e. control plot selection, is also incorporated. Finally, some less frequently used approaches are shortly described.

3.3.1 Image classification

Since long, multispectral image classification is known to be a powerful technique to translate remotely sensed data into ecologically relevant cover classes. Both supervised (Jakubauskas et al. 1990; Hall et al. 1991; Stueve et al. 2009; Mitri and Gitas 2010) and unsupervised (Steyaert et al. 1997) techniques have been applied in post-fire recovery studies. Most applications rely on pixel-based classifiers such as the minimum-distance-

to-mean (Jakubauskas et al. 1990; Stueve et al. 2009) and maximum likelihood classifiers (Hall et al. 1991). While the majority of the studies focused on four or more cover classes (Jabukauskas et al. 1990; Hall et al. 1991; Steyaert et al. 1997; Mitri and Gitas 2010), the study of Stueve et al. (2009) was restricted to a binary classification of tree establishment along an alpine treeline border. A major problem associated with pixel-based classifications is the occurrence of salt-and-pepper artifacts. As a solution, object-based classification schemes include both spectral and contextual information (Wicks et al. 2002) (See more in Section 4).

Apart from multispectral classification approaches Palandjian et al. (2009) applied density slicing on post-fire Normalized Difference Vegetation Index (NDVI) data. As such, they discriminated four different regeneration classes. Generally spoken, relatively few studies applied image classification to monitor post-fire recovery. This is mainly explained by the fact that the spatial resolution of most popular satellite systems (e.g. Landsat) exceeds the size of individual regenerating plants. As a result, it is very difficult in these applications to find pure training data because most image pixels are mixed. This incites a need to explore the potential of high resolution imagery (e.g. Quickbird, IKONOS) to classify individual plants. This would also open new research pathways to study the small-scale spatial patterns of post-fire vegetation recovery.

3.3.2 VIs

By far the most widely used remote sensing technique to assess post-fire recovery is the NDVI (Tucker 1979) because of its strongly established relationship with above-ground biomass in a wide range of ecosystems (Carlson and Ripley 1997; Henry and Hope 1998; Cuevas-Gonzalez et al. 2009). The post-fire environment typically consists of a mixture of vegetation and substrate. Theoretically, Soil Adjusted Vegetation Indices (SAVIs) (Huete 1988; Baret and Guyot 1991; Qi et al. 1994) are better suited for these mixed environments. Relatively few studies have assessed the correlation between field estimates of vegetative cover and VIs. Clemente et al. (2009) contrasted the NDVI with the SAVI (Huete 1988), Transformed SAVI (TSAVI), (Baret and Guyot 1991) and Modified SAVI (MSAVI) (Qi et al. 1994) for estimating post-fire vegetation regrowth 7 and 12 years after a fire in Spain. The NDVI was stronger related to 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. Van Leeuwen et al. (2010) also retrieved high correlations between NDVI and field data of recovery. Veravrbeke et al. (2012b) comprehensively evaluated thirteen R-NIR vegetation indices for assessing post-fire vegetation recovery. They found that the NDVI indeed obtained the best correlations with line transect field data and the failure of the SAVIs was due to their inability to account for variations in background brightness. This approves the use of the NDVI as an appropriate recovery measure, however, it should be noted that the potential of spectral indices with a SWIR or MIR spectral band has not been fully explored yet. These spectral regions have proven to be very effective in discriminating soil and vegetation (Drake et al. 1999; Asner and Lobell 2000). In the context of post-fire recovery, VIs including a SWIR or MIR band have shown prospect in the studies of Marchetti et al. (1995), Cuevas-Gonzalez et al. (2009) and Jacobson (2010).

Several studies used NDVI data as a linkage to more ecologically relevant parameters such as fractional vegetation cover (Clemente et al. 2009; Vila and Barbosa 2010; Veraverbeke et

al. 2012b), fraction of Absorbed Photosynthetically Active Radiation (fAPAR), (Cuevas-Gonzalez et al. 2008), Net Primary Production (NPP), (Hicke et al. 2003) and Leaf Area Index (LAI), (McMichael et al. 2004). Usually, these index transforms are based on thorough field calibration. Only few studies incorporated a substantial number of field plots to calibrate and validate the VI approach (Shaw et al. 1998; Bisson et al. 2008; Clemente et al. 2009; Jacobson 2010; Segah et al. 2010; van Leeuwen et al. 2010; Vila and Barbosa 2010; Veraverbeke et al. 2011b Hernandez-Clemente et al. 2009). Figure 1 presents an example of the relationship between the NDVI and field estimates of vegetative cover which was used to model post-fire vegetation cover in the burned area. The majority of the authors, however, use the NDVI as a well-accepted methodology without additional field efforts. In a mono-temporal context NDVI were related to climatic variables (Belda and Meliá 2000), topographic parameters (Mitchell and Yuan 2010) and fire severity (White et al. 1996; Mitchell and Yuan 2010).

Other studies employed multiple images to construct recovery trajectories (Viedma et al. 1997; Henry and Hope 1998; Ricotta et al. 1998; Carranza et al. 2001; Díaz-Delgado and Pons 2001; Diaz-Delgado et al. 2002; Riaño et al. 2002; Malak and Pausas 2006; Wittenberg et al. 2007; Bisson et al. 2008; Vicente-Serrano et al. 2008; Clemente et al. 2009; Hernandez-Clemente et al. 2009). Where Landsat-based studies allow only a few cloud-free images a year (Ju and Roy 2008), satellite sensors with high temporal frequency permit the construction of continuous time series. More recently, several authors have explored this data type for assessing post-fire effects (Idris et al. 2005; Goetz et al. 2006; Telesca and Lasaponara 2006; Li et al. 2008; van Leeuwen 2008; Alcaraz-Segura et al. 2010; Gouveia et al. 2010; Lhermitte et al. 2010; Segah et al. 2010; van Leeuwen et al. 2010; Lhermitte et al. 2011; Veraverbeke et al. 2012a; Veraverbeke et al. 2012c). Thanks to this it is possible to discriminate between regeneration patters and seasonal fluctuations (Veraverbeke et al. 2010b; Lhermitte et al. 2011; Veraverbeke et al. 2012b). A major advantage of multi-temporal data is that regression fits between time since fire and NDVI data give reliable recovery rate estimates (Viedma et al. 1997; Díaz-Delgado and Pons 2001; Gouveia et al. 2010). Extension of these regeneration rates allows prediction on the future state of biomass. This is of major interest for decision makers in rangeland management. NDVI data also served as the preferred data source for the control plot selection procedure (Díaz-Delgado and Pons 2001; Diaz-Delgado et al. 2002; Lhermitte et al. 2010; Lhermitte et al. 2011) and landscape ecological applications (Ricotta et al. 1998; Carranza et al. 2001).

3.3.3 Spectral mixture analysis

The post-fire environment typically consists of a mixture of vegetation and substrate. Thus, monitoring post-fire regeneration processes essentially poses a sub-pixel issue at the resolution of most operational satellite systems such as Landsat. A number of image analysis techniques accommodating mixing problems exist (Atkinson et al. 1997; Arai 2008) with SMA being the most common technique utilized in many applications (Roberts et al. 1998; Asner and Lobell 2000; Riaño et al. 2002; Roder et al. 2008; Somers et al. 2010). SMA effectively addresses this issue by quantifying the sub-pixel fraction of cover of different endmembers, which are assumed to represent the spectral variability among the dominant terrain features. A major advantage of SMA is its ability to detect low cover fractions, something which remains difficult with the traditional vegetation indices (VIs) approach (Henry and Hope 1998; Elmore et al. 2000; Rogan and Franklin 2001). Moreover, SMA

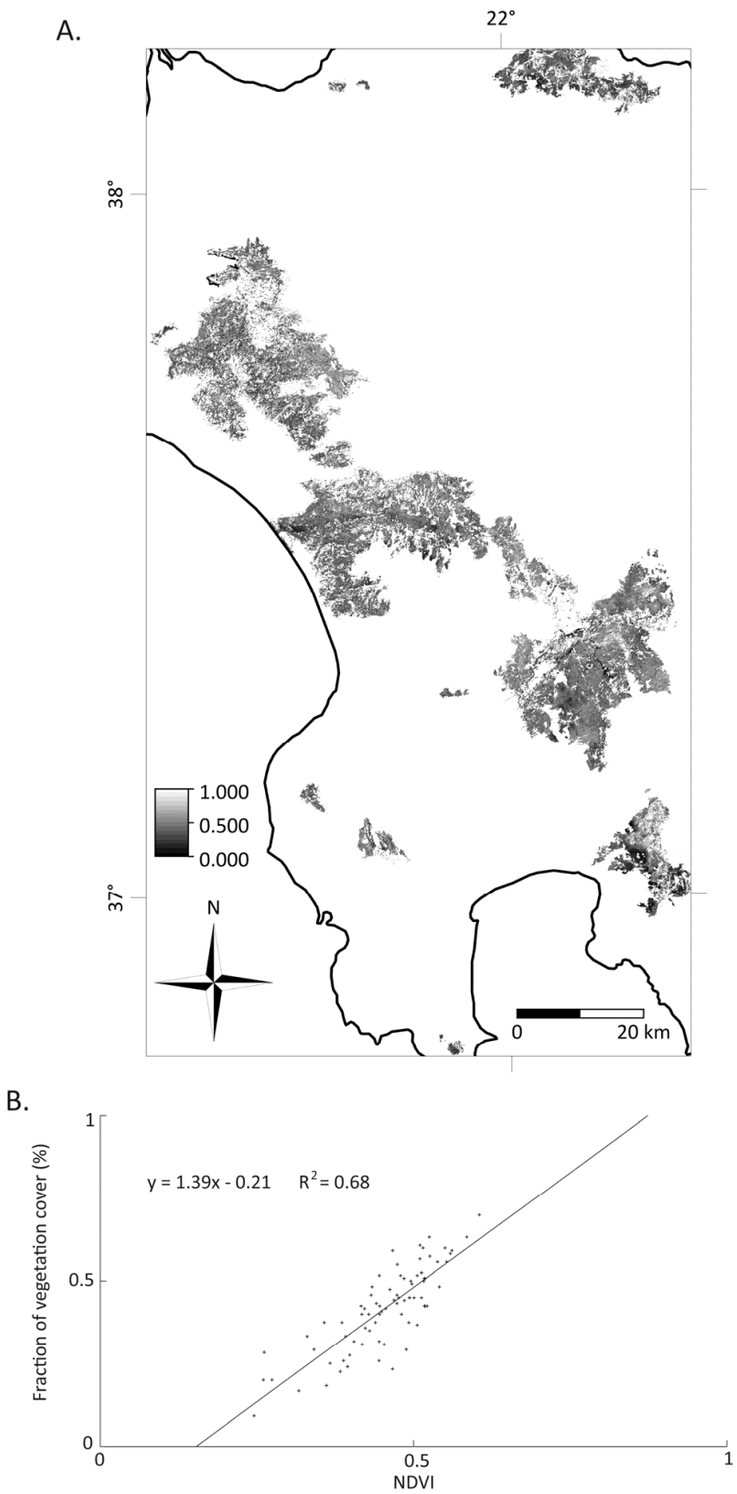


Fig. 1. Fractional vegetation cover map (A) three years after the large Peloponnese (Greece) fires based on the regression fit between the Landsat Normalized Difference Vegetation Index (NDVI) and line transect field ratings of vegetation cover (B) (Veraverbeke et al. 2012b).

directly results in quantitative abundance maps, without the need of an initial calibration based on field data as with VIs (Somers et al. 2010; Vila and Barbosa 2010). With regards to post-fire effects, rather few studies employed SMA to monitor post-fire vegetation responses (Riaño et al. 2002; Peterson and Stow 2003; Roder et al. 2008; Sankey et al. 2008; Vila and Barbosa 2010; Veraverbeke et al. 2012a). Although results of these studies were consistent, most of them were all restricted to simple linear SMA models in which only one spectrum was allowed for each endmember. As a consequence, the performance of these SMA models often appeared to be suboptimal (Roder et al. 2008; Vila and Barbosa 2010) because these models did not incorporate the natural variability in scene conditions of terrain features inherent in remote sensing data (Asner 1998). To overcome this variability effect Peterson and Stow (2003) applied multiple endmember SMA (MESMA), (Roberts et al. 1998). MESMA incorporates natural variability by allowing multiple endmembers for each constituting terrain feature. These endmember sets represent the within-class variability (Somers et al. 2010) and MESMA models search for the most optimal endmember combination by reducing the residual error when estimating fractional covers (Asner and Lobell 2000). Rogge et al. (2006) and Veraverbeke et al. (2012a), however, clearly demonstrated that reducing the residual error by applying MESMA not always results in the selection of the most appropriate endmember spectrum. An initial segmentation of the area prior to the unmixing process in order to retain areas which reveal a high similarity in the spectral properties of a certain endmember has been presented as a sound and computationally efficient solution to address this issue (Rogge et al. 2006; Veraverbeke et al. 2012a).

A possible amelioration in post-fire vegetation mapping using SMA could be the inclusion of SWIR and MIR spectral regions in the unmixing process. These spectral regions have proven to be very effective in discriminating soil and vegetation (Drake et al. 1999; Asner and Lobell 2000). Carreiras et al. (2006) demonstrated that adding the SWIR-MIR Landsat bands resulted in better estimates of tree canopy cover in Mediterranean shrublands. Additionally, enhancing the spectral resolution by employing hyperspectral data would increase the amount of spectral detail which would benefit the differentiation between spectra (Mitri and Gitas 2008). By including more and other spectral wavebands the unmixing model could gain discriminative power. Potentially, this would make it even possible to distinguish between non-photosynthetic vegetation and substrate (Asner and Lobell 2000; Somers et al. 2010), which appeared to be impossible in current applications.

3.3.4 Control plot selection

A major difficulty in post-fire time series analysis is that the analysis can be hampered by phenological effects, both due to the differences in acquisition data and due to inter-annual meteorological variability (Díaz-Delgado and Pons 2001). To deal with these phenological effects Diaz-Delgado and Pons (2001) proposed to compare vegetation regrowth in a burned area with unburned reference plots within the same image. As such, external and phenological variations are minimized among the compared areas. Several authors have successfully adapted the reference plot approach (Diaz-Delgado et al. 2002; Diaz-Delgado et al. 2003; Idris et al. 2005; Li et al. 2008; van Leeuwen et al. 2010). The reference plot selection procedure has, however, two main difficulties. Firstly, large scale application remains constrained due to the necessity of profound field knowledge to select relevant control plots.

Secondly, the reference plot approach fails to describe within-burn heterogeneity as it uses mean values per fire plot. To solve these problems, Lhermitte et al. (2010) proposed a pixel-based control plot selection method which follows the same reasoning with respect to the minimization of phenological effects by comparison with image-based control plots. The difference with the reference plot procedure, however, is situated in the fact that the pixel-based method assigns a unique unburned control pixel to each burned pixel. This control pixel selection is based on the similarity between the time series of the burned pixel and the time series of its surrounding unburned pixels for a pre-fire year (Lhermitte et al. 2010). The method allows the quantification of the heterogeneity within a fire plot since each fire pixel is considered independently as a focal study pixel and a control pixel is selected from a contextual neighbourhood around the focal pixel. This approach has been used in studies assessing the temporal dimension of fire impact and subsequent recovery (Veraverbeke et al. 2010b; Lhermitte et al. 2011; Veraverbeke et al. 2011a; Veraverbeke et al. 2012c). Figure 2 presents an example of the principle of the control plot selection procedure on a NDVI time series. With the exception of Veraverbeke et al. (2012c) who also incorporated Land Surface Temperature (LST) and albedo data in the procedure, so far, the control plot selection procedure has only been applied on NDVI data. Nevertheless, in theory, the control plot selection procedure allows any kind of remotely sensed data as input. Moreover, the procedure has the potential to provide valuable reference information other disturbance in which external forces abruptly remove the vegetation (e.g. volcanic eruptions, landslides, hurricanes, tsunamis, etc.).

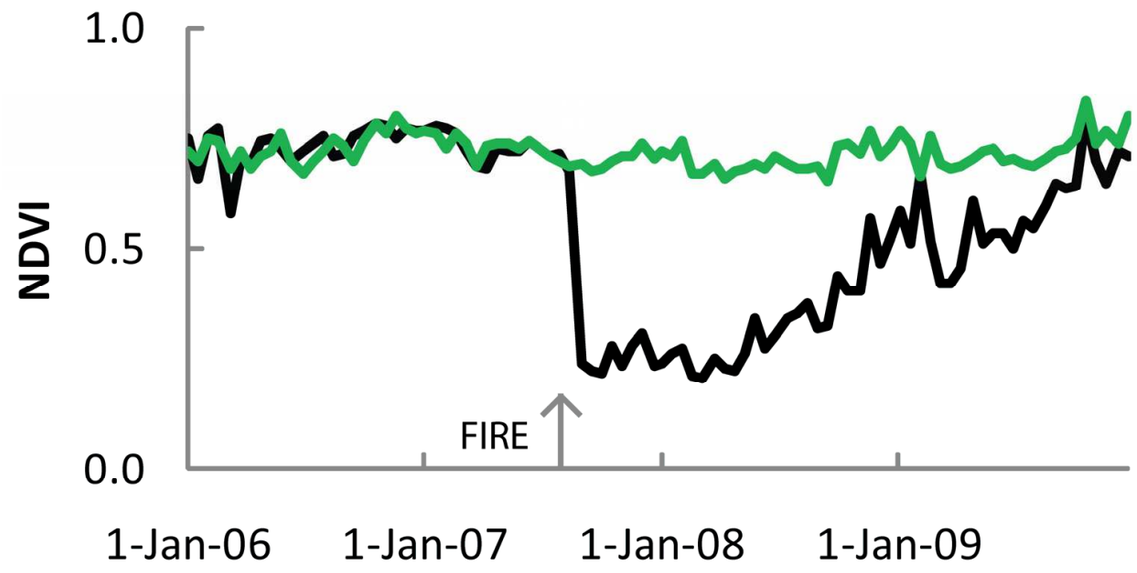


Fig. 2. Example of Normalized Difference Vegetation Index (NDVI) time series of a burned pixel (black line) and its corresponding control pixel (green line). The control pixel mimics how the burned pixel would have behaved without fire occurrence (after Veraverbeke et al. (2012c)).

Despite of the merits of the control pixel selection procedure as presented by Lhermitte et al. (2010) and Veraverbeke et al. (2010b) two constraints remain. Firstly, due to the necessity to search in larger windows for pixels in the middle of the burn the performance of the procedure is likely to be better near the contours of the burn perimeter. On one hand this is inevitable as the potentially most similar neighbour pixels are burned. On the other hand one could argue that this phenomenon incites to make the control pixel selection settings dependent on the distance to the fire perimeter. The procedure is also affected by a second constraint, i.e. the heterogeneity of the unburned landscape matrix. It is obvious that the procedure will be more optimal in highly homogeneous landscapes, even for large search windows. In contrast, in highly heterogeneous mixtures of different land cover types the procedure will potentially fail to retrieve similar pixels for small window sizes. It is a hard task to uncouple and quantify the effects of both constraints. Solutions to this have the potential to further improve the selection procedure.

3.3.5 Post-fire albedo and land surface temperature

Besides the use of optical data and its derivatives (e.g. VIs) some authors focused on the recovery of remotely sensed bioclimatic variables such as albedo and Land Surface Temperature (LST) (Amiro et al. 1999; Lyons and Randerson 2008; Veraverbeke et al. (2012c)). The increase in post-fire LST progressively weakens over time (Veraverbeke et al. (2012c)), whereas Lyons et al. (2008) and Veraverbeke et al. (2012c)) observed that albedo quickly recovers after an initial post-fire drop. The albedo even exceeds pre-fire values when char materials are removed and vegetation starts to regenerate (Veraverbeke et al. (2012c)). Thus, where the immediate fire effect results in an increased absorption of radiative energy, the long-term effect generally is an increased albedo (Amiro et al. 2006; Randerson et al. 2006). The quantification of these effects, together with an accurate estimation of the amount of greenhouse gasses emitted by the fire and the subsequent post-fire carbon sequestration of regenerating vegetation, are necessary for a holistic comprehension of the effect of wildfires on regional and global climate. In this context, Randerson et al. (2006) comprehensively demonstrated that, although the first post-fire year resulted in a net warming, the long-term balance was negative. As such they concluded that an increasing fire activity in the boreal region would not necessarily lead to a net climate warming. Remotely sensed proxies of albedo and LST can also be used to estimate the spatio-temporal behaviour of several radiative budget parameters of paramount biophysical importance such as sensible and latent heat fluxes (Bastiaanssen et al. 1998; Roerink et al. 2000). The immediate post-fire surface warming and its ecological consequences as well as the long-term post-fire temporal development of heat fluxes could form a relatively unexplored and captivating research topic.

3.3.6 Post-fire monitoring using SAR

Synthetic-aperture radar (SAR) data has been extensively used for various ecological processes (Kasischke et al. 1997) and have been especially useful in areas characterized by frequent cloud conditions such as the tropics and in the remote locations of the boreal forests. However, the application of SAR data in monitoring vegetation regrowth has been rather limited, while in most of the studies empirical relationships between field measurements and the backscatter values have been investigated.

Ramsey et al (1999) investigated the use of multiple-polarization aircraft L-band to monitor burn recovery in a coastal marsh. The authors found a significant relationship between VH-polarization and time-since-burn. In addition, Ramsey et al 1999 examined the same relationship with scaled SAR returns. Scaled by control data [e.g. VH(burn)-VH(control)], all three polarizations (VV, HH, VH) regressions were found significant, with 83% of the time-since-burn explained by the VH variable.

Kasischke et all (2011) investigated the utility of L-band ALOS PALSAR data (23.6 cm wavelength) for estimating low aboveground biomass in a fire-distributed black spruce forests in interior Alaska nearly 20 years after the fire events. Field measurements were analyzed against the radar backscatter coefficient. Significant linear correlations were found between the log of the aboveground biomass and σ^o (L-HH) and σ^o (L-HV), with the highest correlation found when soil moisture was high. Kasischke et all 2011 concluded that using spaceborne SAR systems to monitor forest regrowth will not only require collection of biomass data to establish the relationship between biomass and backscatter, but may also require developing methods to account for variations in soil moisture.

Kasischke et al (2007) based on the findings of Bourgeau-Chavez et al (2007) explored the relations between soil moisture patterns and post-fire tree recruitment in fire-disturbed black spruce forests in Interior Alaska using ERS-1 and ERS-2 C band (5.7 cm wavelength). Both Kasischke et al (2007) and Bourgeau-Chavez et al (2007) found high correlations between ERS SAR backscatter and measured soil moisture in the burned areas. Furthermore, Kasischke et al (2007) found that the measured levels of tree recruitment are related to the levels of soil moisture: aspen seedlings were able to germinate and grow within the severely burned areas because of adequate soil moisture was present during the growing season. In contrast, low aspen recruitment at a severely burned area was attributed to lower soil moisture.

Minchella et al. (2009) used multitemporal ERS SAR images to monitor the vegetation recovery in a Mediterranean burned area. Following a qualitative approach (analysis of the multitemporal backscattering signatures) they observed that, due to the increase in soil moisture in the backscattering, the measurements, taken throughout at least one year, of the similarity between the backscattering of the burned area and the backscattering of a bare soil around or inside the burned area, may provide a SAR-based index for the vegetation recovery in the burned area. In addition, Minchella et all 2009 used a microwave scattering model. A minimization of the distance between simulated results and measured data has been carried out using the re-growth rate as the key variable. Results showed that the retrieved values were in agreement with in-situ measurements.

Tanase et al 2011 analyzed SAR metrics from burned forested areas in Spain and Alaska. SAR dataset that were used consisted of ERS (C band), TerraSAR-X (X-band), Environmental Satellite (Envisat) Advanced SAR (ASAR) (C-band) and ALOS PALSAR (L-band) images. The authors concluded that for Mediterranean forests, the L-band HV-polarized SAR backscatter allowed the best differentiation of regrowth phases whereas at X- and C-band the HV-polarized backscatter was less sensitive to modification in forest structure due to the rapid saturation of the signal. For boreal forest four different regrowth phases were separated. Co-polarized repeat-pass coherence presented weak sensitivity to the different forest regrowth phases. Separation was possible only for the most recently affected sites (<15 year since disturbance) regardless of the radar frequency.

4. Advances in remote sensing of post-fire monitoring

Given that older generation sensors have many known limitations with respect to their suitability for studying complex biophysical characteristics (De Jong et al. 2000, Steininger 2000, Sampson et al. 2001, Salas et al. 2002), the need to benefit from new generation of high spatial and spectral resolution sensors as well as active sensors is of critical importance. Accurate quantification of vegetation regeneration could be essential for biodiversity assessment, land cover characterization and biomass modelling (Blackburn and Milton 1995). High spectral resolution facilitates the identification of features while high spatial resolution permits accurate location of features (Gross and Scott 1998). Additionally, advanced multispectral sensors also allow significantly improved signal to noise ratios (Levesque and King 2003).

The development of new hyperspectral remote sensing instruments, both airborne and spaceborne, has provided an opportunity to study vegetation recovery after wildfire (Riaño et al. 2002). A number of recent studies have indicated the advantages of using discrete narrowband data from specific portions of the spectrum, rather than broadband data, to obtain the most sensitive quantitative or qualitative information on vegetation characteristics.

Mitri and Gitas (2010) mapped post-fire vegetation recovery using EO-1 Hyperion imagery and OBIA and an overall accuracy of 75.81 % was reported (Figure 3). Object-oriented image analysis has been developed to overcome the limitations and weaknesses of traditional image processing methods for feature extraction from high resolution images (Mitri and Gitas 2004; Mitri and Gitas 2010). The basic difference, especially when compared with pixel-based procedures is that image object analysis does not classify single pixels but rather image objects that have been extracted in a previous image segmentation step (Baatz and Schape 1999). The concept here is that the information that is necessary to interpret an image is not represented in a single pixel, but in image objects. Object-based classification involves three main steps, namely, image segmentation, object training, and object classification. "Ground truth" information using field spectroradiometry instruments is equally important for validation of representative image wavebands to be used in object-based classification. According to Wicks et al. (2002), object-based classification may result in an increased accuracy and more realistic presentation of the environment.

Furthermore, many applications of remote sensing require high spatial resolution data for a correct determination of small objects. For instance, high spatial resolution imagery can be used before, during, and after a fire to measure fuel potential, access, progress, extent, as well as damage and financial loss. High spatial resolution multispectral data such as QuickBird (60 centimetres in panchromatic and 2.4 m in multispectral) can identify not only individual tree crowns, but often also the type of tree, estimate biomass, condition and age class (Wang et al. 2004, Palandjian et al. 2009).

LIDAR data have been used extensively for estimating various forest attributes such as canopy height, biomass, basal area and LAI forest variables as diameter at breast height, volume and density (Dubayah and Drake 2000; Lim et al. 2003a; Bortolot and Wynne 2005) and individual tree heights. The limited use of LIDAR data for monitoring vegetation regrowth can be attributed to the limited existence of spaceborne LIDAR Also, the operation of airborne LIDAR can be hampered by weather conditions, it is cost prohibited and can cover only limited areas.

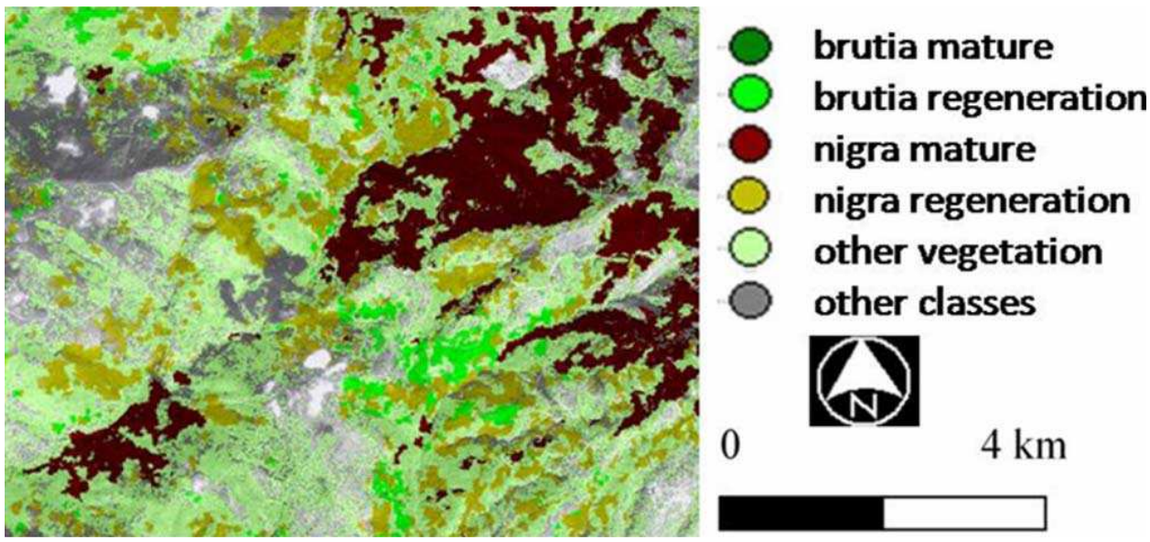


Fig. 3. Example of post-fire recovery map obtained after applying object-based classification in a Mediterranean ecosystem (Mitri and Gitas 2010).

However, it is worth mentioning the work of Wulder et al (2009) who used the integration of Landsat TM/ETM+ imagery and profiling LIDAR transects to characterize post-fire conditions on boreal forest in Canada shortly after the fire event. The main goals of their research were to evaluate whether LIDAR can be used to detect changes in vertical forest structural characteristics associated with the wildfire and find relationships between the vertical information extracted from the LIDAR datasets and horizontal information such as the indices NBR, dNBR and RdNBR extracted from the Landsat datasets in pre- and post-fire conditions. The authors had available LIDAR data collected along the same transect pre- and post-fire and could identify differences in forest structure before and after the fire, but those differences in structure were more related to post fire effects in dense forest than open or sparse forests. However, no significant correlation was found between the Landsat measures of post-fire effect and the LIDAR -derived measures of pre-fire forest structure. Kim et al (2009) used LIDAR intensity values in conjunction with field measurements to distinguish between live and dead standing tree biomass in a mixed coniferous forest in USA. Result of their regression analysis showed that low intensity returns from LIDAR were associated with dead tree biomass. It was suggested that knowing the background value of dead biomass in the forest (from field observations) one can estimate the additional contribution of dead standing tree biomass associated with a fire.

In addition to the airborne LIDAR applications, there has been a study using the satellite-based LIDAR instrument Geoscience Laser Altimeter System (GLAS) onboard ICESAT. Goetz et al (2010) used the LIDAR data acquired from GLAS to derive canopy structure information in burned areas and associated forest regrowth across Alaska. The LIDAR data were stratified by age class (using fire perimeters) and vegetation type (using the EVI calculated from MODIS NBAR). Data were also analyzed in relation to the burn severity. Tree height estimates derived from GLAS data were then compared to field measurements. The results showed that the GLAS data have the utility for inferring height properties of vegetation in fire disturbed areas of boreal forest, but it was mentioned that the data require both careful screening and some knowledge of the study area.

Furthermore, even though Polarimetric Interferometric SAR (PolInSAR) data has not been used so far for monitoring vegetation regrowth in fire affected areas, PolInSAR proved capable in estimating tree height (Papathanasiou and Cloude, 2001). The height estimation with PolInSAR has been successfully demonstrated on various forest types, ranging from boreal to tropical forests, and achieves high accuracies, (Praks et al. 2007; Garestier et al. 2008; Hajnsek et al. 2009). The operation of single-pass interferometric systems (TanDEM-X has been operating since May 2010) in space opens the door to a new set of unique applications (Krieger et al. 2010), one of them being the monitoring of forest biomass after fire.

5. Future investigation

Given that older generation sensors have many known limitations with respect to their suitability for studying complex biophysical characteristics, the need to benefit from new generation of high spatial and spectral resolution sensors as well as active sensors is of critical importance. The development of new remote sensing instruments, both airborne and spaceborne, has provided an opportunity to advance studies and researches on vegetation recovery after wildfire. Future research related to advances in remote sensing in post-fire monitoring is expected to focus on the following:

- Ecosystems with high environmental importance such as tropical forest and savannah ecosystems urgently require a knowledge gain.
- The need to conduct research on the remote sensing of post-fire vegetation recovery supported by field campaigns.
- The potential of spectral indices with a SWIR or MIR spectral band.
- Given that older generation sensors have many known limitations with respect to their suitability for studying complex biophysical characteristics, the need to benefit from new generation of high spatial and spectral resolution sensors and active sensors with different characteristics is of critical importance. Also the use of combined data acquired from more than one sensor.
- New research pathways to study the small-scale spatial patterns of post-fire vegetation recovery are required (e.g. the need to explore the potential of high resolution imagery such as QuickBird and IKONOS to classify individual plants).
- Investigation of the potential of Polarimetric Interferometric SAR data (TanDEM-X) to estimate post-fire biomass.
- Exploitation of advanced image analysis techniques in order to develop automated and transferable procedures.

6. Conclusions

Based on a review of the literature, a number of conclusions can be drawn:

- The role of remote sensing is increasingly becoming very important in post-fire monitoring.
- Most research has so far been carried out in areas covered by Mediterranean forests and shrublands.
- Current research is mainly based on the employment of Landsat, MODIS, VGT and AVHRR data. The extensive use of moderate and low resolution imagery is related to time series analysis.

- Vegetation indices and SMA are the main techniques employed so far in post-fire monitoring while the NDVI is the most commonly used index due to its strong relationship with above-ground biomass in a wide range of ecosystems. Only a small number of studies employ image classification due to the fact that the spatial resolution of the most commonly used satellite sensors exceeds the size of individual regenerating plants
- A number of developments including: the increase in the number of sensors with different characteristics suitable for post-fire monitoring (e.g. LIDAR, hyperspectral), the improved access to and availability of satellite data and derived products, and the development of new methods and advanced digital image analysis techniques (e.g. OBIA, Control plot selection) are expected to move forward research and establish RS an operational tool for post-fire monitoring.

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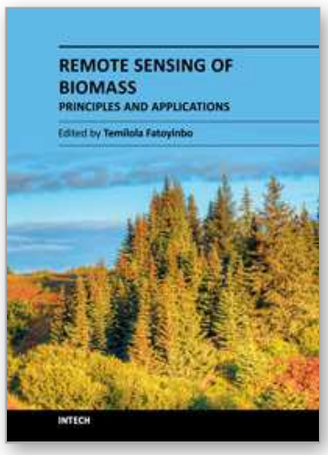
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The accurate measurement of ecosystem biomass is of great importance in scientific, resource management and energy sectors. In particular, biomass is a direct measurement of carbon storage within an ecosystem and of great importance for carbon cycle science and carbon emission mitigation. Remote Sensing is the most accurate tool for global biomass measurements because of the ability to measure large areas. Current biomass estimates are derived primarily from ground-based samples, as compiled and reported in inventories and ecosystem samples. By using remote sensing technologies, we are able to scale up the sample values and supply wall to wall mapping of biomass. Three separate remote sensing technologies are available today to measure ecosystem biomass: passive optical, radar, and lidar. There are many measurement methodologies that range from the application driven to the most technologically cutting-edge. The goal of this book is to address the newest developments in biomass measurements, sensor development, field measurements and modeling. The chapters in this book are separated into five main sections.

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