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**MONITORING POST-FIRE VEGETATION
COVER REGENERATION IN THE EUROPEAN
MEDITERRANEAN BASIN BY MEANS OF
REMOTE SENSING**

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MONITORING POST-FIRE VEGETATION COVER
REGENERATION IN THE EUROPEAN MEDITERRANEAN
BASIN BY MEANS OF REMOTE SENSING

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and under the supervision of **Dr. Paulo Barbosa**.



To Martina

To my family

ABSTRACT

Obtaining quantitative information about the recovery of fire affected ecosystems is of utmost importance from the management and decision-making point of view. Nowadays the concern about natural environment protection and recovery is much greater than in the past. However, the resources and tools available for its management are still not sufficient. Thus, attention and precision are needed when decisions must be taken. Quantitative estimates on how the vegetation is recovering after a fire can be of help for evaluating the necessity of human intervention on the fire-affected ecosystem, and their importance will grow as the problem of forest fires, climate change and desertification increase.

This thesis presents a comparison of methods to extract quantitative estimates of vegetation cover regrowth in burned areas with remote sensing data. In order to eliminate possible sources of error, a thorough pre-processing was carried out, including a careful geometric correction (reaching RMSE lower than 0.3 pixels), a topographic correction by means of a constrained Minneart model and a combination of absolute and relative atmospheric correction methods. Pseudo Invariant Features (PIF) were identified either by visual inspection methods or by a new automated selection method based in temporal Principal Component Analysis (PCA), which has been called multi-Temporal n-Dimensional Principal Component Analysis (mT-nD-PCA). This automated method demonstrated its capability in selecting accurate and objective PIFs within the satellite images.

Spectral Mixture Analysis (SMA) was compared against quantitative vegetation indices which are based on well known traditional vegetation indices like Normalised Difference Vegetation Index (NDVI) and Modified Soil Adjusted Vegetation Index (MSAVI). Accuracy assessment was performed by regressing vegetation cover results obtained with each method, against field data gathered during the field work campaigns. Results obtained showed how vegetation cover fractions obtained with the NDVI based quantitative index were the most accurate, being superior to the rest of the techniques applied, including SMA.

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1. INTRODUCTION

1.1 OVERVIEW ABOUT FOREST FIRES ON THE MEDITERRANEAN ENVIRONMENT

During the last decades the importance of the Mediterranean environment and the urgent need to develop new management and protection tools has been stressed out.

Mediterranean environment importance is not only limited to the Mediterranean basin geographical area and other geographical areas with similar characteristics (e.g. southern Californian area, south-western African area, south-western Australian area, central Chile) (Shoshany, 2000) but has to be seen in a global context. It represents a transition zone between arid and humid regions of the world. The effects of climate change (Shoshany, 2000) are more evident in this small fraction of the world's forest cover due to its transitional character.

Physical, geological and biological complexity and anthropological history makes Mediterranean environment a difficult and challenging system from a scientific and managerial point of view.

Mediterranean climate, with a pronounced bi-seasonality (dry hot summers with high solar irradiance, and humid cool winters with low solar irradiance) and an important variability and distribution of rainfall, together with its elevated topographical variability and its long history of human manipulation of forests and landscapes, has produced one of the most highly diversified anthropic natural ecosystems of the world (Shoshany, 2000; Scarascia-Mugnozza, 2000).

The paradox of putting together "anthropic" and "natural" seems evident, but looking at the Mediterranean environment, with its complex mosaic of patches, the explanation appears logic. Climax forests are non-existent due to the human action. However, the term natural forests is often used when referring to forests that nowadays have no human induced impacts. This so called natural forests are altered woods that have been once managed by man and that nowadays correspond to different stages of the original forest regressive succession. The last anthropic action suffered by these natural forests normally has occurred long time ago and possibly with less intensity than in other forests.

Therefore, some natural processes of self-management have already started. However, in most Mediterranean forests, human action is still present or very recent.

In recent times, the environmental and social functions of Mediterranean forests have increased in importance, possibly due to the social alarm in front of more frequent signs of climate change. Indeed, forests are a key factor in bio-geochemical cycles (e.g. water and carbon cycles), in protection of soil from erosion, regulating water runoff in watersheds and stabilizing slopes.

Despite the crucial importance of these functions, no economical revenue is received by the forest owners (Aunós, A.; personal communication). This becomes a major problem when the main type of ownership of Mediterranean forests is private. The fact that the productive capacity of Mediterranean forests is limited due to the ecological constraints of the climate, contributes to even decrease the interest of forest owners in maintaining and investing in their forests. As a consequence the risk of natural disasters (land slides, forest fires, soil erosion, and desertification) has increased largely (Pausas & Vallejo, 1999; Scarascia-Mugnozza, 2000).

Forest fires are possibly the most important disturbance problem of Mediterranean forests. Other natural disasters are closely linked with fires and the disappearance of vegetation, with these fires being the starting point of a critical process. Despite the traditional well known role of fire as one of the most important ecological factors influencing the Mediterranean landscape, in recent decades the general trend in number, intensity and size of fires has increased spectacularly. This is mainly due to:

- a) Land use changes: changes in fire occurrence closely reflect the recent socio-economic changes in European Mediterranean countries, like depopulation of rural areas, increase of agricultural mechanization, decrease of grazing and wood gathering, increase of the “weekend” urbanization and recreational use of rural areas. All this has caused the abandonment of large areas of farmland, which have been recovered by forests. This becomes a problem when dealing with a highly humanized type of landscape like the Mediterranean forest. The

lack of traditional uses of forests in these areas is causing an increase in accumulated fuel.

- b) Increase of ignition sources: the technology applied nowadays in agriculture, new uses of the forest (recreational), particular behaviours induced by social and/or economical circumstances, electric nets, ... are potential sources of ignition increasing in number each day.
- c) Extreme meteorological events: the fire-prone character of Mediterranean areas is not only a consequence of the typical climate of the area, but also of the increase of extreme meteorological events (i.e., recurrent and long periods of drought, extremely high summer temperatures, ...). The latter lead to an increase of water stress conditions for plants, changes in fuel conditions and increases in fire risk (increase in ignition probability and fire propagation).

During the last decades, research and political efforts have been focused in the pre-fire and fire-fighting phases. Risk assessment, fire-preventive silvicultural treatments, improvement of fire extinction methods and tools, development of fire behaviour models, new political compromises and legal regulations have been the main issues of interest. However, the number of forest fires is still high with burned areas increasing in some of the last years of the current decade (2000, 2003, 2005, and 2007). Burned areas have to be correctly managed in order to return to their pre-fire conditions. This correct management of burned areas will acquire more and more importance if climate change and desertification processes become more evident.

As a consequence, precise information about fire effects, their location and extent is needed in order to help not only prevent future events but also in restoring areas already affected. In order to support the latter aspect, information about post-fire regeneration dynamics is required. Post-fire resource management and reforestation programs depend on how accurate this information is.

1.2 IMPORTANCE AND AIM OF THIS RESEARCH

Obtaining quantitative information about the recovery of fire affected ecosystems is of utmost importance from the management and decision-making point of view. Nowadays the concern about natural environment protection and recovery is much greater than in the past. However, the resources and tools available for its management are still not sufficient. Thus, attention and precision is needed when decisions must be taken. Quantitative estimates on how the vegetation is recovering after a fire can be of help for evaluating the necessity of human intervention on the fire-affected ecosystem, and their importance will grow as the problem of forest fires, climate change and desertification increase. Satellite imagery has proven to be a useful, economic and reliable data to derive these estimates (Roman-Cuesta *et al.*, 2005; Chuvieco, 2002).

From the literature review performed it could be observed that few studies have evaluated unmixing methods using medium resolution data from sensors such as Landsat and SPOT (Satellite Pour l'Observation de la Terre) (Olthof, 2006). To the author's knowledge, no studies have compared the performances of unmixing techniques and vegetation indices taken from the quantitative point of view applied to vegetation regeneration on the Mediterranean environment. All comparisons have pointed to the classification of landscape features or to define vegetation regeneration trends.

This study is focused in the study and comparison of performances and accuracy of quantitative estimates of vegetation cover extracted from satellite data, in order to define which one provides more reliable results.

1.2.1 Research Aim

The principal aim of this research is to provide information for the decision making process and management of fire-affected forest ecosystems, by implementing an accurate and simple method for retrieving quantitative estimates of vegetation regeneration in fire-affected ecosystems, from remotely sensed data.

Four study areas were selected within the European Mediterranean basin (Italy, centre Portugal, southern Portugal and Cyprus). For each one, time series of satellite imagery

were processed and analysed and the accuracy checked. Different sensors were used for this purpose: SPOT 2 and 5, Landsat TM and ETM+, and CHRIS-Proba.

1.2.2 Research Objectives

The following specific objectives were established for the project:

- To compare different spectral analysis techniques for monitoring burned area changes in order to select the best among them. This will contribute to devise a global post-fire vegetation regeneration monitoring methodology for European Mediterranean conditions.
- To analyse the performance of different satellite sensors, including the experimental CHRIS-Proba instrument, when sensing changes in vegetation regrowth after forest fires.
- To study the dynamics of post-fire vegetation regeneration in the European Mediterranean basin in order to model it and extract post-fire vegetation regeneration paths from field and satellite data.

1.2.3 Thesis Structure

This thesis is organized in 6 main chapters, with a 7th chapter for the references and an 8th chapter for the appendices. Chapter 1 consists in a small introduction to the thesis subject, followed by an explanation of the importance of the study, and the list of objectives. Chapter 2 consists in the literature review performed about post-fire regeneration strategies in the Mediterranean environment and the study of vegetation regeneration with remote sensing techniques. Chapter 3 describes the type of data used for the study and the datasets and ancillary data available for each study area. It also explains why the study areas have been selected. Chapter 4 describes the methodology used for the field work survey, pre-processing of the images, and spectral analysis of the images. Chapter 5 presents the results obtained for each study area and the accuracy of these results. Finally Chapter 6 presents the conclusions extracted from the obtained results and some recommendations for future work in this field.

2. LITERATURE REVIEW

2.1 POST-FIRE REGENERATION STRATEGIES IN THE MEDITERRANEAN ENVIRONMENT

In order to survive under the difficult Mediterranean ecological conditions, vegetation has created several adaptation strategies which protect vegetation from the extreme events of this environment (e.g. forest fires) and help the remaining post-event vegetation to reproduce and regenerate.

In relation to forest fires, Mediterranean vegetation has implemented different fire resistance strategies: in broadleaf species, a high resprouting ability and a thick protective bark; and in conifers, serotinous cones, early and large seed production and high ecological plasticity (Scarascia-Mugnozza, 2000).

Post-fire regeneration mainly depends on the type of vegetation community existing prior the fire (which influences the capacity and speed of recovery) and on site environmental factors (climatic and terrain parameters) (Pausas & Vallejo, 1999; Calvo *et al.*, 2003). It also depends on fire dependent factors, like period of year when fire occurs, time interval until a new fire occurs, size and severity of fire.

Post-fire regeneration in Mediterranean environments has been defined as an auto-succession process due to its high resilience (that is, ecosystem capacity to return to pre-fire conditions), as the burnt area quickly looks like the non burnt area from a compositional and structural point of view (Habrouk, 2001; Kozlowski, 2002). Lloret *et al.* (2002) compared unburned areas with burned areas resulting that they are likely to be comparable in a short time lapse because of fast-recovery of the structure and composition of Mediterranean-type communities after disturbance. This fast establishment of pre-fire vegetation characteristics is mainly due to the regeneration strategies of the type of vegetation community existing prior to fire (Habrouk, 2001) and how these strategies are stimulated by fire:

- Resprouting from fire resistant structures (shoots on the rhizome or the stem of subterranean roots). This is typical of several genera (i.e. *Quercus*, *Arbutus*, *Erica*) over the Mediterranean area, and their recovery is quite fast.

- Germination of protected and/or stored seeds (serotiny and seed banks). Serotiny refers to the retention of the seed in the canopy until a fire occurs, is typical of *Pinus halepensis* and *Pinus brutia* over the Mediterranean area. Their recovery is slower than typical resprouters, and depends on fire interval, age of maturity of trees at the moment of fire, seed longevity, and seed resistance to fire. However, the advantage of this strategy is that it increases the genetic variability and stability of the populations (Pausas & Vallejo, 1999; Calvo *et al.*, 2003). Seed banks refers to the accumulation of dormant seeds on the first soil horizon where they remain until the fire activates their germination. The genus *Cistus spp.* uses this strategy, and its dormant seed bank can last until 15 years.

Rapid recovery of the affected area depends also on environmental factors. The most important of these factors that may affect either positively or negatively vegetation regeneration of a burned area are relief and climatic characteristics. Intense post-fire rains may cause a soil erosion process where soil, nutrients and seed bank are washed and reduced. This may decrease seriously the recovery capacity of the area. This reduction, in turn, is proportionally related to the steepness of the slopes and shallowness of soils inside the area. Considering that the forested land in the Mediterranean environment corresponds mainly to the non-arable land (not interesting for agricultural purposes), with steep slopes and/or shallow soils as principal and common characteristics, the natural regeneration process in the burned areas is not easy at all. In the other hand, some rain in the adequate moment would help the recovery process catalyzing the germination of the seed bank.

In relation to fire dependent factors, the period of time when fire occurs may affect post-fire regeneration, as the hydration state of the resprouting plant at the moment of the fire event can constrain greatly its regeneration capacity. Also, hydration state of seeds on seeder species affect the regeneration capacity, as humid seeds are more sensitive to heat than dry seeds (Moreno & Cruz, 2000).

Recurrent fires are a great problem for post-fire regeneration. If plants have not had enough time to recover from the stress and effort of regenerating from the last fire event,

when the new fire comes, they may have not the capacity to regenerate afterwards, as the reserves of seeds and energy have been exhausted previously and they had no time to produce new reserves. Thus, regeneration after recurrent fires is strongly compromised.

Size of fire seems to affect regeneration, but in Mediterranean ecosystems its effect is still a poorly known aspect of fire ecology (Moreno & Cruz, 2000). Large burned conifer areas (> 500 ha) may have problems on the regeneration of the central areas, which are far from the edges of the burned area and thus, from any source of seed. But at the same time, they are the most protected areas from the depredation of herbivores that feed with seedlings, as these herbivores return to the burned areas from the contiguous unburned areas, so the fire perimeter zone is the most affected by this depredation.

Fire severity depends on wind strength and temperature, humidity state of air, soil and plant tissues, and on the total biomass available (combustible). It affects directly the regeneration capacity of plants and also affects future ecosystem processes (Moreno & Cruz, 2000).

2.2 REMOTE SENSING AND VEGETATION REGENERATION MONITORING

Remote sensing has been widely used to study vegetation characteristics and its dynamics over time. Spectral and spatial responses of the vegetation after fires are suitable properties to analyse the regeneration process (Belda & Melià, 2000). The development of high spatial resolution remote sensing instruments has allowed this technique to be used for such purposes. Several remote sensing studies have addressed the study of the vegetation recovery after wildfires. Most of them have used vegetation indices in order to characterize the vegetation recovery. These vegetation indices studies resulted mainly in qualitative estimates of vegetation evolution, that is, if the vegetation was or not regrowing in the burned area, but no cover fraction percentages were obtained from these studies. Marchetti *et al.* (1995) used Landsat TM to monitor vegetation growth on a large burnt area by using the Infrared Index (II) finding that it was appropriate for monitoring post-fire vegetation evolution. Diaz-Delgado & Pons (2001) monitored radiometric response of vegetation recovery after fire by means of the Normalized Difference Vegetation Index (NDVI). They concluded that this index may be used for monitoring and

modelling plant response to fire in order to quantify the different recovery rates. Diaz-Delgado *et al.* (2003) used NDVI also to monitor plant regeneration measurements in order to determine the influence of fire severity on plant regeneration by using Landsat Thematic Mapper (TM) and Multispectral Scanner (MSS) imagery. They found that NDVI was useful in discriminating spectral variability generated by fire severity, but they pointed out that their results, even being statistically significant, were weak. They specified that NDVI can aid monitoring of post-fire recovery by indicating main tendencies, but not for accurate quantitative modelling. Viedma *et al.* (1997) used Landsat TM imagery to monitor the recovery process after fire assessing the regrowth pathways followed by different species populations and the speed of recovery in the years following fire. They analysed the relation between NDVI, Leaf Area Index (LAI), and time to estimate recovery pathways. They established an empirical relationship between canopy reflectance (measured as NDVI) and time elapsed after fire to describe the regeneration processes.

Another technique applied to the study of post-fire regeneration patterns and for burned area classification is Spectral Mixture Analysis (SMA). This technique allows getting abundance maps representing the fraction of endmembers (dominant features which have relatively constant spectral properties). Thus it can be considered a technique that yields quantitative measures of the principal features present in the study area (e.g. soil, vegetation, shade). Despite its quantitative character, it has been widely used mainly to detect and classify landscape features, being its results often compared to other techniques like vegetation indices. Souza *et al.* (2003) used SPOT 4 (Satellite Pour l'Observation de la Terre) imagery to derive fraction images of vegetation, non photosynthetic vegetation (NPV), soil and shade, linking them with a 1 m resolution IKONOS image in order to obtain forest degradation maps in Eastern Amazon. The resulting forest degradation map obtained from the NPV fraction image showed good agreement with the visually interpreted degraded forest areas from Ikonos image. Quintano *et al.* (2005) used NOAA-AVHRR (National Oceanic and Atmospheric Administration – Advanced Very High Resolution Radiometer) uni-temporal data to evaluate the usefulness of SMA for estimating the area burned by forest fires in

Mediterranean countries. Their results showed that SMA seems to be a valid technique for identifying burned areas. Again Quintano *et al.* (2006) tested a uni-temporal methodology for mapping large fires in the Mediterranean area, based on using SMA applied to low (NOAA-AVHRR) and medium (Landsat TM) spatial resolution remotely sensed data followed by the segmentation and classification of the fraction images obtained. Their results showed that, when compared to results based on NDVI, SMA performed better, reducing the problem caused by variation in soil background in burned areas, since soil radiance alterations could be grouped in the soil fraction image. Román-Cuesta *et al.* (2005) used IRS LISS III (Linear Imaging Self Scanning) image to compare 5 different techniques (SMA and Vegetation Indices –VIs- among them) to quickly classify a large forest fire. They concluded that spectral unmixing techniques, together with the use of raw reflectance data, were the most accurate methods for discriminating burned area. Peedle *et al.* (2001) performed an interesting study of comparison between ten different VIs and SMA. They tested their ability to predict forest biophysical parameters like biomass Leaf Area Index (LAI) and Net Primary Productivity (NPP) using data from the NASA COVER Project (Landsat TM). In all cases, SMA surpassed the VIs approaches in their ability to predict forest biophysical parameters. Riaño *et al.* (2002) compared Spectral Mixture Analysis (SMA) with NDVI on Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) imagery to understand regeneration patterns after fire in two semi-arid shrub communities of the Santa Monica mountains (California). They found that when using hyperspectral images, SMA worked better than NDVI in following the regeneration patterns. Twele (2003) compared the performance of SMA versus several vegetation indices when deriving regeneration trends finding SMA to be the most accurate technique. He also tested the capability of SMA to quantitatively estimate vegetation cover. His results showed that SMA is capable of deriving physically accurate estimates of fractional vegetation cover.

Some studies have focused their interest in the quantitative character of SMA. Peterson & Stow (2003) tested the ability of a multiple endmember SMA approach applied to multi-temporal Landsat TM data, to produce realistic and meaningful endmember fractions for the study of post-fire regrowth in a southern Californian chaparral landscape. The

reliability of this methodology was tested using fractions derived from the 1 m resolution Airborne Data Acquisition and Registration (ADAR) data, aggregated to 30 m pixels. Their results showed that fractions derived from ADAR and Landsat TM data were highly correlated and all of the correlations were significant.

Studies of SMA have shown the promising results of this technique. Normally, it surpasses results obtained with traditional techniques like vegetation indices. However, accuracy of SMA results mainly depends on the endmembers selected. Selection of endmembers is not simple at all. The number of endmembers must account for the number of classes in the pixel, and their spectral separability should be sufficient in order to avoid confusion (Theseira *et al.*, 2002). Too few endmembers would split any non-identified endmember into the other endmembers. Too many endmembers would increase model sensitivity to instrumental noise, atmospheric interference and natural variability in spectra (Sabol *et al.*, 1992). Normally, the quantity of endmembers that can be used with remote sensing data depends on the dimensionality of this data, which represents an important limitation to the number of endmembers when using multi-spectral imagery like Landsat or SPOT. Therefore, despite the promising results observed by different authors, this technique has to be implemented carefully and bearing in mind its inherent limitations.

Some authors have invested efforts in deriving quantitative measurements from vegetation indices. Verstraete & Pinty (1991) studied how NDVI varied in semi-arid lands and they argued that NDVI is more controlled by changes in vegetation cover than by changes in the optical thickness of canopies. They concluded that for partially vegetated landscapes it is more direct and reasonable to derive vegetation fraction rather than LAI from NDVI. Gutman & Ignatov (1998) derived green vegetation cover from a scaled NDVI taken between bare soil NDVI and dense vegetation NDVI. Despite several other studies showed that NDVI and fractional vegetation cover have a strong linear relation (e.g. Gitelson *et al.*, 2002; Wittich & Hansing, 1995), other investigations concluded that this relation between NDVI and vegetation fractional cover is nonlinear, depending this nonlinearity mainly on the soil background (Huete *et al.*, 1985) which reflects the already

widely known problem of NDVI with the background effect when studying sparsely vegetated areas. Dymon *et al.* (1992) used SPOT HRV to derive NDVI and percent vegetation cover, founding a nonlinear relationship between them. Carlson & Ripley (1997) showed a square root relation between a scaled NDVI and vegetation fractional cover. Baret *et al.* (1995) tested different vegetation indices in relation with vegetation cover retrieval founding a nonlinear relation for all vegetation indices.

3. STUDY AREAS AND DATA SETS

3.1 STUDY AREAS

3.1.1 Justification of Study Areas Selection

The ideal study areas needed to fulfil several criteria in order to become eligible for the project:

- a) Size of the burned area: As explained in section 2.1, size of fire can affect vegetation regeneration. The size of the burned area should be big enough in order to be able to study it by means of remote sensing data, but not so big to become a serious limitation for the vegetation regeneration strategies. Therefore, a size around 500 ha was considered ideal. This dimension of fire is considered as an approximate threshold to determine large forest fires (Moreno & Cruz, 2000; Habrouk, 2001).
- b) Type of ecosystem present: it was considered that the study areas should have a Mediterranean ecosystem type of vegetation in order to fulfil the objectives of the project. Also, the fire should have affected different vegetation communities with different regeneration strategies (e.g. conifer and broadleaf forests, shrubs) in order to allow evaluation of the possible different regeneration trends.
- c) The area should have not burned in the recent past (at least, 25 years): species present in the area should have reached sexual maturity in order to produce enough seeds for ensuring post-fire regeneration of the area.
- d) Study areas spread along the European Mediterranean basin: European Mediterranean basin was divided in three geographical main areas: western Mediterranean, central Mediterranean and eastern Mediterranean. Burned areas should be spread over these areas in order to allow evaluation of the methodology for different Mediterranean ecosystems.
- e) Availability of remote sensing and ancillary data: for each study area, cloud free anniversary satellite data should be available, as well as the ancillary data required for the project.

- f) Accessibility of the study areas for the field work campaigns: study areas should be accessible in order to perform the field work campaigns.

By taking into consideration these six requirements, a research was conducted on the burned areas database of the Land Management and Natural Hazards Unit of the Joint Research Centre (Ispra, Italy). Four areas were considered appropriate for the study:

- **Lythrodontas (Cyprus)**: this fire started on the 18th July 2001 and it burnt 602 ha. This study area represents a typical eastern Mediterranean area (hot and dry climatic area). The vegetation structure consists mainly of open coniferous forests with maquia. The principal tree species present is *Pinus brutia*, which is one of the pines with serotinous cones (they remain on the tree until an extreme and sudden heat, like in a forest fire, makes them explode). The previous fire that affected this area was more than 25 years ago. Figure 1 shows the location of the study area.

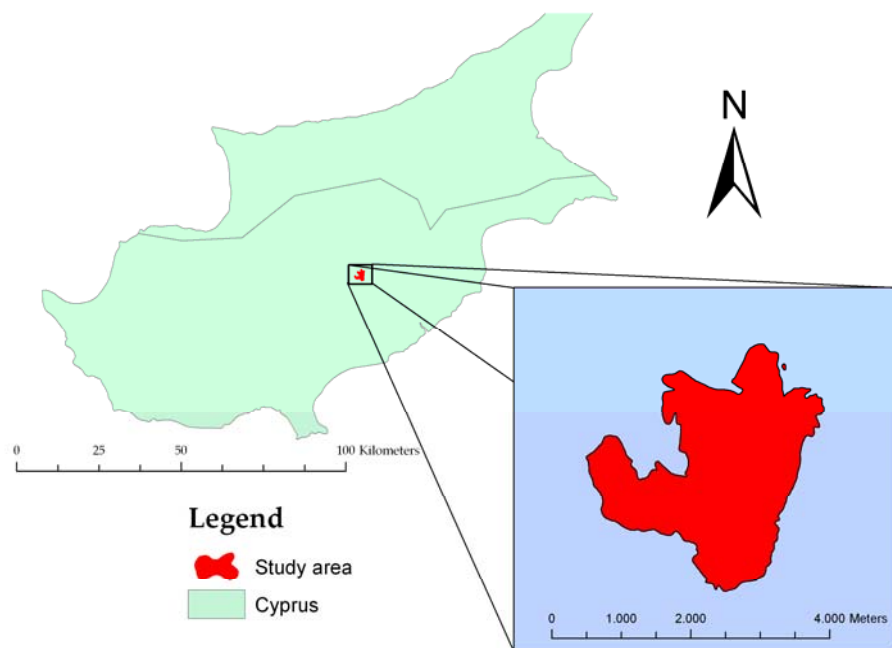


Figure 1. Lythrodontas study area location

- **Deiva Marina (Italy):** the fire started on the 5th of August 1998 and it burnt 612 ha. This study area represents a typical centre Mediterranean area. The vegetation structure consists mainly in coniferous forests with maquia. The principal tree species present is the Mediterranean pine (*Pinus pinaster*). The previous fire that affected this area was more than 15 years ago. Figure 2 shows the location of the study area.

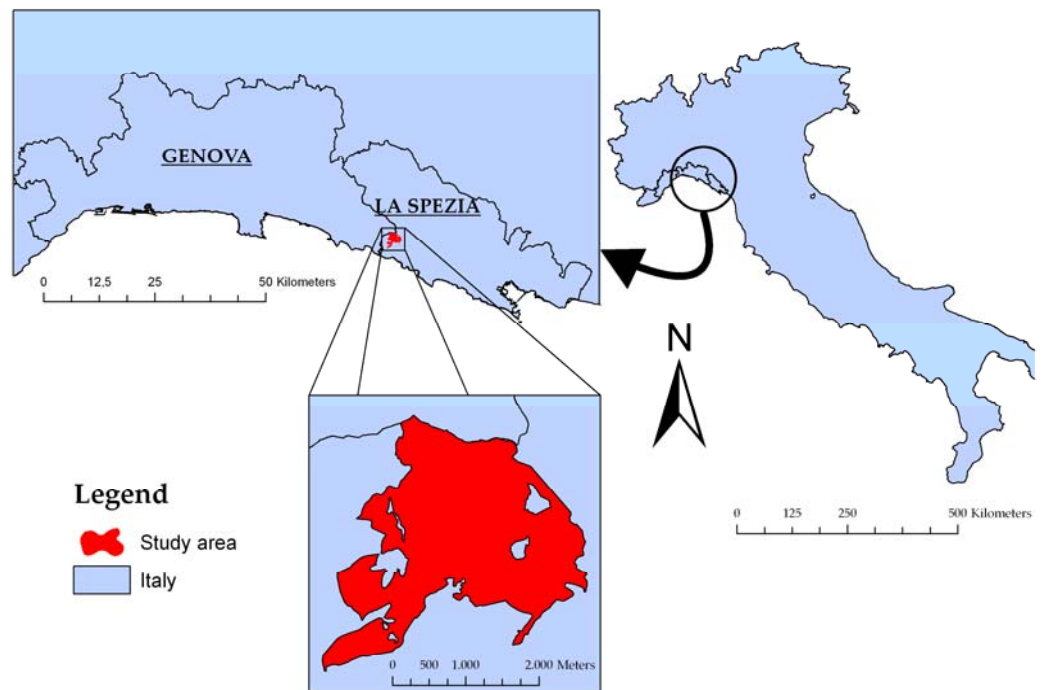


Figure 2. Deiva Marina study area location

- **Parra (South Portugal):** this study area burned during August 2003. The study area does not represent the limits of the fire, as the burnt area was much bigger. The limits correspond to the boundary of the Herdade de Parra, which is a public forest of 922 ha, managed by the Portuguese Forest Service of Portimao. It represents a typical western Mediterranean area, with a mixed forest of *Pinus pinaster* and *Quercus suber*, and an important presence of *Arbutus unedo*. This area has not burned for the last 20 years. Figure 3 shows the location of the Parra study area.

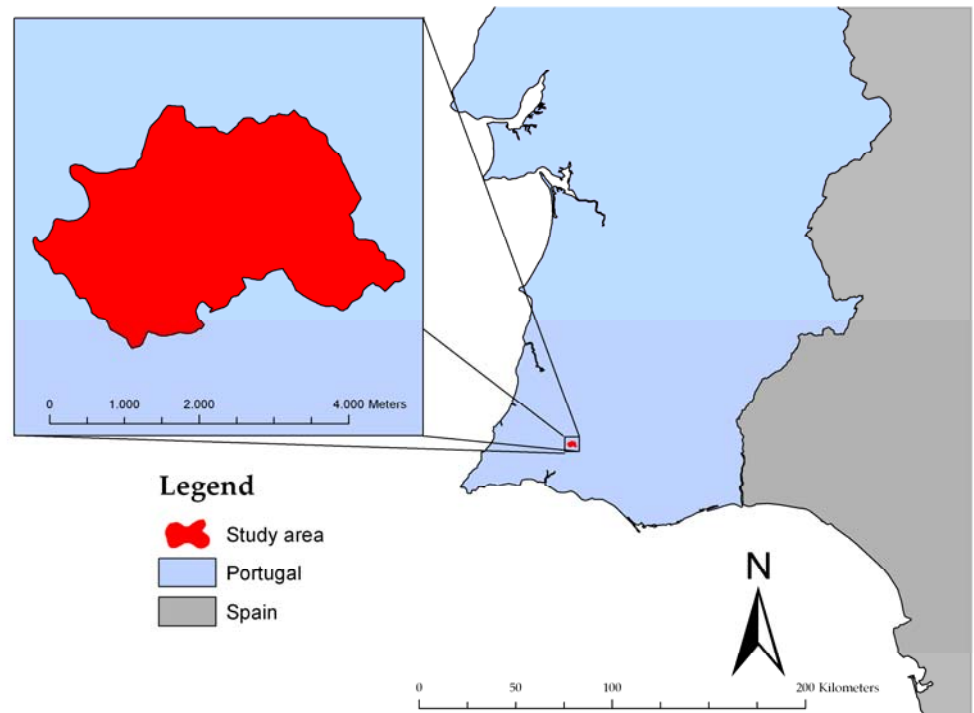


Figure 3. Parra study area location

- **Mação (Centre Portugal):** this study area burned during July 2003. The study area does not represent the limits of the fire, as the burnt area was much bigger. Therefore, a rectangular section of approximately 1250 ha was considered for the study. It represents a typical western Mediterranean area, with a forest of *Pinus pinaster*, and an important presence of eucalyptus plantations. This area has not burned for the last 20 years. Figure 4 shows the location of the Mação study area.

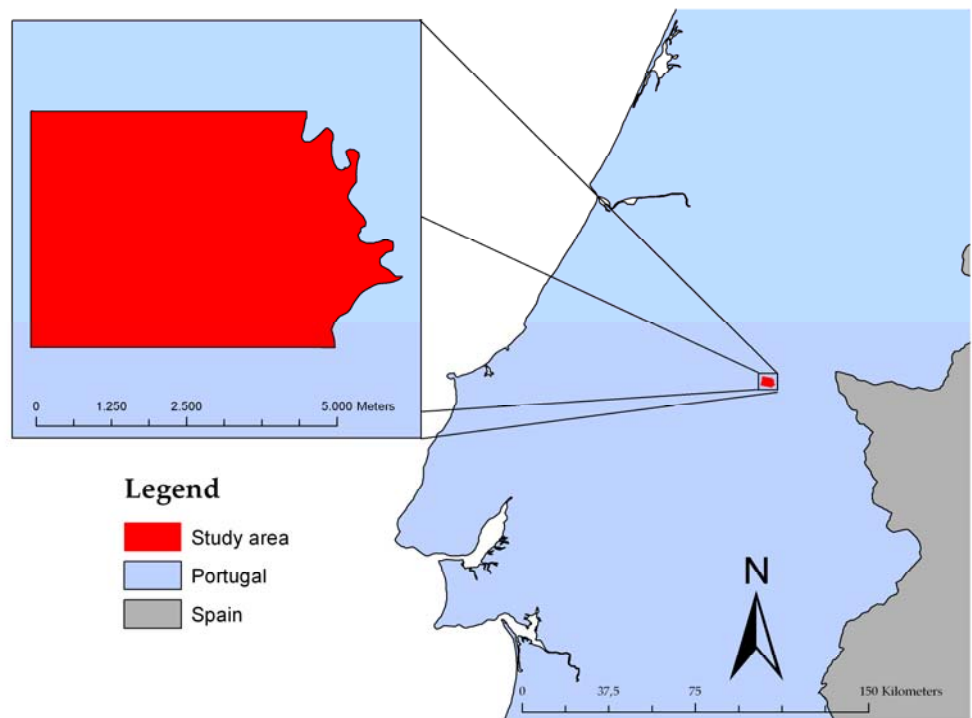


Figure 4. Mação study area location

3.2 SATELLITE, ANCILLARY DATA AND SOFTWARE ENVIRONMENT

3.2.1 Landsat TM and ETM+

Landsat data is commonly used for vegetation change studies (Adams *et al.*, 1995; Elmore *et al.*, 2000; Monteiro *et al.*, 2003; Peterson & Stow, 2003). Both Landsat TM and ETM+ were used within this study. The Landsat sensors have a spatial resolution of 30 m with six bands in the visible-infrared wavelength region (Table 1). The thermal band was not used in this research. Cyprus and Italy study areas were studied by means of this sensor.

Table 1. Characteristics of Landsat TM and ETM+ sensors.

TM & ETM+								ETM+
Band	1	2	3	4	5	6 (TIR)	7	8 (Pan)
μm	0.45-0.52	0.52-0.6	0.63-0.69	0.76-0.9	1.55-1.75	10.42-12.5	2.08-2.35	0.52-0.9
Pixel size	30	30	30	30	30	120 (60)	30	15

Source: <http://www.eurimage.com/products/landsat.html>

3.2.2 SPOT 2 and 5

Despite its poorer spectral information compared to other sensors, SPOT data has also been used for forest mapping (e.g. Dymon *et al.*, 1992; Souza *et al.*, 2003). The SPOT 2 sensor has a spatial resolution of 20 m with three spectral bands in the visible-infrared wavelength region. SPOT 5 includes a fourth spectral band on the middle infrared region, with increased spatial resolution to 10 m in all bands (Table 2). Southern Portugal study area was studied by means of this sensor.

Table 2. Characteristics of SPOT 2 and SPOT 5 sensors.

	SPOT 5		SPOT 2	
	Bandwidth (μm)	Spatial resolution (m)	Bandwidth (μm)	Spatial resolution (m)
Panchromatic	0.48 – 0.71	2.5 or 5	0.50 – 0.73	10
Band 1: Green	0.50 – 0.59	10	0.50 – 0.59	20
Band 2: Red	0.61 – 0.68	10	0.61 – 0.68	20
Band 3: NIR	0.78 – 0.89	10	0.78 – 0.89	20
Band 4: MIR	1.58 – 1.75	10	----	----

Source: www.spotimage.com (Las fichas técnicas –Resolución y modos espectrales–)

3.2.3 CHRIS-Proba

The Project for Onboard Autonomy (Proba) satellite was launched in October 2001. It follows a sun-synchronous orbit at an altitude between 681 and 561 km, with an inclination of 97,9 degrees. Its revisit period is about one week.

Proba's main payload is a hyperspectral instrument called CHRIS (Compact High Resolution Imaging Spectrometer). CHRIS acquires 14 km square images of the Earth's surface to a resolution of 18 m up to 18 spectral bands in the visible and near-infrared (NIR) region (Table 3). Centre Portugal images acquired with this sensor were used in this project in order to test its abilities in detecting vegetation regeneration.

Table 3. Spectral characteristics of CHRIS sensor.

Band	Min (nm)	Max (nm)
L1	420	421
L2	438	447
L3	486	495
L4	526	534
L5	546	556
L6	566	573
L7	627	636
L8	656	666
L9	666	677
L10	694	700
L11	700	706
L12	706	712
L13	738	745
L14	745	752
L15	773	788
L16	863	881
L17	891	900
L18	900	910

Source: <http://earth.esa.int/missions/thirdpartymission/proba.html>

3.2.4 Satellite and Ancillary Data used in the Project

3.2.4.1 LYTHRODONTAS STUDY AREA

Both Landsat TM and Landsat ETM+ images were available for this study area. Eight near anniversary images were acquired from 1999 to 2006 (see Table 4). Due to the problem that affected Landsat 7 sensor on 2003 (the Scan Line Corrector –SLC- remained off from that moment), it was preferably to use Landsat 5 images for the remaining years of the time series).

Table 4. Lythrodontas Landsat imagery characteristics

Date	Sensor	Path/Row	Cloud cover (%)	Sun azimuth (°)	Sun elevation (°)
20/7/1999	ETM+	176/36	18	116.2	64.25
7/8/2000	ETM+	176/36	12	123.09	61.14
25/7/2001	ETM+	176/36	30	116.85	62.83
28/7/2002	ETM+	176/36	10	117.61	62.28
23/7/2003	TM	176/36	10	113.54	61.25
25/7/2004	TM	176/36	30	114.97	61.62
28/7/2005	TM	176/36	20	117.61	62.18
31/7/2006	TM	176/36	10	120.59	62.77

The ancillary data available for the project in this study area consisted of:

- DEM of the Lythrodontas area (provided by the Forestry Department of the Government of Cyprus);
- Geometrically corrected Landsat RGB image (15 m resolution) of Cyprus (provided by the Joint Research Centre –JRC-);
- Several shapefiles containing information about the fire boundary, river and road networks and landuses of the area (provided by the Forestry Department of the Government of Cyprus).

3.2.4.2 *DEIVA MARINA STUDY AREA*

As in the previous study area, both Landsat TM and ETM+ were used for the same reasons. Ten near anniversary images were acquired from 1997 to 2006 (see Table 5).

Table 5. Deiva Marina Landsat imagery characteristics

Date	Sensor	Path/Row	Cloud cover (%)	Sun azimuth (°)	Sun elevation (°)
14/8/1997	TM	193/29	8	134.38	52.00
18/9/1998	TM	193/29	25	148.38	42.81
3/7/1999	TM	193/29	8	127.80	60.03
29/7/2000	ETM+	193/29	8	136.71	57.88
1/8/2001	ETM+	193/29	2	136.56	57.05
19/7/2002	ETM+	193/29	23	133.11	59.54
30/7/2003	TM	193/29	20	141.72	48.44
1/8/2004	TM	193/29	18	134.44	56.24
4/8/2005	TM	193/29	20	136.99	56.26
22/7/2006	TM	193/29	12	135.89	59.54

The ancillary data available for the project in this study area consisted of:

- DEM of the Deiva Marina area;
- Geometrically corrected Landsat RGB image (15 m resolution) of Liguria region (provided by the Joint Research Centre –JRC-);
- Several shapefiles containing information about the fire boundary, river and road networks and landuses of the area (provided by the Joint Research Centre –JRC-).

3.2.4.3 PARRA STUDY AREA

Both SPOT 2 and SPOT 5 sensors were used for this study area. No SPOT 5 pre-fire image was available, so a SPOT 2 image was acquired. Table 6 presents the satellite data used for this study area.

Table 6. Parra study area imagery characteristics

Date	Sensor	GRS ref	View angle (°)	Sun azimuth (°)	Sun elevation (°)
24/7/2002	SPOT 2	026/275	20.3	140.40	68.93
15/9/2003	SPOT 5	026/275	26.85	163.39	54.90
29/7/2004	SPOT 5	026/275	7.5	138.22	66.82
29/9/2005	SPOT 5	026/275	10.6	156.15	47.94
22/7/2006	SPOT 5	026/275	1.75	132.38	67.25

The ancillary data available for the project in this study area consisted of:

- DEM of the Parra area (provided by the Portuguese Forest Service);
- Orthophoto of the area with a spatial resolution of 0.5 m (provided by the Portuguese Forest Service);
- Several shapefiles containing information about the fire boundary, river and road networks and landuses of the area (provided by the Portuguese Forest Service).

3.2.4.4 MAÇÃO STUDY AREA

CHRIS-Proba images were available for this study area, but only post-fire images, as this experimental sensor was not programmed for acquisition over central Portugal until 2004. Table 7 presents the images available for this study area.

Table 7. Mação study area imagery characteristics

Date	Sensor	Mode	View angle	Sun azimuth (°)	Sun elevation (°)
08/6/2005	CHRIS-Proba	3 (Land)	Nadir	150.27	71.30
19/6/2006	CHRIS-Proba	3 (Land)	Nadir	147.36	71.46

The ancillary data available for the project in this study area consisted of:

- DEM of the Mação area (provided by the Camara Municipal de Mação);
- Orthophoto of the area with a spatial resolution of 0.5 m (provided by the Camara Municipal de Mação);
- Several shapefiles containing information about the fire boundary, river and road networks and landuses of the area (provided by the Camara Municipal de Mação).

4. METHODOLOGY

4.1 FIELD WORK

Sampling may be used to calibrate and validate remote sensing results and to relate detected radiometric change to actual bio-physical changes on the ground. The objective of collecting field data within this project is to compare the results obtained by means of the different image analysis methodologies with the field data in order to determine the most accurate image analysis method.

“Sampling” is a method of selection from a population, carried out in order to reduce the time and cost in examining the whole population. The resultant individuals that are sampled are known as *sample units* which in a geographical context are often areal units (Justice & Townshend, 1981).

Sampling techniques vary with the nature of the question being asked and the population sampled, but desirable characteristics of all sampling techniques are:

- a) Unbiased: the sample should be representative of the population as a whole.
- b) Repeatable
- c) Logistically feasible in the field

These characteristics can be fulfilled with a careful planning of the sampling performing a thorough research and selection of the most appropriate sample design, sample size and sample unit size and shape.

4.1.1 Sample Design

Sample design or sample scheme defines how the samples are distributed across the study area. Several statistical based sample designs have been defined, each one with their own characteristics and appropriate application environment. In studies where remote sensing data is used, the most applied sample designs are *simple random sampling* and *stratified random sampling* (Congalton, 2001; Twele, 2003). Congalton (1991) stated that the latter one, if the stratification of the area is possible, can overcome the problem of under-sampling areas that have a small size but are important for the study.

- Simple Random Sampling (SRS): is a sample design where each element in the population has an equal chance of being selected. It tends to under-sample small but potentially important areas (Congalton, 1991) mainly when the size of the study area to be sampled is big. The most successful use of this sample design occurs in relatively small geographical areas where a degree of homogeneity is known to exist. This is the case of burned areas, where fire acts as a landscape homogenization factor (Lloret *et al.*, 2002).
- Stratified Random Sampling (StrRS): is an area-frame sample design where the study area is first divided into subareas (strata), which are non-overlapping and together they comprise the whole study area (Figure 5). The criteria for the subdivision may be based on environmental heterogeneity (aspect, slope, forest classes, landcover...). Sampling units may be randomly chosen in such a way that the total number of samples would be distributed across all strata (to ensure that each stratum has the number of sampling units proportional to its area). Randomness provides good statistical properties that are important for further analysis of the results.

This type of sampling is the most appropriate for heterogeneous populations which can be subdivided into homogeneous strata. It attempts to minimize variability within different strata. The best results are achieved when there is a low intra-strata variance and a high inter-strata variance.

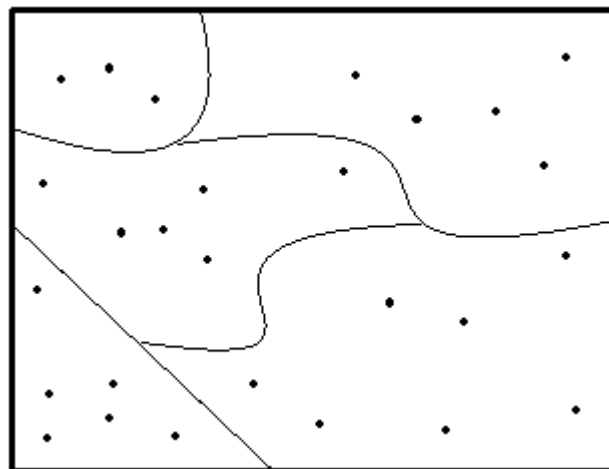


Figure 5. Stratified Random Sample example scheme.

Some advantages of this sampling scheme are: 1) ensures that each strata is well estimated, 2) can result in estimates with smaller standard errors if sampling is well allocated, and 3) different samples can be sampled with different sampling strategies. On the other hand, disadvantages are: 1) more complicated than SRS, and 2) need to identify strata ahead of field campaign time. Hence, more information needed prior to sampling than for SRS

4.1.2 Sample Size

Field sampling is quite consuming both in terms of time and money. Therefore, when determining the sample size, that is the number of samples to collect, one should try to minimize these costs. However, in order to preserve the statistical soundness of the sample, the size should be big enough: the larger the sample size, the greater the confidence one can have in assessments based on that sample (Justice & Townshend, 1981; Congalton, 1991; Banko, 1998).

The total number of segments chosen is usually expressed as the percentage of the total study area. Adequate sampling rates are normally between 0.5% and 2% (Taylor, J.C.; personal communication). Twele (2003), in his study of vegetation regeneration in the south of France, found that a minimum sample size of 0.075% of the total pixels of each stratum was appropriate in relation to time constraints and the scope of his study.

4.1.3 Sample Unit

Resolution of the imagery and inherent variability of the terrain are the two factors that control size of the sample unit. In remote sensing, spatial resolution is defined as the size of the image minimum unit of information, known as pixel (picture element) (Chuvieco, 2002). Thus, the pixel provides a clear basic sample unit. However, it should be noted that the pixel should not be used as the sampling unit because of our inability to accurately locate it on the ground (even using GPS) and on the imagery (Justice & Townshend, 1981; Banko, 1998; Puhr & Donoghue, 2000; Congalton, 2001). Congalton (2001) proposes as sample unit a 3x3 grouping of pixels, or a user-defined polygon. As a simplified approach, it would help on fastening the process of sample unit size calculation, giving

enough statistical robustness for the analysis of the data. On the other hand, it could lead to an over-calculation of the sample size needed to fulfil satisfactorily the statistical requirements. Justice & Townshend (1981) proposed a formula (Equation 1) to determine the minimum dimensions of the sample plot:

Equation 1

$$A = [P(1 + 2L)]^2$$

where:

A = minimum dimensions of the sample plot in m²

P = pixel dimensions in metres

L = geometric accuracy of satellite data (in number of pixels)

It should be mentioned that increasing the size of the plot generally results in a lower variance in the observations (Arvanitis & Portier, 1997). This is important to bear in mind when dealing with natural or semi-natural forest ecosystems because of the spatial variability of their canopy structure (Puhr & Donoghue, 2000). This canopy variability combined with the use of low resolution satellite imagery would require the use of large sample units. Despite the reduction of the variance in the observations, large units could lead to logistic problems during the survey. Justice & Townshend (1981) suggested that to overcome this problem and to ensure that observations are representative of the unit as a whole, a scheme of sampling within the unit could be devised (using smaller areal subunits or line transects).

Regarding the shape of the sample units for remote sensing applications, they should be preferably rectangular or square, and orientated parallel to the scan lines for ease of location (Justice & Townshend, 1981).

4.1.4 Sample Unit for Vegetation Cover Sampling

The most commonly used sample units for sampling vegetation cover fraction are the *Quadrat Sampling Method* and the *Line-Intercept Sampling Method*.

- a) Quadrat Sampling Method (QSM): The term “quadrat” refers to a plot that can be a square, rectangle, circle or other regular shape area used as a sample unit. Quadrats are not natural sampling units and one must choose the dimensions and shape of the quadrat prior to implementation. The spatial pattern obtained and the resulting index of dispersion (precision and accuracy of the parameter estimates computed) depends on quadrat size and shape. Regarding quadrat shape, it is important to consider the edge effect, which could lead to miscounting errors, as every time an individual is at the edge a decision must be made. This requires the definition and adoption of some reasonable conventions. The more edge to the quadrat, the more opportunity to miscount individuals. The ratio of length of edge to the area inside a quadrat is:

$$CIRCLE < SQUARE < RECTANGULAR$$

However, long thin quadrats are better than circular or square ones of the same area. The reason for this lies on the habitat heterogeneity: long quadrats cross more patches.

Arvanitis & Portier (1997) argued that quadrats are the sampling unit of choice when the parameter of interest relates to area coverage or density.

The size of the quadrat in vegetation studies depends on the local conditions of the study site and the population being studied. There are several size definitions in the literature depending on the type of vegetation sampled, and even different quadrat sizes for the same type of vegetation. Arvanitis & Portier (1997) proposed 10 m² plots for bushes, shrubs and saplings up to 4 m tall, and 100 m² plots for mature forest trees over 4 m tall.

- b) Line-Intercept Sampling Method (LISM): line intercepts, also called line segments are often used as sampling units when attempting to estimate coverage of a species in a habitat. The fraction of a line which crosses a vegetation patch is proportional to the fraction of total area covered by the vegetation. They are used when resources are limited, quadrats may be impractical or too time consuming and what is needed is a quick method of

selection of individuals for observation or measurement (Arvanitis & Portier, 1997). To estimate cover with this method, one has to assume that either (a) the individual vegetation patches are randomly oriented with no preferred orientation of the major axis of the patch or, (b) the sample lines are randomly oriented across the study area.

This method is suited for most forest and rangeland communities and is used mainly to monitor changes in plant species cover and height for a macroplot. It uses multiple line transects to sample the variation within the plot and to quantify statistically changes in plant cover and height over time. The line transect is typically a measuring tape which contacts the vegetation canopy, either at the ground or at a certain height (Figure 6). Percent cover is sampled by recording the length of intercept for each plant measured along the tape by noting the point on the tape where the plant canopy begins and the point on the tape where the plant canopy ends (Figure 7). Each stratum is considered as if other stratum did not exist. This means that in case of overlaps between shrubs and trees, each one is measured in its complete length (Figure 8).



Figure 6. The measuring tape is stretched tight below, in or above the canopy vegetation , whatever position allows the easiest estimation of cover without zigzagging around plants.

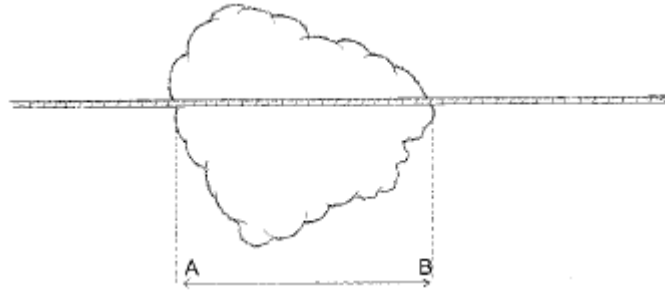


Figure 7. The canopy intercept is measured along the measuring tape in centimetres.

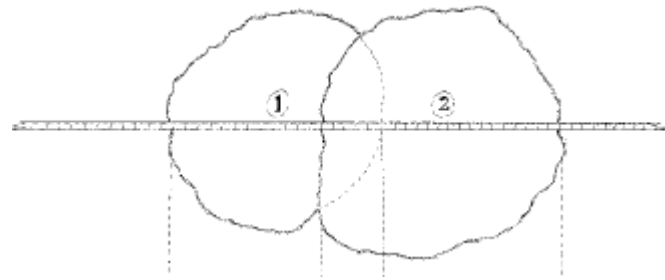


Figure 8. Overlap phenomenon example.

In order to get percent cover, the intercept lengths of the plants found along the metric tape are summed and divided by the total transect length. The result obtained is the percent cover for the vegetation strata along the transect (Equation 2).

Equation 2

$$Cover \% = \frac{\sum_{i=1}^n (e - s)_i}{L}$$

where:

e = ending point on the tape where the plant canopy ends.

s = starting point on the tape where the plant canopy begins.

L = total length of the transect.

4.1.5 Field Work Methodology Implemented in the Project

The sample design that was selected for the field work within this project was Simple Random Sampling. Its simplicity, statistical robustness, the relatively small size of the study areas (500 ha) and the high degree of homogeneity present in them justified this selection.

Sample size was one of the most difficult factors to establish due to time constraints of the project. Lythrodontas and Deiva Marina study areas are the smallest in size (around 600 ha each). Their size, together with the spatial resolution of the sensor used for their analysis (Landsat) allowed defining a minimum sample size of 1% of the total study area. This sample size was considered feasible for these two study areas. The two Portuguese study areas are the biggest in size (around 1000 ha each). Their size, together with the spatial resolution of the sensors used for their analysis (SPOT and CHRIS) allowed defining a minimum sample size of 0.5% of the total study area.

The shape of the sample unit in remote sensing based studies is normally a square (as the pixel shape) in order to locate it accurately on the images. Sample unit size depends on the spatial resolution of the sensor used (Justice & Townshend, 1981). Therefore, for this project three different sample unit sizes were defined: one for Landsat imagery based study areas (Lythrodontas and Deiva Marina), one for SPOT imagery based study area (Parra) and one for CHRIS-Proba imagery based study area (Mação). The formula proposed by Justice & Townshend (1981) was used, considering the pixel size of each sensor, and a minimum geometric accuracy of 0.5 pixels. This yielded the sample unit minimum size for each sensor:

- Sample unit minimum size for Landsat study areas = 60x60 m
- Sample unit minimum size for SPOT study area = 20x20 m
- Sample unit minimum size for CHRIS-Proba study area = 36x36 m

Due to the time constraints, there was no possibility to survey completely the square. Therefore the use of transects across the whole sample plot was performed by implementing the Line Intercept Sampling Method. This method was also selected

because the cover measured with LISM is less prone to observer bias than ocular estimates of cover in quadrats. Orientation of transects within the plot was set to constant for this project in order to ease the location of the same transects when repeating the field work campaign. Thus, the assumption adopted within the method was that individual vegetation patches are randomly oriented with no preferred orientation of the major axis of the patch. Four transects were determined in each plot; their directions were N, E, S and W, starting at the centre of the plot.

In order to get meaningful comparisons between both field and remotely sensed data, the collection of the former one should be synchronous with the acquisition of the images (Justice & Townshend, 1981). In annually-spaced multi-temporal studies, all the images should be from the same date or the closest possible between them temporally. Therefore, field work was planned for the dates when the images were going to be acquired.

The material used in each campaign consisted:

- GPS for locating the plots (depending availability, a Garmin ETREX or a Trimble Pathfinder ProXRS were used).
- Clinometer in order to determine the slope present in the plot.
- Metric tape
- Iron stick to fix the metric tape at the centre of the plot. This maintained the centre of the plot well located.
- Local flora book.
- Study area map
- Field forms: it was devised as one only DIN-A4 sheet for ease of use. These forms can be found in Appendix A of this thesis. General characteristics of each plot were stated in the front page, while the line-intercept records were stated in the back page. Different code forms were used to homogeneously characterize the different plots. Even if only one surveyor was performing the field work, some guidelines are necessary to maintain the criteria while carrying out the work and also between different field campaigns.

4.2 PRE-PROCESSING

4.2.1 Need of Pre-processing

Pre-processing of satellite sensor images prior to actual change detection or multi-temporal spectral analysis is essential and has as its unique goal the establishment of a more direct linkage between the data and biophysical phenomena, the removal of data acquisition errors and image noise, and the masking of contaminated (e.g. clouds) and/or irrelevant (e.g. water bodies when looking at changes in vegetation) scene fragments (Coppin *et al.*, 2004).

Two aspects of the pre-processing step in a change detection study are of enormous importance: multi-date image registration and radiometric rectification. Accurate spatial registration of the multi-date imagery is essential to digital change detection. However, the spatial resolution of digital imagery affects the precision of this registration rendering impossible an absolute accuracy. Thus, a certain amount of within-pixel shift is inherent to any digital change detection study and consequently, change detection capabilities are intrinsically limited by this (Coppin *et al.*, 2004).

The second aspect for successful change detection is that a common radiometric response is required for quantitative analysis of one or more image pairs acquired on different dates. Therefore, radiometric properties of an image need to be adjusted to those of a reference image (normalization).

Different sources of error affecting regeneration detection have been identified. They can be grouped in two categories: parameters that affect the calibration of the sensor, and factors that affect the solar radiation in its complex path from the Sun to the Earth and back to the sensor (Pons & Solé-Sugrañes, 1994). Atmospheric correction uncertainty, topographic effects, sun and sensor angles, and shifts in the phenological state of the vegetation between data acquisition due to interannual or seasonal climate differences are some of the factors that affect the solar radiation received by the sensor.

It has been proved that a strict and thorough pre-processing must be carried out when willing to compare images through time. Henry & Hope (1998) proved that variations in illumination and atmospheric conditions, scene background and sensor calibration deeply

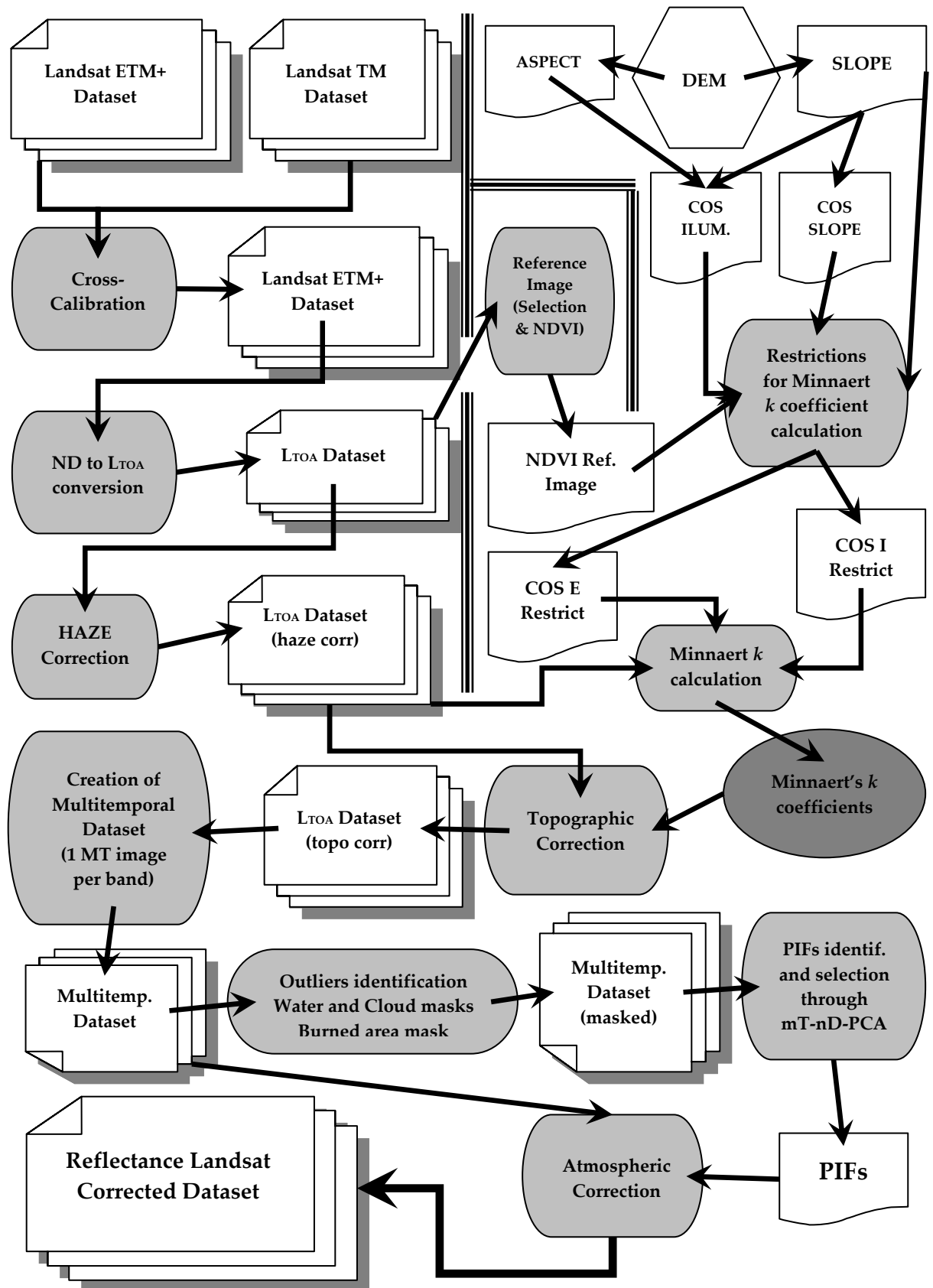
affect NDVI signal corresponding to changes in vegetation. As the aim of this project is to detect changes due to regeneration of burned areas, a strict and thorough pre-processing must be carried out.

Even though some of the data acquired for this project has already some kind of pre-processing done, this has to be checked and in most of the cases redone. The pre-processing criteria of the methodologies applied by the image servers do not meet the accuracy which this project requires.

Pre-processing comprises different groups of image corrections: *Geometric Correction/Orthorectification*, *Radiometric Correction*, *Topographic Correction*, and *Atmospheric Correction*.

- The first group (Geometric Correction/Orthorectification) changes the location/coordinates of the image pixels without aiming to change the digital numbers (DN) of the image.
- Radiometric Correction transforms the DN of the image into meaningful physical units (radiance and/or reflectance).
- Topographic Correction aims at removing effects on the signal received by the sensor derived from the slope and aspect of the area of interest.
- Atmospheric Correction aims at removing the effects of the atmosphere from the signal received at the sensor. This sets the dataset to a common radiometric scale.

4.2.2 Pre-Processing Flowchart



All the steps of the pre-processing process were implemented by constructing models with the ERDAS Model Maker tool. These models can be consulted in the Appendix B of this thesis.

4.2.3 Geometric Correction

Traditionally, geometric correction has been considered as a previous and unavoidable operation to any kind of analysis performed on the image. However, during last years, the need of geometric correction prior to any analysis has been discussed. In several types of products derived from satellite images, the geometric correction is applied as a last step of the analytical process (e.g. uni-temporal classification maps). However, in certain applications, geometric correction remains an obligate step prior to the analysis of the images (e.g. multi-temporal studies, studies that need to cross the satellite data with ancillary data, cartographic products derived from satellite images). In these applications, the quality and accuracy of the final product depends strongly on the accuracy of the geometric correction, as commonly these kind of studies are implemented in a pixel-per-pixel basis. Thus, if an important geo-location error is present between the images, the results obtained can be considered non reliable. The present study can be included in the second case, as a change detection study needs to be carried out with several images taken over a defined time period.

The majority of the geometric correction methods consists in the following three steps:

1. Localization of common points between the image and a reference image already correctly geo-referenced. Distinctive objects in both images should be detected and then the coordinates in both images should be recorded.
2. Calculation of transformation equations. Type and parameters of the mapping functions, aligning the sensed image and those detected in the reference image should be established, by computing the relations between the coordinates recorded in step one.
3. Image resampling and transformation. Transform equations are applied and as a last step –resampling-, digital numbers (DN) must be placed in their correct

defined position. This resampling can be applied in two manners: the first maintains the original values of the DN only relocating them into the nearest correct position (Nearest Neighbour resampling method), and the second applies some kind of calculation, modifying the original value of the DN (Bilinear Interpolation and Cubic Convolution resampling methods).

The objective of the geometric correction is to relocate as accurately as possible the image in its correct geographic position (geo-referencing). This is done in a bi-dimensional way, as the coordinates taken into account are X and Y. In order to achieve this bi-dimensional relocation and at the same time remove erroneous image displacements caused by the interaction between terrain relief or local elevation changes and sensor orientation variations, an orthorectification process should be carried out (Tucker *et al.*, 2004). The use of a digital elevation model (DEM) and ground control coordinates (Ground Control Points –GCP-) is the most used technique and probably the most accurate when working with sensor platforms lacking accurate orientation parameters (García-Haro *et al.*, 2001; Chuvieco, 2002; Twele, 2003; Tucker *et al.*, 2004). This technique has been defined as an empirical geometric correction technique. Empirical models are applied when no ephemeris data or other explicit information on the sources of geometric distortions are available (Armston *et al.*, 2002).

Another step could be added in this first group regarding multi-temporal studies: image-to-image registration (Chuvieco, 2002; Twele, 2003). It is indeed a crucial step in studies based in satellite imagery aiming to extract information from the combination of several images like change detection analysis. Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors (Zitová *et al.*, 2003). Regardless of approach of the change detection analysis, temporal sequences of images need to be geometrically registered to sub-pixel accuracy to avoid spurious results when detecting changes in reflectance for land cover (Armston *et al.*, 2002). This ensures that the set of images used in the study are spatially matching and, therefore, comparison and operations between them can be carried out, minimizing miss-registration errors.

Accuracy analysis of the geometric correction/Orthorectification process should involve two measures: *quality of the adjustment* and *quality of the correction*. The former evaluates how the polynomial transform equations (PTE) calculate the coordinates of the GCP on the new reference projection. This adjustment might be very accurate, or even perfect, but it does not give guarantees of the final product quality. The quality of the correction, on the other hand, is a location accuracy measure of the final product. This measure can only be obtained through a set of GCP independent from the set used for the correction.

For each one of the sensors used in this study, the geometric correction applied by the image providers, if existing, was checked and evaluated. As expected this correction did not meet the accuracy requirements for this project. Thus, geometric correction was redone.

The GCP methodology combined with the use of a DEM has been used for geo-referencing the images. This has been carried out by selecting common points (GCPs) between the image and the cartographic map and/or orthophoto from which their coordinates both on the map/orthophoto and on the image could be determined. Permanent features such as cross-roads, buildings, mountain tops, have been collected as GCPs. With this set of points the polynomial transform equations (PTE) were calculated. These equations give the mathematical relationship between the distorted image and the desired corrected image. A re-sampling step is needed in order to place the DN of the original image in the geometrically corrected image. The re-sampling technique used was the Nearest Neighbour one, as is the only one that preserves the original brightness values taken by the sensor. Topographic relief may add displacement errors that have to be corrected in order to optimize the accuracy of the geometric correction. For that purpose a DEM was integrated in the process in order to obtain the z coordinate of the GCP's defined. Accuracy of the results was checked by means of the RMS error of the adjustment (quality of the adjustment), and by choosing independent points and comparing their coordinates in both the reference map and the corrected image (quality of the correction).

4.2.4 DN to Physical Units Transformation

Radiometric correction or sensor calibration aims to remove the gain and offset effects introduced by the imaging system (Chavez, 1996) and is a necessary prerequisite to atmospheric correction methods that further convert apparent at-satellite radiance to surface reflectance. The intensity of electromagnetic radiation which reaches the detectors of a sensor is recorded as voltage and stored in digital numbers (DN) for each spectral band. Calibration values are commonly listed in the satellite image header files or technical notes of the data supplier to permit to recalculate the original radiance values and hereby to neutralise the effects of calibration when different sensors are compared (e.g. Landsat TM and ETM+).

Using calibrated values of at-sensor radiance instead of raw DN is particularly crucial when multi-temporal and multi-sensor satellite data is used. Calibration parameters used to store digital numbers can be different from each other, producing unfavourable effects when not accounted for. Additionally, it is desirable to derive the actual energy recorded by a satellite sensor in units of radiance or reflectance instead of unitless digital numbers, as DN is a function not only of plant and soil conditions, but also of sensor calibration, solar zenith angle, sensor viewing angle, seasonally variable Earth-sun distance, and diurnally variable atmospheric conditions (Moran *et al.*, 2001).

Different sensors (e.g. Landsat TM and Landsat ETM+) were used simultaneously in single study areas in this project. Teillet *et al.* (2001) showed how between Landsat TM and ETM+ there are significant differences in their radiometric responses. As inter-comparability between images was required for the aim of this thesis, a cross-calibration step was implemented before any radiometric correction following the indications of Vogelmann *et al.* (2001). By using the *slope* and *intercept* values provided by the latter (Table 8), Landsat TM digital numbers were converted to Landsat ETM+ digital numbers with Equation 3:

Equation 3

$$L5' = L5 \cdot \text{slope} + \text{intercept}$$

where $L5'$ represents Landsat TM digital numbers converted to Landsat ETM+ digital numbers, and $L5$ represents original Landsat TM digital numbers.

Table 8. Cross-calibration coefficients between Landsat TM and Landsat ETM+

Band	Slope	Intercept
1	0.94	4.29
2	1.77	4.73
3	1.53	3.98
4	1.42	7.03
5	0.98	7.02
7	1.30	7.66

A DN to physical units transformation was then applied to each band of all images in order to transform the DN into top-of-atmosphere (TOA) spectral radiance. Information about specific calibration coefficients of each sensor type coming with each satellite image header file were used in order to apply this transformation. Appropriate conversion equations were applied for each type of sensor used in this project.

For Landsat sensors Equation 4 was applied to transform DNs into TOA spectral radiance (L_λ) ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$):

Equation 4

$$L_\lambda = DN \cdot \text{gain} + \text{offset}$$

where *gain* ($\text{W m}^2 \text{sr} \mu\text{m DN}^{-1}$) and *offset* (DN) are the calibration coefficients for each band obtained from the image header file

For SPOT images the transformation from DNs into TOA spectral radiance was achieved using Equation 5 (Bishop & Colby, 2002):

Equation 5

$$L_\lambda = \frac{DN}{\alpha}$$

where α ($\text{DN m}^2 \text{sr} \mu\text{m W}^{-1}$) is the absolute calibration coefficient for each band.

CHRIS-Proba images were supplied from the image server directly in TOA spectral radiance units. Thus, this step was skipped for that study area.

4.2.5 Topographic Correction

Measured spectral radiances also vary according to the irregular shape of the terrain, just as they are subject to the effects of atmospheric and illumination conditions (Teillet *et al.*, 1982). Different solar illuminations derived from slope and aspect are notorious especially in the shadow areas (Figure 9), which show less than expected reflectance, whereas in sunny areas the effect is the opposite (Riaño *et al.*, 2003).

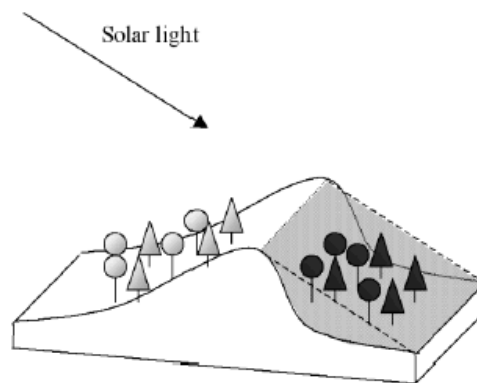


Figure 9. Effect of topography on reflectance (from Riaño *et al.*, 2003)

The actual availability of DEM allows performing this correction with more guarantees than when using band ratios (methodology that does not account for scene physical behaviour). Several correction methods have been developed for removal of the topographic effect by means of a DEM (Teillet *et al.*, 1982; Leprieur *et al.*, 1988; Ekstrand, 1996).

Two groups that uses this approach can be identified: the first group uses the Lambertian assumption, being a Lambertian surface a perfect diffuse reflector (surface reflectance is assumed to be isotropic, that is, reflectance is equal in all directions –Teillet *et al.*, 1982-); the second group does not use this assumption, trying to model the non-Lambertian behaviour of the majority of surfaces.

The Lambertian models are easy to use and to apply but they only correct changes in the illumination due to the orientation of the surface, while non-Lambertian models correct for variations of not only the sun incidence angle but also the sensor location (García-

Haro *et al.*, 2001). The most common non-Lambertian model is the Minnaert model (Minnaert, 1941). This model uses the constant k to indicate the extent to which the surface shows Lambertian behaviour ($k=1$, for perfect Lambertian surfaces). This constant k describes the bidirectional reflection distribution function (BDRF) of the surfaces and is related to the surface roughness. Several studies have chosen this approach due to its relative simplicity and better performance (García-Haro *et al.*, 2001; Martínez *et al.*, 2002; Twele, 2003; SPREAD project, 2004).

The Minnaert model was used in this project as all the study areas have moderately high relief. DEMs for each study area were used to compute the sun incidence angle (γ_i), that is, the angle between the sun rays and the normal to the ground (Figure 10). The cosine of this angle models the illumination conditions, and is computed as follows:

Equation 6

$$IL = \cos \gamma_i = \cos \theta_p \cdot \cos \theta_z + \sin \theta_p \cdot \sin \theta_z \cdot \cos(\phi_a - \phi_o)$$

where:

IL = illumination factor

θ_p = slope angle of the terrain

ϕ_a = solar azimuth angle

γ_i = sun incidence angle

θ_z = solar zenith angle

ϕ_o = surface aspect angle

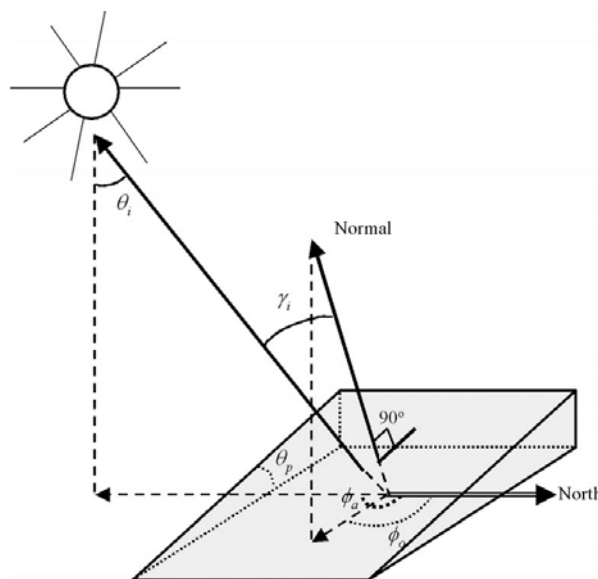


Figure 10. Angles involved in the computation of IL (from Riaño *et al.*, 2003)

Once the sun incidence angle is computed for the whole image, the normalized reflectance of each pixel should be estimated. The Minnaert model approach requires the calculation of a landcover-specific photometric constant (k), which, as stated above, models the non-Lambertian behaviour of the terrain. Its value was calculated for each band, as k varies with wavelength, by linearizing the following Equation 7 (Colby, 1991; Tokola *et al.*, 2001; García-Haro *et al.*, 2001; Riaño *et al.*, 2003):

Equation 7

$$L_{\lambda}^{hc} = L_N \cdot \cos^k \gamma_i \cdot \cos^{k-1} \theta_p$$

where L_{λ}^{hc} is the haze corrected (hc) TOA spectral radiance observed over sloped terrain (see section 4.2.6 for an explanation on why is used haze corrected radiance instead of TOA radiance), and L_N is the normalized radiance obtained after the application of the normalization process (both in $W \text{ m}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$).

On the resultant Equation 8:

Equation 8

$$L_{\lambda}^{hc} \cdot \cos \theta_p = L_N \cdot \cos^k \gamma_i \cdot \cos^k \theta_p$$

$\log$ of both sides are taken, yielding a linear equation:

Equation 9

$$\log(L_{\lambda}^{hc} \cdot \cos \theta_p) = \log L_N + k \cdot \log(\cos \gamma_i \cdot \cos \theta_p)$$

This Equation 9 is in the linear form $y = kx + b$ where:

$$y = \log(L_{\lambda}^{hc} \cdot \cos \theta_p), \text{ the dependent variable,}$$

$$x = \log(\cos \gamma_i \cdot \cos \theta_p), \text{ the independent variable,}$$

$$b = \log L_N,$$

$$k = \text{Minnaert's constant.}$$

From Equation 9 the Minnaert constant k can be calculated easily for implementing it in the topographic normalization process. The use of this equation can be implemented

either by considering for calculation the entire image (global k) or using *a priori* knowledge of the study area for stratifying the landcover and computing the Minnaert value for particular strata (local k). The problem with the first approach is that it assumes the anisotropic nature of reflectance is homogeneous over the image (SPREAD project, 2004). Terrain relief and landcover heterogeneity yield this assumption invalid resulting in spatially non-consistent normalization results. The local k approach requires a thorough knowledge of the area in order to have a large enough input data set. The quantity of effort and time dedicated to get this *a priori* knowledge might be a strong limitation.

Garcia-Haro *et al.* (2001), Martinez *et al.* (2002) and SPREAD project (2004) proposed a compromise between the two approaches: only pixels that accomplish for certain conditions would be considered in the computation of the Minnaert value. These conditions are related, firstly, to the slope, constraining the calculation to the areas with certain degree of slope, avoiding flat areas that would mask the normalization (a significant value could be $slope > 10^\circ$). Another constraint would be related to the vegetated character of the area, using only these pixels with an NDVI value greater than, i.e. 0,1 (based on radiance values –SPREAD project, 2004–). The dataset obtained using these conditions is big enough and leaves out of consideration areas that may blur the normalization (flat areas), and areas that are not of interest for the study (i.e. soil areas in vegetation monitoring studies). This last compromise between a global k and a local k was implemented in this project. A slope map was produced for each study area from the corresponding DEM. Then areas with slope greater than 15° were selected for the extraction of k . In order to apply the NDVI constraint, an NDVI image was produced from the pre-fire image for each time series and then areas with less than 0.2 NDVI were eliminated for the extraction of k .

Once the k constants for each band of each image were computed, the topographic normalization was implemented using Equation 10 (Martínez *et al.*, 2002):

Equation 10

$$L_N = L_{\lambda}^{hc} \cdot \omega = L_{\lambda}^{hc} \cdot \frac{\cos^k \theta_z}{\cos^k \gamma_i \cdot \cos^{k-1} \theta_p}$$

where ω is a measure of the topographic effect. When this value is lower than 1 indicates that the pixel is sun oriented. If it is greater than 1 indicates that the pixel is obscured.

Following the recommendations of European Commission (2000) and SPREAD project (2004), the topographic correction was performed prior to the atmospheric correction. By doing this, the possible reduction of radiance values in areas with low illumination that could appear if atmospheric correction was done first was avoided.

4.2.6 Atmospheric Correction

Atmospheric corrections could be divided into two groups: *absolute atmospheric correction methods*, and *relative atmospheric correction methods*. The former use radiative transfer models in conjunction with *in situ* atmospheric measurements. These techniques are more precise, but also complex as they require collection of atmospheric measurements at the time of data acquisition, which are very difficult to obtain when using historical remotely sensed data. The software packages most applied in absolute correction methods are MODTRAN (Berk *et al.*, 1989) and 6S (Vermote *et al.*, 1997). Relative atmospheric correction methods usually do not require these atmospheric measurements, using instead information within the images.

Schott *et al.* (1988) proposed a scene-to-scene normalization technique (relative correction method) called Pseudo Invariant Features technique (PIF technique) which corrects for atmospheric degradations, illumination effects, and sensor response differences in multi-temporal multi-spectral imagery. This technique allows comparison between images acquired at different moments, avoiding the masking of true changes due to non-scene-dependent changes. With this technique, no ground truth or elaborate atmospheric measurements or models are required (Schott *et al.*, 1988; Caselles & López, 1989). Pons & Solé-Sugrañes (1994) pointed that Caselles & López (1989) obtained results very similar to those given by the 5S code. Henry & Hope (1998) also applied this technique and checked the results by implementing regressions between the corrected images and the reference image, obtaining for all of them 1:1 relations in the plotted regressions. Martinez *et al.* (2002) applied this technique in combination with absolute atmospheric correction methods, in order to establish an accurate atmospherically corrected reference image. PIF

technique was then applied to the rest of the images with the former image as a reference. In the same line, Hall *et al.* (1991) pointed that if sensor calibration and atmospheric turbidity data are available for any one of a sequence of atmospherically rectified images (relative atmospheric correction method similar to the PIF technique, differing in how the scene atmospheric control sets are obtained), the calibration data, an atmospheric radiative transfer code, and the atmospheric turbidity data from the one image may be used to correct each image in the sequence to absolute surface reflectance. This would allow relating temporal image normalized satellite data with ground measurements since relative methods on their own are not suitable for quantitative analysis in combination with ground data.

A drawback of applying this technique in forest environment would be that PIF are not common in these areas, since these PIF normally are human-made structures such as roads, parking lots, roofs (Schott *et al.*, 1988). However, it could be possible to implement if natural PIFs are present in the scene: sand, water, bare soil (Caselles & López, 1989; García-Haro *et al.*, 2001), which is more common in predominantly natural landscapes.

Also, several authors have pointed that the selection of PIFs is subjective as it depends on a visual analysis (Song *et al.*, 2000; Janzen *et al.*, 2006; Du *et al.*, 2002). Therefore, several alternative methodologies have been proposed in order to objectively select these PIFs. Statistical methods using Principal Components Analysis (PCA; Du *et al.*, 2002), the Pseudo Invariant Features Regression method (PIFR; Janzen *et al.*, 2006), the Multivariate Alteration Detection (MAD; Canty *et al.*, 2004) are some of the alternatives that have been developed in the last years.

A combination of absolute and relative atmospheric corrections techniques was implemented in this project.

As a first step and before the topographic correction, a haze correction was applied to the TOA spectral radiance images, in order to eliminate the atmospheric scattering component in advance as suggested by some authors (Ekstrand, 1996; Martínez *et al.*, 2002). This was done by means of the image-based dark-object subtraction technique (DOS –Chavez, 1988-). The DOS model assumes that some pixels of the image are

completely shadowed and that the radiances received at the satellite from these pixels are due to atmospheric scattering (path radiance). Therefore this path radiance term should be subtracted from the TOA radiance of the image pixels in order to eliminate the atmospheric scattering effect (Equation 12). However, very few targets on the Earth's surface are absolutely black, so it is assumed that any object has a minimum reflectance of 1% (Chavez, 1996). This 1% has to be subtracted from the path radiance in order to obtain the amount of radiance produced by the atmospheric scattering (Equation 11).

Equation 11

$$L_{haze} = L_{min} - L_{1\%}^{\rho}$$

where L_{haze} is the upwelling atmospheric spectral radiance scattered in the direction of and at the sensor entrance pupil and within the sensor's field of view, i.e. the path radiance, L_{min} is the minimum TOA spectral radiance level present in the image, and $L_{1\%}^{\rho}$ is the radiance equivalent to a reflectance of 1%.

The haze corrected images were obtained applying Equation 12.

Equation 12

$$L_{\lambda}^{hc} = L_{\lambda} - L_{haze}$$

where L_{λ}^{hc} is the haze corrected TOA spectral radiance, and L_{λ} is the TOA spectral radiance.

Once the haze correction was applied, and after the implementation of the topographic correction, a *reference image* was selected in each time series by checking the lower path radiance term (L_{haze}), which ensures that the image selected is the most haze and cloud free image of the series. The selected reference image was then converted from haze corrected TOA spectral radiance units (L_{λ}^{hc}) to surface reflectance units (ρ_s) by means of the cosine of the solar zenith angle correction (COST method -Chavez, 1996-) which is considered as an absolute atmospheric correction. This method has proven to be as accurate as the methods that use *in situ* atmospheric field measurements or radiative transfer codes (RTC) (Chavez, 1996; Renzullo, 2004). The equation to implement the COST method is presented below as Equation 13:

Equation 13

$$\rho_s = \frac{\pi \cdot L_{\lambda}^{hc} \cdot d^2}{\tau_v \cdot (E_{\lambda}^{SUN} \cdot \cos \theta_z \cdot \tau_z + E_{down})}$$

where:

ρ_s = Surface spectral reflectance

L_{λ}^{hc} = haze corrected (*hc*) TOA spectral radiance ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)

d = normalized sun-Earth distance (astronomical units –AU–)

E_{λ}^{SUN} = mean exo-atmospheric solar spectral irradiance ($\text{W m}^{-2} \mu\text{m}^{-1}$)

E_{down} = downwelling spectral irradiance at the surface due to scattered solar flux in the atmosphere ($\text{W m}^{-2} \mu\text{m}^{-1}$). The quantity of this irradiance is very small compared with E_{λ}^{SUN} which is the principal term of the parenthesis. Therefore, E_{down} does not influence heavily the result (Chavez, 1996). In this project the assumption that there was no diffuse contribution at the surface was made.

θ_z = angle of incidence of the direct solar flux onto the Earth's surface, i.e. solar zenith angle

τ_v = atmospheric transmittance along the path from the ground surface to the sensor (see Figure 11 for a graphic representation). Its calculation is based on the cosine of the sensor viewing angle. In nadir viewing sensors (Landsat) this transmittance is equal to 1.

τ_z = atmospheric transmittance along the path from the sun to the ground surface (see Figure 11 for a graphic representation). Its calculation is implemented with Equation 14, which takes into account the relation between τ_z and wavelength (τ_z increases with wavelength):

Equation 14

$$\tau_z = e^{-\left(\frac{\tau_r}{\cos \theta_z}\right)}$$

where τ_r represents the optical thickness of Rayleigh dispersion. For its calculation, Equation 15 was used (Kauffman, 1989),

Equation 15

$$\tau_r = 0.008569 \cdot \lambda^{-4} \cdot (1 + 0.0113 \cdot \lambda^{-2} + 0.00013 \cdot \lambda^{-4})$$

where λ is the band central wavelength (μm).

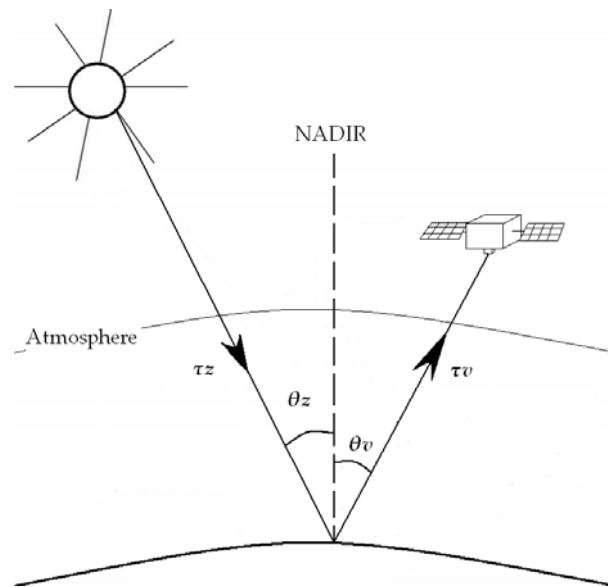


Figure 11. Graphic representation of τ_z and τ_v

Once the reference image was atmospherically corrected (absolute correction), the remaining images of the series were normalized to the reference image. The method used for normalization is based on the PIF technique. This method is advantageous when the image scene has changed considerably in a short time (i.e. area affected by forest fires) as it extracts multi-date image values for multiple features that should have relatively stable reflectance over time that are common between images. By using this invariant features the normalization process accounts only for the atmospheric and illumination variations from one image to another, without considering other type of changes that might have

affected the area. Linear regression for each band is then used to transform image values from one image to match those of the reference image.

As stated above, a common problem when using this technique is the absence of adequate PIF areas on the image. However, as the reference image is corrected through an absolute correction method and considering that the images are near-anniversary (which removes potential differences due to seasonal changes in phenology), the collection of PIF areas should be reliable even in areas that normally are not suitable for this purpose (e.g., rock outcrops, vegetated areas that have not been affected by the fire).

Another potential disadvantage to the PIF approach is its requirement of a wide range of brightness values with an equal representation of dark to light features. This affects directly the regression equation that normalizes multi-temporal imagery. In order to solve this problem, much care was taken in order to select enough PIFs from both dark and bright invariant features.

As stated above, collection of PIFs by visual inspection could give a subjective character to the selection which adds to the process an inherent error. Therefore, in order to avoid this error, in this project PIFs were selected by implementing a *multi-temporal n-dimensional Principal Components Analysis approach* (mT-nD-PCA) (see section 4.2.6.1 of this thesis for a description of this technique).

Only for both the Portuguese study sites (Parra and Mação) visual inspection was implemented for PIF selection. In order to implement the mT-nD-PCA technique, the image must contain enough surface not affected by a traumatic change (e.g. forest fires), which is not the case of these areas, which are just subsets of a bigger area affected by the enormous fires that affected Portugal during summer 2003. Furthermore, the orthophotos available had an extremely precise spatial resolution (0.5 m), and SPOT 5 and CHRIS images have also a high spatial resolution (10 m and 18 m respectively), which allowed the easy and reliable detection of invariant targets in the images and in the orthophotos.

Once the set of PIF pixels was selected, the haze corrected spectral radiances in each band for each PIF were recorded. The reflectances of the reference image were also recorded for the same PIF pixels. Once these values were collected, their mean and standard deviation

for each band in each image were calculated. The normalization factors (gain and offset) were then calculated as follows:

Equation 16

$$gain_{(i)} = \frac{\sigma_i^{\rho \text{ ref}}}{\sigma_i^L}$$

Equation 17

$$offset_{(i)} = \overline{\rho_i^{ref}} - \left(\frac{\sigma_i^{\rho \text{ ref}}}{\sigma_i^L} \cdot \overline{L_{\lambda(i)}^{hc}} \right)$$

where:

$gain_{(i)}$ = normalization gain for band i

$offset_{(i)}$ = normalization offset for band i

$\sigma_i^{\rho \text{ ref}}$ = reference image's PIFs reflectance standard deviation value for band i

σ_i^L = PIFs radiance standard deviation value of image to normalize for band i

$\overline{\rho_i^{ref}}$ = reference image's PIFs reflectance average value for band i

$\overline{L_{\lambda(i)}^{hc}}$ = PIFs radiance average value of image to normalize for band i

These two values ($gain$ and $offset$) were used to normalize the radiance images to the reflectance reference image with Equation 18:

Equation 18

$$\rho_{(i)}^{norm} = gain_{(i)} \cdot L_{\lambda(i)}^{hc} + offset_{(i)}$$

where $\rho_{(i)}^{norm}$ is the resulting normalized reflectance value of the images for each band i , and $L_{\lambda(i)}^{hc}$ is the radiance value of the image to be normalized for each band i .

The main assumption when using this methodology to normalize the images is that linear effects are much greater than non-linear effects impacting the images.

Once this procedure is finished, the complete set of haze corrected radiance images appear converted to reflectance images as if they were imaged through the same sensor and same atmospheric conditions as the reference reflectance image.

In order to check the accuracy of the PIF normalization results, the error due to the PIF transformation was computed following Martínez *et al.* (2002). This error can be expressed as Equation 19:

Equation 19

$$E_{PIF} = \sqrt{(E_{rms}^2 - E_{samp}^2)}$$

where E_{PIF} is the error due to the PIF transformation, E_{rms} is the raw error associated with the transform expressed in Equation 20, and E_{samp} is the error due to other sources as differences in the same invariant target on different dates due to the sampling process, or slight changes in reflectance. E_{rms} can be computed as:

Equation 20

$$E_{rms} = \frac{\sqrt{\sum_{i=1}^n (\rho_{ref} - \rho_{norm})^2}}{n}$$

where ρ_{ref} represents the PIF reflectance values of the reference image, ρ_{norm} represents the PIF reflectance values of the normalized images of the dataset, and n is the number of PIF pixels considered.

In order to obtain E_{samp} the COST atmospheric absolute correction was performed for all images of the dataset, and these reflectance values were considered as true absolute reflectance values, as no spectral field data was available for this purpose:

Equation 21

$$E_{samp} = \frac{\sqrt{\sum_{i=1}^n (\rho_{COST} - \rho_{norm})^2}}{n}$$

where ρ_{COST} represents the true PIF reflectance values of the normalized images of the dataset, computed with the COST model.

4.2.6.1 MULTI-TEMPORAL N-DIMENSIONAL PRINCIPAL COMPONENT ANALYSIS (MT-ND-PCA)

The results of a Principal Component Analysis when implemented in a multi-temporal manner show how the First Principal Component is highly correlated with the unchanged areas of the image, while the Second Principal Component is highly correlated with areas that suffered major and sudden changes, i.e. forest fires (Chuvieco, 2002). By taking advantage of this property, invariant pixels can be defined for the whole image time series without the need of using visually detected man-made features.

Multi-temporal images for each band were created. The resulting images had equal number of bands as images had the time series, and the number of multi-temporal images created was equal to the number of bands of the sensor used. For example, in the Lythrodontas study area eight Landsat TM/ETM+ images were acquired. Therefore, six multi-temporal images (one for each band) were created with eight bands each image (one for each image of the dataset). In order to consider only areas that had not suffered a drastic change (e.g. forest fire), the burned area must be masked from the image. Principal Component Analysis was then performed on these masked multi-temporal images. The n -dimensional character of this technique relies on the fact that more than three images give the multi-temporal Principal Component major axis geometric space an n -dimensional character. The major axis of this Principal Component Analysis contains the pixels of that single band that had not suffered changes for the whole period of time considered for the study. Therefore, all pixels contained along this major axis could be considered pure PIF. In order to achieve a minimum number of PIF pixels, an arbitrary threshold is defined by iteration. This threshold could be considered as the distance H between any pixel of the image and its closest pixel belonging to the major axis. This distance defines an n -dimensional volume (n -DVol) (see Figure 12 for a 3-dimensional representation of this n -DVol) where all pixels contained inside are considered PIFs.

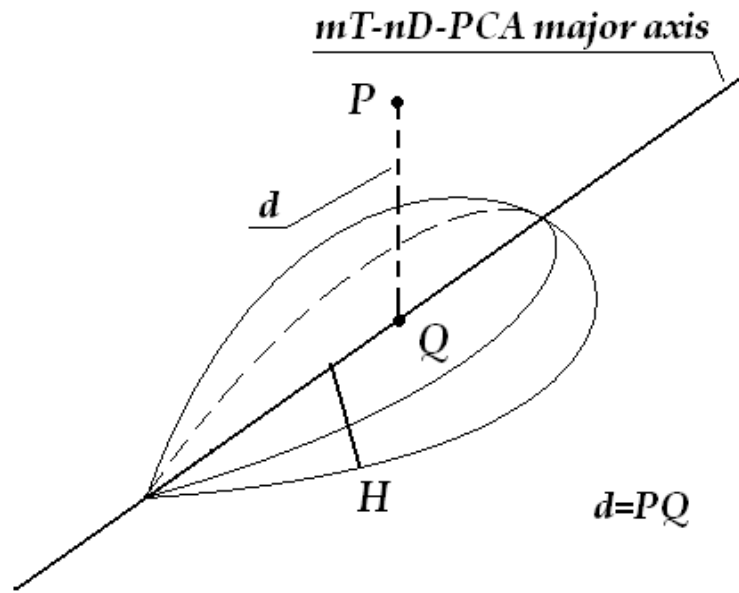


Figure 12. 3-dimensional representation of the n -DVol.

H is the threshold distance, P represents any point in the n -dimensional mT-nD-PCA geometric space, and Q represents any point belonging to the mT-nD-PCA major axis.

The mathematical formulation of the above explained methodology starts with the analysis of the mT-nD-PCA results. The eigenvector of the first principal component ($\overrightarrow{PC1_\lambda}$) gives the equation of the n -dimensional volume (n -DVol) axis ($\overrightarrow{A_{nD}^{vol}}$):

Equation 22

$$\overrightarrow{PC1_\lambda} = \overrightarrow{A_{nD}^{vol}} = (Ev_1, Ev_2, Ev_3, \dots, Ev_n)$$

where λ is the band wavelength, Ev represents the eigenvector components, and n is the number of images that compounds the time series.

In order to decide if a pixel should be considered PIF or not, the distance d between this pixel and the multi-temporal n -dimensional principal components major axis ($\overrightarrow{A_{nD}^{vol}}$) must be defined. This distance can be considered as the magnitude of the vector that connects a point Q of the n -DVol axis with a point P of a parallel line to the n -DVol axis.

In order to obtain the distance $\overrightarrow{PQ}$, points P and Q must be defined. Point P is defined as follows:

Equation 23

$$P = (p_{\lambda,1}, p_{\lambda,2}, p_{\lambda,3}, \dots, p_{\lambda,n})$$

where $p_{\lambda,n}$ represents the reflectance/radiance value of point P (any pixel P of the image) in spectral band λ of image n .

Point Q can be defined as the closest point of the n -DVol axis to point P :

Equation 24

$$Q = (q_{\lambda,1}, q_{\lambda,2}, q_{\lambda,3}, \dots, q_{\lambda,n})$$

where $q_{\lambda,n}$ represents the reflectance/radiance value of point Q (first principal component axis point) in spectral band λ of image n . Point Q can be obtained through the product between the magnitude of the vector $\overrightarrow{Qv}$ that passes through point Q (Qv_m), and the vector $\overrightarrow{A_{nD}^{vol}}$ (point Q is on the n -DVol axis, so the vector $\overrightarrow{Qv}$ has the same direction as $\overrightarrow{A_{nD}^{vol}}$):

Equation 25

$$Q = Qv_m \cdot \overrightarrow{A_{nD}^{vol}} = (Qv_m \cdot Ev_1, Qv_m \cdot Ev_2, Qv_m \cdot Ev_3, \dots, Qv_m \cdot Ev_n)$$

The magnitude of the vector $\overrightarrow{Qv}$ (Qv_m) can be calculated as the scalar product between the vector $\overrightarrow{A_{nD}^{vol}}$ and vector $\overrightarrow{Pv}$. The vector $\overrightarrow{Pv}$ is the vector parallel to the n -DVol axis and passes through point P . Therefore, vector $\overrightarrow{Pv}$ is parallel to vector $\overrightarrow{A_{nD}^{vol}}$, and due to this parallelism both vectors have the same direction. Being P and Q the points that define the shortest distance between both vectors (i.e. the perpendicular to both vectors), point P and vector $\overrightarrow{A_{nD}^{vol}}$ can be used to obtain the magnitude of vector $\overrightarrow{Qv}$. Therefore, the equation for the calculation of the magnitude Qv_m is:

Equation 26

$$Qv_m = \overrightarrow{A_{nD}^{vol}} \cdot P = Ev_1 \cdot p_{\lambda,1} + Ev_2 \cdot p_{\lambda,2} + Ev_3 \cdot p_{\lambda,3} + \dots + Ev_n \cdot p_{\lambda,n}$$

Having defined points P and Q , the distance between them must be calculated in order to compare it with the threshold distance H . The distance d between two points is computed as:

Equation 27

$$d = \sqrt{(q_{\lambda,1} - p_{\lambda,1})^2 + (q_{\lambda,2} - p_{\lambda,2})^2 + (q_{\lambda,3} - p_{\lambda,3})^2 + \dots + (q_{\lambda,n} - p_{\lambda,n})^2}$$

As stated above, the threshold value that decides if a pixel can or not be considered as a PIF is the threshold distance H . The distance d between any point in the n -dimensional multi-temporal principal components geometric space and the axis of the n -DVol is calculated. If this distance d is smaller than the threshold distance H , the pixel is classified as PIF:

Equation 28

$$PIF \Rightarrow d < H$$

All this process was repeated for each band multi-temporal image.

The value of H was defined by using the standard deviation (σ) of the first band of the mT-nD-PCA image (i.e. the first principal component of the multi-temporal image). As the first temporal principal component contains the unchanged information of the image, it was considered that the standard deviation of this first principal component would give a statistical sound starting point for the determination of H . Obviously, standard deviation of the first principal component changes for each multi-temporal image, so also H is different for each multi-temporal image. By doing this, a similar number of PIF pixels are selected from each multi-temporal image. However, there is no guarantee that these PIF pixels selected in one band are the same as the ones selected in the other bands. Only PIF pixels common to the whole set of band multi-temporal images are true PIFs, as these are the pixels that have not changed in time in any of the spectral bands of the sensor. Therefore, only these pixels should be selected for implementing the radiometric normalization. The H value was defined by taking into consideration these two conditions:

- firstly, the pixels selected as PIFs must be common to all the images of the time series;
- and secondly, the number of common PIFs should be at least a 1% of the total pixels of the image.

All this process was implemented by means of the models created with ERDAS Model Maker tool, which can be found in the Appendix B of this thesis. Once the models for the implementation of the process are constructed, this methodology for PIF selection is quite straight forward, and is applicable to any sensor type and with no limitation in the number of images of a time series.

4.3 SPECTRAL ANALYSIS AND CLASSIFICATION

4.3.1 Technique Selection and Justification

The main objective of this thesis is to provide quantitative measurements of vegetation cover regrowth in burned areas. As it could be observed during the literature review, not many methods exist that provide quantitative measurements. Spectral Mixture Analysis is the one most used, so it was included in this thesis. Also some vegetation indices have been already applied quantitatively and their accuracies showed to be adequate for quantitative studies. However, to the author's knowledge, no comparisons between these quantitative vegetation indices and the spectral mixture analysis technique have been performed.

Other methodologies were analysed and studied in order to check if their use would be limited only to qualitative studies. Spectral Angle Mapper (SAM) was taken into account, and no way to extract quantitative measurements from it was found. Literature review reference values that correlate the qualitative measurements of the technique to vegetation cover quantities were not found. The possibility of building these reference values within this project was taken into account, but field spectral measures of endmembers and spectral characteristics of areas with different levels of vegetation cover would have been needed. These data were not collected during the field campaign. Thus, Spectral Angle Mapper was not used in this project, but it remains an interesting spectral

classification technique that, with proper field data, could be correlated with quantitative measurements.

4.3.2 Quantitative Vegetation Indices

Vegetation indices are the most popular tool used to analyse remotely sensed data for various vegetation characteristics. Despite most of the remotely sensed vegetation indices are not intrinsic physical quantities, they are indeed related with several physical properties of vegetation like leaf area index (LAI), fractional vegetation cover, vegetation condition and biomass (Carlson & Ripley, 1997). More often vegetation indices have been used to estimate LAI than vegetation cover. However, Leprieur *et al.* (1994) conclude in their study that channel reflectances (specially the red one) have low sensitivity towards LAI. They argue that the correlation observed by some authors between vegetation indices and LAI may be due to the sensitivity of these indices to the fractional vegetation cover and the natural association between these two canopy parameters. In the same line, Verstraete & Pinty (1991) studied the nature of NDVI changes in semi-arid areas, and argued that NDVI is more strongly controlled by changes in vegetation cover than by changes in the optical thickness of canopies. Therefore, when dealing with partially vegetated areas (e.g. semi-arid areas, vegetation communities after forest fires), it is more reasonable to derive vegetation fraction rather than LAI from NDVI.

Several studies have addressed the relation between vegetation indices and percent vegetation cover. Leprieur *et al.*, (1994) showed how NDVI, SAVI (Soil Adjusted Vegetation Index) and GEMI (Global Environment Monitoring Index) are capable to estimate vegetation cover and LAI from AVHRR data. Dymond *et al.* (1992) used SPOT data to extract percentage vegetation estimates from normalized vegetation index (NVI), developing a nonlinear calibration curve. Baret *et al.*, (1995) tested the performance of several vegetation indices (SAVI-like indices, NDVI, PVI, and GEMI) when estimating canopy gap fraction from the red and near-infrared reflectance, finding that the indices that account and correct for soil background effects performed better than the others.

In this project three different indices were used to derive percent vegetation cover from satellite data: NDVI, MSAVI and DVI.

NDVI was selected because is probably the most commonly used index in the last decades when studying vegetation. Its deficiencies and advantages have been thoroughly studied and are actually well known. This provided to the project results a kind of point of reference from where the performance of the other techniques was evaluated. NDVI is defined as:

Equation 29

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}$$

where ρ_R and ρ_{NIR} represent the surface reflectance on the red and near infrared regions of the spectrum, respectively.

MSAVI (Modified Soil Adjusted Vegetation Index) was selected in order to test a soil background effect insensitive index. In areas affected by forest fires, soil remains exposed for several years until the vegetation recovers from the disturbance, hence vegetation indices that do not account for this effect could produce unreliable results. MSAVI is defined as:

Equation 30

$$MSAVI = \frac{2 \cdot \rho_{NIR} + 1 - \sqrt{(2 \cdot \rho_{NIR} + 1)^2 - 8 \cdot (\rho_{NIR} - \rho_R)}}{2}$$

DVI (Difference Vegetation Index) was also selected for application in this project. Jiang *et al.* (2006) argued that there are sources of uncertainty caused by the scale effect of NDVI in retrieving vegetation fraction from it. NDVI of mixed pixels and that of the components in mixed pixels are not at the same spatial scale, as the first is at pixel scale and the second at sub-pixel scale. The relationship between NDVI and fractional vegetation cover appears to be directly influenced by the scale effect of NDVI. Thus they proposed to use DVI (a scaled DVI) in order to avoid the problems related with NDVI. Difference Vegetation Index (DVI) is defined as:

Equation 31

$$DVI = \rho_{NIR} - \rho_R$$

4.3.2.1 EXTRACTION OF FRACTIONAL VEGETATION COVER FROM VEGETATION INDICES

The formula used in this project for retrieval of vegetation fraction with both NDVI and MSAVI indices was defined by Baret *et al.* (1995). They developed semi-empirical relationships to relate a vegetation index (VI) to the vertical gap fraction (f_s), being the latter the fraction of soil seen in a given direction. For nadir viewing sensors, the gap fraction (f_s) is the complement in unity to the vegetation cover fraction (f_v):

Equation 32

$$f_v = 1 - f_s$$

The gap fraction in canopies could be expressed as a simple exponential function of LAI (Nilson, 1971; Ross, 1981):

Equation 33

$$f_s = e^{-k_{fs} \cdot LAI}$$

where k_{fs} represents the coefficient of extinction and depends on the canopy architecture.

Baret & Guyot (1991) argued on a theoretical plane (confirmed by some experimental observations) that most vegetation indices can be computed as an exponential function of LAI, given an specific geometrical view and incidence configuration:

Equation 34

$$VI = VI_{\infty} + (VI_s - VI_{\infty}) \cdot e^{-k_{VI} \cdot LAI}$$

where VI_s is the vegetation index value for the soil, VI_{∞} is the vegetation index value for dense vegetation, and k_{VI} represents the coefficient of extinction and depends mostly on canopy architecture, sun and view directions.

The relation between vertical gap fraction and a vegetation index is obtained by combining Equation 33 and Equation 34:

Equation 35

$$f_s = \left(\frac{VI - VI_{\infty}}{VI_s - VI_{\infty}} \right)^{k_{fs} / k_{VI}}$$

By combining Equation 32 and Equation 35, the fractional vegetation cover (f_v) can be extracted directly from a VI (Jiang *et al.*, 2006):

Equation 36

$$f_v = 1 - \left(\frac{VI_{\infty} - VI}{VI_{\infty} - VI_s} \right)^{k_{fs}/k_{VI}}$$

In order to maximize the comparison robustness between the different vegetation cover extraction techniques applied in this study, the vegetation indices values from the pixels selected as pure image endmembers of green vegetation (GV) and soil (S), were proposed as vegetation indices reference values for dense vegetation and for bare soil respectively,. The selection of these pixels as pure image endmembers was obtained firstly for application with Spectral Mixture Analysis (SMA) (see 4.3.3.2 for a complete description of the process). Therefore, fractional vegetation cover retrieval equations using NDVI and MSAVI were defined as follows:

Equation 37

$$f_v^{NDVI} = 1 - \left(\frac{NDVI_{GV} - NDVI}{NDVI_{GV} - NDVI_s} \right)^{0.6175}$$

Equation 38

$$f_v^{MSAVI} = 1 - \left(\frac{MSAVI_{GV} - MSAVI}{MSAVI_{GV} - MSAVI_s} \right)^{1.4290}$$

The exponent values correspond to the estimated values of k_{fs}/k_{VI} obtained by Baret *et al.* (1995) in their work using experimental data from three different sites in Europe.

The same pixels used in the application of Equation 37 and Equation 38 were used as reference DVI values of dense vegetation and bare soil. The Scaled Difference Vegetation Index (SDVI) is equal in value to the fractional vegetation cover (Jiang *et al.*, 2006), so it can be used directly as a fractional vegetation cover index. The equation is:

Equation 39

$$f_v^{SDVI} = \frac{SDVI - SDVI_s}{SDVI_{GV} - SDVI_s}$$

4.3.3 Spectral Mixture Analysis (SMA)

4.3.3.1 BACKGROUND THEORY

In remote sensing data, most vegetated ecosystems are comprised of a mixture of diverse physical components (e.g., canopy structures, exposed soil, shadows). This becomes even more evident in areas where a forest fire occurred, where the mixture of components is more extreme due to the vegetation regrowth of the exposed soil. The theory of spectral mixing is based on the theory of mixed pixels, which states that every pixel consists of a relative proportion of dominant features which have relatively constant spectral properties (Figure 13). Spectral mixture analysis techniques measure the reflectance of a pixel in each spectral band as a combination of the reflectances of its component dominant features (referred to as endmembers), weighted by their respective surface proportions (Rogan *et al.*, 2002). As a result abundance maps are calculated representing the fraction of the chosen endmembers.

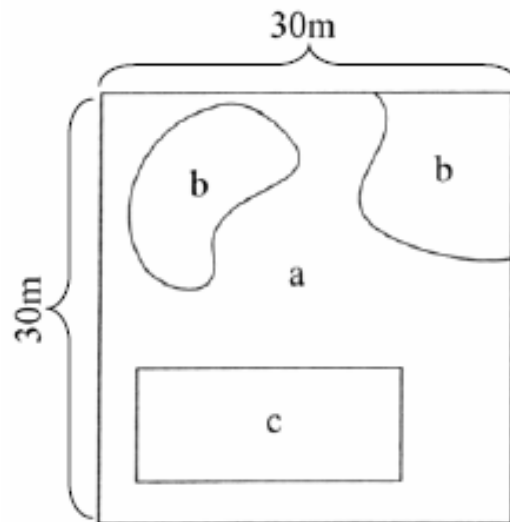


Figure 13. Mixed pixels scheme (here Landsat pixel) with three different dominant features (*a* to *c*) (from Twele, 2003)

One of the most important constraints of this technique is the number of endmembers. Possible endmembers are restricted to the number of spectral bands of the image plus one (Hill, 1993), but in general, in order to get realistic results the number is rather limited by the inherent dimensionality of the data. For example, when using Landsat TM/ETM+ data

mainly only four endmembers are used: green vegetation –GV-, soil, non-photosynthetic vegetation –NPV- (plant material lacking chlorophyll), and shade (Adams *et al.*, 1995; Cochrane & Souza, 1998; Sabol *et al.*, 2002; Peterson & Stow, 2003).

Spectral mixing techniques can be divided into linear spectral unmixing and nonlinear spectral unmixing depending on the complexity of scattering. If photons predominantly interact with a single component (i.e., undergo minimal multiple scattering), the mixing can be considered linear. However, when scattered photons interact with multiple components (e.g. vegetation, soil), the mixture has the potential of becoming nonlinear. Multiple scattering is assumed to be negligible for most applications, even though nonlinear mixing can become significant for some types of vegetation (Huete, 1986; Roberts *et al.*, 1993, 1998, 2001; Elmore *et al.*, 2000; Sabol *et al.*, 2002).

In the linear spectral unmixing, the mixed spectrum can be modelled as the sum of the pure spectra (endmembers) within the instantaneous field of view (IFOV), weighted by the areal proportion of each component:

Equation 40

$$R_B = \sum_{i=1}^n f_i R_{i,B} + \epsilon_B$$

where R_B is the reflectance of the mixed spectrum in image band B for each pixel, f_i is the fraction of each endmember i calculated by band, $R_{i,B}$ is the reflectance of endmember i in band B , and ϵ_B is the unmodelled residual error in band B .

The ideal case is that f_i are nonnegative and sum to 1. These characteristics of the ideal case are set as constraints in order to allow interpreting these f_i coefficients as cover fractions:

Equation 41

$$0 \leq f_i \leq 1 \quad \text{and} \quad \sum_{i=1}^n f_i = 1$$

Cover fractions are derived by inverting Equation 40 and solving for the fractions that provide the best fit between the measurement and the model (Roberts *et al.*, 2001; Theseira *et al.*, 2003). The assessment of the model fit is expressed as either an error in the fraction

residuals (negative or greater than 1 fractions) at each band (ε_B) or as a root mean squared (RMS) error across all bands (Equation 42):

Equation 42

$$RMS = \left(\frac{\sum_{B=1}^m \varepsilon_B^2}{m} \right)^{1/2}$$

where m is the number of bands.

As an ultimate step of the SMA application, a shade normalization is often implemented. The elimination of the shade endmember and the normalization of the remaining endmember fractions can reduce remaining topographic sun illumination influences. Moreover, this approach can be useful in environments where, due to the shadow-casting canopies, the shade fraction is strongly correlated to vegetation fraction. Hence, the shaded pixel portion is eliminated by employing a scaling factor f derived from the shade fraction (Equation 43). This scaling factor is applied to normalize the remaining endmember fractions by applying Equation 44:

Equation 43

$$f = \frac{1}{1 - Sh}$$

Equation 44

$$\sum_{i=1}^{n-1} F_i \times f = 1$$

where f is the shade normalization factor, Sh is the fractional abundance of shade endmember, and F is the fractional abundance of endmember i .

4.3.3.2 ENDMEMBER SELECTION

Endmember selection is of utmost importance for an accurate application of the SMA technique. The major source of error in this technique comes from an incorrect endmember selection. Fraction errors can originate when a spectrum in the image is poorly represented by the endmembers (e.g. the target is darker or brighter than any of

the endmembers) or if the dimensionality of the data differs from the number of endmembers used in the model (Roberts *et al.*, 2001). Therefore, an accurate selection of the number and spectrum of the endmembers is the key factor of SMA.

Endmembers can be defined using the image itself or using pure field-spectra measured *in situ* or in laboratories (also available in spectral libraries) (Roberts *et al.*, 2001; SPREAD project, 2004). The former are known as *image endmembers* while the latter are called *reference endmembers*.

Application of reference endmembers is considerably difficult as it requires the use of an appropriate spectral library collected at an appropriate scale. If no spectral library is available for the study area, it has to be created with *in situ* or laboratory measurements. This represents a huge time consuming task which could not be addressed in this project.

Most SMA applications use image endmembers. Their advantage is that they are easily obtained, represent spectra measured at the same scale as the data, and provide a simple measure of abundance. There are several methods to derive image endmembers. A simple way is to locate them directly based on *a priori* knowledge due to survey or other available detailed maps of the area of interest (Theseira *et al.*, 2003). However, this applies only to high spatial resolution imagery where pixel will be more likely relatively pure. Since SMA has been mainly applied to intermediated resolution sensors as Landsat, other simple methods for retrieving pure pixels are available in literature (see Theseira *et al.*, 2003 for a complete review of methods). PCA (Principal Component Analysis) seems to be one of the most accurate methods for endmember selection (Theseira *et al.*, 2003), since it minimizes the influence of the inter-band correlation and puts almost 90% of the variances on the first three components (SPREAD project, 2004). Commonly the first two components are used to build the scatterplot in order to determine the image endmember (Casals-Carrasco *et al.*, 2000; Theseira *et al.*, 2003).

SMACC (Sequential Maximum Angle Convex Cone) is an image endmember selection technique that seems to yield good results. SMACC is a spectral tool provided by ENVI. It uses a convex cone model (also known as residual minimization) with certain constraints to identify image endmember spectra. Instead of using a two dimensional spectral space

to obtain the pure pixel (as PCA does), it uses extreme vectors to determine a convex cone in the n -dimensional geometric space of the dataset (being n the number of bands of the sensor). An extreme vector cannot be approximated by a positive linear combination of other vectors in the dataset. Oppositely, non-extreme vectors can be modelled by a positive linear combination of extreme vectors. The set of extreme vectors within the dataset forms a convex cone that contains the rest of the vectors in the data.

The SMACC method finds first the brightest pixel within the image, which defines the first endmember. A second endmember is found by applying a constrained oblique projection to the existing cone, finding the most different pixel from the first one in terms of brightness. Then SMACC finds the most different pixel from the two already selected, defining the third endmember. The process is repeated until a projection derives an endmember that already exists within the convex cone or until the specified number of endmembers has been found. All the endmembers found form the spectral library of the image materials (for further information, please refer to Gruninger *et al.*, 2001, 2004).

In this project SMACC was applied separately to each image of a time series, obtaining one set of endmembers for each image of the time series. The number of endmembers was limited following Equation 45 (Gillespie *et al.*, 2006):

Equation 45

$$e \leq n + 1$$

where e is the maximum number of endmembers that can be extracted for an image, and n is the number of non-correlated bands of the image (dimensionality of the image).

Extracting endmember abundances from each image using its own set of endmembers would result in important differences caused not by real changes of cover between dates, but by spectral differences within the materials, even if the images have been accurately atmospherically normalized. Taking the endmembers of one image as reference endmembers, i.e. the pre-fire endmembers, would cause errors in the vegetation cover retrieval from the post-fire images, as the spectral characteristics of the pre-fire vegetation of the area may not be the same as the post-fire vegetation. Therefore, in order to avoid this, average endmembers were extracted for the time series. Endmembers of one material

in the whole set of images of the study areas were plotted together. Their reflectance values in each band were recorded and the average for each band was then extracted. This yielded an average reflectance for each band, resulting in an average endmember spectrum. This was repeated for each endmember material, creating a set of average endmembers. The latter was the one used for application of the Spectral Mixture Analysis technique. By doing this, a kind of spectral library was created for the study area.

4.3.4 Accuracy Assessment

Accuracy of the vegetation cover images obtained after the application of the four techniques was checked by regression against the field data collected during the field campaigns. From these accuracy assessment results, the best technique for quantitative determination of vegetation cover was identified.

5. RESULTS

5.1 FIELD WORK RESULTS

5.1.1 Lythrodontas Study Area

This study area was visited from the 6th until the 13th of August in 2005 and from the 16th until the 21st of July in 2006. The number of plots collected was 18, being the size of each plot 60x60 m (0.36 ha). This represented approximately a 1% of the total study area. The application of the formula of Justice & Townshend (1981) for the definition of the minimum dimensions of the sample plot yielded exactly a minimum dimension of 0.36ha for a geometric accuracy of 0.5 pixels. Taking into account the high geometric accuracy achieved with the geometric correction (see section 5.2), this minimum dimension was considered large enough. The average vegetation cover surveyed was 38.36% for 2005 and 48.23% for 2006. The data gathered can be found at the Appendix C of this thesis.

5.1.2 Deiva Marina Study Area

In this case, only one field work campaign was done (from the 24th until the 28th of September 2006) due to time constraints and difficulties in contacting the forest services of the area. The number of plots collected was 19, being the size of each plot 60x60 m (0.36 ha). This represented approximately a 1% of the total study area. The application of the formula of Justice & Townshend (1981) for the definition of the minimum dimensions of the sample plot yielded exactly a minimum dimension of 0.36ha for a geometric accuracy of 0.5 pixels. Taking into account the high geometric accuracy achieved with the geometric correction (see section 5.2), this minimum dimension was considered large enough. The average vegetation cover surveyed was 60.24% for 2006. The data gathered can be found at the Appendix C of this thesis.

5.1.3 Parra Study Area

This area was visited from the 4th until the 9th of September on 2005 and from the 7th until the 11th of June on 2006. The number of plots collected was 23, being the size of each plot 40x40 m (0.16 ha). This represented approximately a 0.4% of the total study area. The application of the formula of Justice & Townshend (1981) for the definition of the minimum dimensions of the sample plot yielded exactly a minimum dimension of 0.04ha

for a geometric accuracy of 0.5 pixels. This minimum dimension was increased from 0.04ha to 0.16ha. However, time constraints did not allow to survey a minimum of 1% of the study area, as the small size of the plots (due to the high spatial resolution of the SPOT sensor) required an elevated number of plots to sample in order to achieve the 1% objective (more than 200 plots). This elevated number of plots was not possible to survey in the short time available for the field campaign. The average vegetation cover surveyed was 27.90% for 2005 and 43.35% for 2006. The data gathered can be found at the Appendix C of this thesis

5.1.4 Mação Study Area

This area was visited from the 12th until the 17th of June on 2005 and from the 19th until the 22nd of June on 2006. The number of plots collected was 22, being the size of each plot 50x50 m (0.25 ha). This represented approximately a 0.5% of the total study area. The application of the formula of Justice & Townshend (1981) for the definition of the minimum dimensions of the sample plot yielded exactly a minimum dimension of 0.13ha for a geometric accuracy of 0.5 pixels. This minimum dimension was increased from 0.13ha to 0.25ha. However, time constraints did not allow to survey a minimum of 1% of the study area, as the small size of the plots (due to the high spatial resolution of the CHRIS-Proba sensor) required an elevated number of plots to sample in order to achieve the 1% objective (more than 40 plots). This elevated number of plots was not possible to survey in the short time available for the field campaign. The average vegetation cover surveyed was 40.54% for 2005 and 49.43% for 2006. The data gathered can be found at the Appendix C of this thesis

5.2 PRE-PROCESSING RESULTS

Pre-processing results have been grouped in three main sections:

- The first section of this sub-chapter (5.2.1) shows the pre-processing results obtained in both Lythrodontas and Deiva Marina study areas. The satellite sensed data used for the analysis of these study areas is of the same type (Landsat), and the same pre-processing steps were applied.

- The second section (5.2.2) shows the pre-processing results obtained in the Parra study area. Pre-processing steps for these images (SPOT) were slightly different from the ones used with the Landsat data.
- The third section (5.2.3) shows the pre-processing results obtained in the Mação study area. Pre-processing steps for these images (CHRIS-Proba) were slightly different from the ones used with the previous study areas.

5.2.1 Lythrodontas and Deiva Marina Study Areas

An empirical geometric correction technique was applied in order to relocate as accurately as possible the images in their correct geographic position. For both study areas, a 15 m spatial resolution Landsat RGB ortho-rectified image was used as reference for the geometric correction. Common Ground Control Points between the ortho-rectified image and the images of the datasets were collected on easily identifiable permanent features such as cross-roads, buildings, mountain tops. Polynomial transform equations with a first polynomial degree were computed with the GCPs collected. The re-sampling technique applied to place the DN of the original image pixels into the geometrically corrected image pixels was the Nearest-Neighbour technique. Table 9 and Table 10 show the number of GCPs collected and the least squares regression quality of the adjustment (RMSE) achieved for each image.

Table 9. Geometric correction accuracy (Lythrodontas-Landsat)

Site	Sensor	Acquisition date	Number of GCPs	Quality of the adjustment	Quality of the correction	
				<i>RMSE</i>	<i>Slope</i>	<i>r</i> ²
Lythrodontas	Landsat ETM+	20/07/1999	40	0.175010	1.0008	1
	Landsat ETM+	07/08/2000	40	0.151920	1.0004	1
	Landsat ETM+	25/07/2001	40	0.195536	1.0010	1
	Landsat ETM+	28/07/2002	40	0.210485	0.9998	1
	Landsat TM	23/07/2003	40	0.193988	1.0011	1
	Landsat TM	25/07/2004	40	0.216801	0.9997	1
	Landsat TM	28/07/2005	40	0.178781	1.0009	1
	Landsat TM	31/07/2006	40	0.210005	1.0026	1

Table 10. Geometric correction accuracy (Deiva Marina-Landsat)

Site	Sensor	Acquisition date	Number of GCPs	Quality of the adjustment	Quality of the correction	
				<i>RMSE</i>	<i>Slope</i>	<i>r</i> ²
Deiva Marina	Landsat TM	14/08/1997	40	0.285830	1.0013	1
	Landsat TM	18/09/1998	40	0.278171	1.0009	1
	Landsat TM	03/07/1999	40	0.254076	1.0007	1
	Landsat ETM+	29/07/2000	40	0.265245	0.9995	1
	Landsat ETM+	01/08/2001	40	0.267182	1.0010	1
	Landsat ETM+	19/07/2002	40	0.340314	1.0025	1
	Landsat TM	30/07/2003	40	0.222349	0.9998	1
	Landsat TM	01/08/2004	40	0.242343	0.9994	1
	Landsat TM	04/08/2005	40	0.258386	1.0005	1
	Landsat TM	22/07/2006	40	0.288091	1.0012	1

As it can be observed, the accuracy level achieved with the polynomial transformation (quality of the adjustment) is very high. In order to check the quality of the correction, several points were identified within the reference images and the corrected images and

regressed against each other. The slopes and correlation coefficient (r^2) obtained (see Table 9 and Table 10) show how the geometric correction results have a very high accuracy

Once the geometric correction of the datasets was finished, a cross-calibration was performed in order to ensure the inter-comparability between images. DNs were then converted into TOA spectral radiance and a haze correction was applied. With these images, a Minnaert topographic correction was performed. The values of the k constants were obtained for the areas that fulfilled the NDVI and slope constraints defined. NDVI constraint was set to $NDVI > 0.2$ and the slope constraint was set to $slope > 15^\circ$, in order to consider for k constants calculation only mountainous pixels that contain vegetation. Table 11 and Table 12 show the k constant values obtained for each image and each band for the Lythrodontas and the Deiva Marina study areas, and the correlation values obtained for testing the accuracy of the k constant computation. As expected, k values for smaller wavelengths, where the topography effect is less important, are smaller. However, NIR band does not accomplish with the latter and topography seems to have a greater influence. This is due to the fact that in this spectral range there is a high dependence between the radiance of the vegetation and the illumination in this band. Values obtained are within the range of 0.24 to 0.42 for Lythrodontas area, and 0.16 to 0.31 for Deiva Marina area. The Deiva Marina and Lythrodontas k values are quite low. This could be caused by the marked mountainous character of these study areas and by the constraints of NDVI and slope applied, which confine the calculation to mountainous vegetated areas, leaving out other areas that may smooth the non-Lambertian behaviour of the accounted areas. The correlation values obtained show that, except for bands 5 and 7 in Lythrodontas area, the computation of the Minnaert k constant values is satisfactory.

Table 11. Minnaert's k constant and correlation values for Lythrodontas study area (Landsat).

		B1	B2	B3	B4	B5	B7
1999	k	0.2996	0.3346	0.3816	0.3047	0.3859	0.4178
	$corr$	0.7482	0.7416	0.7314	0.7461	0.6974	0.4104
2000	k	0.2982	0.3391	0.3862	0.3174	0.3912	0.4240
	$corr$	0.7464	0.7389	0.7296	0.7422	0.6947	0.4241
2001	k	0.2904	0.3288	0.3718	0.3067	0.3681	0.3989
	$corr$	0.7409	0.7341	0.7254	0.7377	0.6928	0.4476
2002	k	0.2756	0.3059	0.3468	0.2779	0.3523	0.3832
	$corr$	0.7406	0.7348	0.7256	0.7394	0.6906	0.3820
2003	k	0.2489	0.2878	0.3327	0.2727	0.3278	0.3514
	$corr$	0.7211	0.7136	0.7005	0.7183	0.6652	0.3074
2004	k	0.2508	0.2884	0.3261	0.2803	0.3316	0.3532
	$corr$	0.7247	0.7173	0.7067	0.7208	0.6697	0.2877
2005	k	0.2746	0.3114	0.3479	0.2967	0.3569	0.3831
	$corr$	0.7370	0.7300	0.7205	0.7343	0.6823	0.2798
2006	k	0.2947	0.3317	0.3723	0.3118	0.3847	0.4107
	$corr$	0.7468	0.7402	0.7299	0.7445	0.6926	0.3182

Table 12. Minnaert's k constant and correlation values for Deiva Marina study area (Landsat).

		B1	B2	B3	B4	B5	B7
1997	k	0.1867	0.2032	0.2168	0.2230	0.2540	0.2681
	$corr$	0.7427	0.7348	0.7167	0.7407	0.6442	0.8613
1998	k	0.1630	0.1895	0.2235	0.2238	0.2666	0.2757
	$corr$	0.7494	0.7376	0.7052	0.7406	0.6067	0.8510
1999	k	0.2446	0.2602	0.2745	0.2710	0.2896	0.3022
	$corr$	0.7498	0.7419	0.7241	0.7523	0.6784	0.8043
2000	k	0.2452	0.2642	0.2896	0.2612	0.2872	0.3110
	$corr$	0.7512	0.7428	0.7191	0.7549	0.6782	0.7272
2001	k	0.2336	0.2515	0.2748	0.2573	0.2867	0.3093
	$corr$	0.7508	0.7427	0.7225	0.7525	0.6764	0.7956
2002	k	0.2414	0.2565	0.2677	0.2651	0.2814	0.2916
	$corr$	0.7515	0.7419	0.7165	0.7543	0.6614	0.4013
2003	k	0.1842	0.2085	0.2326	0.2283	0.2610	0.2755
	$corr$	0.7451	0.7357	0.7101	0.7427	0.6405	0.7884
2004	k	0.2191	0.2331	0.2525	0.2536	0.2843	0.3008
	$corr$	0.7468	0.7401	0.7222	0.7464	0.6586	0.8397
2005	k	0.2253	0.2480	0.2676	0.2543	0.2819	0.2990
	$corr$	0.7421	0.7332	0.7104	0.7457	0.6644	0.8328
2006	k	0.2447	0.2578	0.2766	0.2639	0.2870	0.3004
	$corr$	0.7543	0.7477	0.7285	0.7577	0.6877	0.7118

The PIF relative atmospheric normalization was then implemented by selecting PIFs through the mT-nD-PCA technique (see 4.2.6.1 for details).

Multi-temporal images were constructed in order to apply the mT-nD-PCA technique. In each multi-temporal image, Band “ n ” of each year compounded the bands of the multi-temporal image (starting with the oldest date as first band, and finishing with the more recent date as last band). Therefore, for these two study areas (using Landsat sensors) six multi-temporal images were constructed. Multi-temporal images of Lythrodontas had 8

bands, and multi-temporal images of Deiva Marina had 10 bands. In order to extract from the images areas with sudden changes (i.e. burned areas, clouds), a mask was constructed for each study area, and applied to the multi-temporal images. This guarantees that only areas that had not suffered sudden changes are considered, which facilitates the distinction between areas that had not changed at all for the whole period of time considered and areas that may have progressively changed during time. Principal Component Analysis was then applied to the masked multi-temporal images. Principal Component images were then visually inspected in order to check their significance finding, as expected, that PC1 was gathering the non-change information of the whole multi-temporal dataset, while PC2 and PC3 were mainly representing areas with some kind of change. The remaining PCs consisted mainly in noise. In order to give a mathematical expression of the previous assessment, the eigen-values of the PCA covariance matrix were computed and analysed. Table 13 and Table 14 presents the eigen-values (E-val) obtained for each multi-temporal image and the percentage of original variance (V%) that each Principal Component represents, for each study site.

Table 13. PCs eigen-values and % of original variance (Lythrodontas-Landsat)

	B1 mT image		B2 mT image		B3 mT image		B4 mT image		B5 mT image		B7 mT image	
	<i>E-val</i>	V%	<i>E-val</i>	V%	<i>E-val</i>	V%	<i>E-val</i>	V%	<i>E-val</i>	V%	<i>E-val</i>	V%
PC1	505.99	91.64	862.97	91.10	1226.21	90.63	533.14	84.88	42.90	81.42	4.15	74.88
PC2	9.77	1.77	18.74	1.98	30.58	2.26	25.41	4.05	2.31	4.39	0.28	5.04
PC3	8.35	1.51	15.79	1.67	23.97	1.77	18.53	2.95	1.87	3.55	0.25	4.46
PC4	7.05	1.27	13.53	1.43	19.96	1.47	15.94	2.54	1.51	2.86	0.21	3.81
PC5	5.99	1.08	10.82	1.14	15.19	1.12	12.00	1.91	1.19	2.27	0.18	3.27
PC6	5.58	1.01	10.10	1.07	14.38	1.06	9.13	1.46	1.05	1.99	0.17	3.03
PC7	4.89	0.88	8.26	0.87	11.71	0.86	7.97	1.27	0.96	1.83	0.16	2.82
PC8	4.53	0.82	7.09	0.75	11.03	0.81	5.15	0.82	0.88	1.68	0.15	2.69

Table 14. PCs eigen-values and % of original variance (Deiva Marina-Landsat)

	B1 mT image		B2 mT image		B3 mT image		B4 mT image		B5 mT image		B7 mT image	
	<i>E-val</i>	<i>V%</i>	<i>E-val</i>	<i>V%</i>	<i>E-val</i>	<i>V%</i>	<i>E-val</i>	<i>V%</i>	<i>E-val</i>	<i>V%</i>	<i>E-val</i>	<i>V%</i>
PC1	134.22	68.97	209.91	72.31	290.57	76.87	2207.23	78.12	35.72	79.06	1.95	78.46
PC2	18.41	9.46	22.12	7.62	22.70	6.00	131.68	4.66	2.17	4.80	0.12	4.81
PC3	10.10	5.19	13.24	4.56	13.88	3.67	113.18	4.00	1.79	3.98	0.09	3.74
PC4	7.38	3.79	11.51	3.96	10.72	2.83	110.39	3.91	1.31	2.89	0.06	2.57
PC5	5.69	2.93	8.06	2.77	9.17	2.43	60.37	2.14	0.88	1.95	0.06	2.29
PC6	4.94	2.54	6.86	2.36	7.72	2.04	56.35	1.99	0.81	1.79	0.05	1.93
PC7	4.43	2.27	5.77	1.98	7.03	1.86	47.50	1.68	0.73	1.62	0.04	1.83
PC8	3.60	1.85	5.13	1.77	6.22	1.64	37.95	1.34	0.66	1.45	0.04	1.65
PC9	3.33	1.71	4.17	1.44	6.01	1.59	33.23	1.18	0.59	1.32	0.03	1.54
PC10	2.50	1.28	3.52	1.21	3.98	1.05	27.37	0.97	0.49	1.10	0.02	1.17

Looking at Table 13 (*Lythrodontas* study area) it is possible to observe that the eigen-values closely follow the assessment made above. PC1 contains more than 90% of the original variance for the first three multi-temporal images (visible range), and around 80% of the original variance for the last three multi-temporal images (NIR, SWIR, and MIR). This 10% of difference may correspond to slight changes in the phenological state of vegetation between dates or other small changes affecting the landscape outside the burned area (vegetation cleaning in electric lines, timber extraction, reforestations). The high percentages corresponding to the first multi-temporal image (Landsat B1) shows how the atmospheric differences after the haze correction between dates are small, as B1 is normally the spectral range more affected by atmospheric haze.

In Table 14 (*Deiva Marina* study site) a more constant behaviour can be observed. PC1 contains around 80% of the original variance for the last four multi-temporal images (R, NIR, SWIR, and MIR), and around 70% of the original variance for the first two multi-temporal images (B and G). This 10% of difference can be explained by the presence of a cloudy atmosphere in several images. Even if a cloud mask was applied and a haze

correction was performed, some small clouds almost invisible can be still present in the image, and thus resulting as changes in radiance.

In both study areas, PC2 and PC3 mainly contain the major changes in the landscape outside the burned areas through time, containing also major radiometric differences.

Once the eigen-values and their significance were analysed, the eigen-vector of the first Principal Component for each multi-temporal image was extracted. This PC1 eigen-vector represents the n -dimensional cylinder axis that contains pure PIFs, that is, pixels that have not changed through time. Table 15 and Table 16 present the eigen-vectors obtained for each study area. The first eigen-vector (line *b1*) forms the equation coefficients of the n-DVol major axis.

Table 15. PC1 eigen-vector for Lythrodontas study area (Landsat).

	B1 mT image	B2 mT image	B3 mT image	B4 mT image	B5 mT image	B7 mT image
b1	0.374943	0.369367	0.374463	0.333735	0.358928	0.371470
b2	0.380075	0.375200	0.384726	0.233063	0.368703	0.389094
b3	0.378936	0.378323	0.387755	0.376277	0.371341	0.384893
b4	0.391616	0.398087	0.415848	0.423103	0.406945	0.402598
b5	0.318769	0.301662	0.315009	0.290294	0.319926	0.326957
b6	0.342950	0.351511	0.330652	0.401226	0.346569	0.328078
b7	0.320562	0.332324	0.312096	0.387801	0.328272	0.299758
b8	0.309866	0.310150	0.287252	0.343597	0.318599	0.309833

Table 16. PC1 eigen-vector for Deiva Marina study area (Landsat).

	B1 mT image	B2 mT image	B3 mT image	B4 mT image	B5 mT image	B7 mT image
b1	0.216742	0.234179	0.221580	0.281820	0.292550	0.250702
b2	0.244032	0.248072	0.234610	0.301379	0.307751	0.260226
b3	0.294256	0.296683	0.297110	0.381532	0.310037	0.305170
b4	0.374042	0.356746	0.375378	0.364860	0.362365	0.386992
b5	0.337631	0.330167	0.360316	0.333248	0.350228	0.370824
b6	0.344428	0.353292	0.339123	0.362590	0.316586	0.317396
b7	0.331193	0.338099	0.327370	0.250103	0.331727	0.322589
b8	0.257265	0.271055	0.287944	0.249670	0.291725	0.302890
b9	0.329969	0.346559	0.328647	0.314262	0.304107	0.312182
b10	0.386779	0.355839	0.351786	0.291351	0.285935	0.308262

Considering each pixel of a multi-temporal image as a point P in a n -dimensional space (as many dimensions as years have the time series), the closest point Q belonging to the PC1 axis (cylinder axis) to point P was defined. Then the distance d (perpendicular to the PC1 axis) from point P to point Q was computed. The selection of PIFs for this multi-temporal image was then extracted by setting a threshold H (cylinder radius) which has to be fixed iteratively. In order to give statistical soundness to this threshold, the standard deviation (σ_{PC1}) of the first principal component of the multi-temporal image was taken as initial threshold value.

All this process was repeated for each multi-temporal image of the study area, producing a set of possible PIFs for each multi-temporal image.

The definitive value of the threshold H was finally defined as the amount of standard deviation needed to select a number of PIF pixels (common to all the multi-temporal images of the study area) equivalent to at least a 1% of the total image pixels. This threshold value H was set to $\frac{1}{4}$ of the PC1 standard deviation of each multi-temporal image for Lythrodontas study area, and $\frac{1}{3}$ of the PC1 standard deviation of each multi-temporal image for Deiva Marina study area. Table 17 and Table 18 present the H values for each multi-temporal image.

Table 17. H values for Lythrodontas study area (Landsat).

	B1 mT image	B2 mT image	B3 mT image	B4 mT image	B5 mT image	B7 mT image
<i>H</i>	5.623568	7.344085	8.754315	5.772480	1.637482	0.509573

Table 18. H values for Deiva Marina study area (Landsat).

	B1 mT image	B2 mT image	B3 mT image	B4 mT image	B5 mT image	B7 mT image
<i>H</i>	3.861840	4.829477	5.681999	15.660390	1.992227	0.465244

Once a common set of PIFs was extracted for each study area, one reference image was defined for each study area in order to apply the normalization. Converting this reference image from radiance units into reflectance units makes possible to obtain the normalized images directly in reflectance units. If this reference reflectance image is absolutely atmospherically corrected, the normalized images would also be obtained in absolutely atmospherically corrected reflectance values, as if they were sensed at the same time as the reference image. If near-anniversary images are used in the project, these normalized reflectance images could be considered as absolutely corrected.

The image with the lowest path radiance term (L_{haze}) of the dataset was selected as reference image. This ensures that the image selected as reference has the lowest scattered atmospheric spectral radiance received by the sensor. For the Lythrodontas study area the reference image selected was the one from 2003, and for the Deiva Marina study area was the one from 1998. The absolute atmospheric correction of these reference images was then carried out by means of the COST model (Chavez, 1996) (see section 4.2.6). Atmospheric transmittances were computed as stated in section 4.2.6. The optical thickness of Rayleigh dispersion (τ_r) values obtained for Landsat sensors are shown in Table 19.

Table 19. Optical thickness of Rayleigh dispersion values for Landsat sensors.

	B1	B2	B3	B4	B5	B7
Central λ (μm)	0.485	0.560	0.660	0.830	1.650	2.215
τ_r	0.162672	0.090387	0.046362	0.018357	0.001161	0.000357

An ERDAS model was constructed for the application of the PIF normalization. The radiance values for each PIF in each band of each multi-temporal image were extracted as well as the PIF reflectance values of the reference image. These extracted values were used in the model to compute the gain and offset values for the atmospheric normalization. As output, 8 six-bands Landsat normalized reflectance images were obtained for Lythrodontas study area, and 10 six-bands Landsat normalized reflectance images were obtained for Deiva Marina area.

In order to check the accuracy of the PIF normalization, Equation 19, Equation 20, Equation 21 were implemented in an ERDAS model. Table 20 and Table 21 present the PIF error for Lythrodontas and Deiva Marina study areas.

Table 20. PIF Error statistics for Lythrodontas study area (Landsat).

		EPIF (%)	
		Mean	St. dev
1999	B1	0.8959	0.4993
	B2	1.1841	0.8645
	B3	1.3004	1.0787
	B4	1.3477	1.0798
	B5	2.2615	1.7913
	B7	2.8510	1.8830
2000	B1	0.8513	0.5294
	B2	1.0851	0.8251
	B3	1.8137	1.1942
	B4	2.1176	1.3084
	B5	2.7582	1.7320
	B7	2.9493	1.7632
2001	B1	0.7785	0.4974
	B2	0.9895	0.7510
	B3	1.9628	1.2469
	B4	1.2898	1.0534
	B5	2.4052	1.6715
	B7	2.8942	1.7752
2002	B1	0.6479	0.4703
	B2	1.1177	0.8080
	B3	1.3388	1.0192
	B4	2.3090	1.4156
	B5	2.2284	1.8331
	B7	2.6624	1.8455

		EPIF (%)	
		Mean	St. dev
2004	B1	0.8026	0.5140
	B2	0.8675	0.7460
	B3	1.3527	1.0903
	B4	1.3395	1.0933
	B5	2.4751	1.7958
	B7	1.9529	1.7745
2005	B1	0.7963	0.5206
	B2	1.1550	0.8443
	B3	1.2593	1.0420
	B4	1.9199	1.2792
	B5	2.2992	1.8829
	B7	2.2821	1.9506
2006	B1	0.7204	0.4803
	B2	1.1671	0.8425
	B3	1.3172	1.0410
	B4	2.0659	1.3208
	B5	2.1905	1.7523
	B7	2.5287	1.8638

Table 21. PIF Error statistics for Deiva Marina study area (Landsat).

		E _{PIF} (%)	
		Mean	St. dev
1997	B1	0.4561	0.2471
	B2	0.7371	0.3052
	B3	0.6556	0.3177
	B4	2.9108	1.3895
	B5	1.1730	0.7356
	B7	0.5741	0.3722
1999	B1	0.4787	0.2452
	B2	0.5313	0.2761
	B3	0.5002	0.2959
	B4	2.5261	1.6117
	B5	1.4004	0.7911
	B7	0.7252	0.3935
2000	B1	0.4604	0.2192
	B2	0.4926	0.2842
	B3	0.6667	0.2849
	B4	2.5897	1.3684
	B5	1.3946	0.7380
	B7	0.6950	0.3926
2001	B1	0.4916	0.2249
	B2	0.5599	0.2874
	B3	0.5966	0.3168
	B4	2.0991	1.4433
	B5	1.4166	0.7413
	B7	0.7107	0.3959
2002	B1	0.4497	0.2541
	B2	0.5235	0.2832
	B3	0.5674	0.3007
	B4	2.8027	1.4417
	B5	1.4608	0.7455
	B7	0.7374	0.4308

		E _{PIF} (%)	
		Mean	St. dev
2003	B1	0.4202	0.2392
	B2	0.4861	0.2565
	B3	0.4180	0.3220
	B4	2.4035	1.4686
	B5	1.2635	0.7219
	B7	0.6488	0.3835
2004	B1	0.3906	0.2477
	B2	0.5023	0.3425
	B3	0.5333	0.3351
	B4	2.4056	1.3286
	B5	1.2766	0.8492
	B7	0.7430	0.4477
2005	B1	0.4545	0.2342
	B2	0.4351	0.3383
	B3	0.5290	0.3090
	B4	2.6394	1.4922
	B5	1.1952	0.7840
	B7	0.6266	0.4304
2006	B1	0.3647	0.2497
	B2	0.7220	0.2312
	B3	0.5567	0.3356
	B4	2.7838	1.6537
	B5	1.5457	0.9664
	B7	0.9081	0.5488

The previous tables show the final accuracy results for the definitive set of PIF pixels. The accuracy test permits to identify and eliminate pixels that have a PIF error larger than the 5% threshold. This 5% limit has been defined as an acceptable PIF error by several studies (Schott *et al.*, 1998; Martinez *et al.*, 2002). From Table 20 and Table 21 it can be observed that none of the mean PIF errors are greater than this threshold.

5.2.2 Parra Study Area

An empirical geometric correction technique was applied in order to relocate as accurately as possible the images in their correct geographic position. An orthophoto was available for geometric correction. Common Ground Control Points between the orthophotos and the images of the datasets were collected on easily identifiable permanent features (cross-roads, buildings, mountain tops,...).

A multi-spectral SPOT model from the ERDAS Image Geometric Correction tool was selected, as the SPOT type of image is an available concrete model option. It was possible to include the DEM of the study area as elevation source. By doing this, the images of the dataset were ortho-rectified. The polynomial transformation was computed with a first polynomial degree for the images of the dataset. The re-sampling technique applied to place the DN of the original image pixels into the geometrically corrected image pixels was the Nearest-Neighbour technique. Table 22 shows the number of GCPs collected and the least squares regression quality of the adjustment (RMSE) achieved for each image.

Table 22. Geometric correction accuracy (Parra-SPOT)

Site	Sensor	Acquisition date	Number of GCPs	Quality of the adjustment	Quality of the correction	
				RMSE	Slope	r^2
Parra	SPOT 2	24/07/2002	140	0.3599	0.9994	1
	SPOT 5	25/09/2003	162	0.3414	1	1
	SPOT 5	29/07/2004	165	0.2669	1.0001	1
	SPOT 5	29/09/2005	165	0.2458	1	1
	SPOT 5	22/07/2006	165	0.3170	1.0004	1

As it can be observed, the accuracy level achieved with the polynomial transformation (quality of the adjustment) is very high. In order to check the quality of the correction, several points were identified within the orthophoto and the corrected images and regressed against each other. The slopes and correlation coefficient (r^2) obtained (see Table 22) show how the geometric correction results have a very high accuracy.

Once the geometric correction of the datasets was finished, DNs were converted into TOA spectral radiance and a haze correction was applied. With these images, a Minnaert topographic correction was performed. The values of the k constants were obtained for the areas that fulfilled the NDVI and slope constraints defined. NDVI constraint was set to $NDVI > 0.2$ and the slope constraint was set to $slope > 15^\circ$, in order to consider for k constants calculation only mountainous pixels that contain vegetation. Table 23 shows the k constant values obtained for each band of each image of the dataset, and the correlation values obtained for testing the accuracy of the k constant computation. As expected, k values for the first band (smaller wavelength), where the topography effect is less important, are smaller. As observed for the Landsat images, also here the NIR band does not accomplish with the latter, proving that in this spectral range there is a high dependence between the radiance of the vegetation and the illumination. For this study area, values obtained are within the range of 0.41 to 0.8. The correlation values obtained show that the computation of the Minnaert k constant values is highly satisfactory

Table 23. Minnaert's k constant and correlation values for Parra study area (SPOT).

		B1	B2	B3	B4
2002	k	0.5504	0.7649	0.5755	----
	$corr$	0.8586	0.8529	0.8586	----
2003	k	0.4129	0.5899	0.6813	0.7787
	$corr$	0.8631	0.8564	0.8502	0.8313
2004	k	0.6314	0.7564	0.6855	0.8007
	$corr$	0.8572	0.8543	0.8563	0.8456
2005	k	0.4629	0.6882	0.5438	0.7768
	$corr$	0.8730	0.8643	0.8700	0.8456
2006	k	0.5663	0.7529	0.6092	0.7859
	$corr$	0.8537	0.8488	0.8537	0.8404

The PIF relative atmospheric normalization was then implemented by selecting PIFs visually. The mT-nD-PCA technique for the selection of PIFs requires that part of the image is not affected by the disturbance. Parra study area does not represent the boundary of the fire, but the boundary of a public forest, which is managed by the forest services of Portimao. The fire that burned the whole area in 2003 was much larger. Therefore, almost the whole image area is affected by the fire. Therefore, visual selection of PIFs was performed. The accuracy of the orthophoto available of the area (0.5 m of spatial resolution) and the high spatial resolution of SPOT 5 images allowed the easy identification of man-made structures, water and soil. A total of 24 PIFs were selected (6 water PIFs, 4 soil PIFs, and 14 man-made PIFs). The DEM of the area was used to ensure that all PIFs were similar in altitude in order to avoid differences due to light path lengths.

Once PIFs were selected, a reference image was chosen from the dataset by checking the path radiance term. The image with the lowest path radiance term was selected as reference image, and converted into reflectance units. The image of 2003 was selected as reference image. For the reasons explained in the previous section 5.2.1, an absolute

atmospheric correction was performed in this reference image by means of the COST method (see section 4.2.6 for details about the application of the COST method). Atmospheric transmittances were computed as stated in section 4.2.6. The optical thickness of Rayleigh dispersion (τ_r) values obtained for SPOT sensors are shown in Table 24.

Table 24. Optical thickness of Rayleigh dispersion values for SPOT sensors

	B1	B2	B3	B4
Central λ (μm)	0.545	0.645	0.835	1.665
τ_r	0.100966	0.050892	0.017918	0.001119

For each PIF, its reflectance value on the reference image, and its radiance values on the rest of the images of the dataset were extracted. Once these values were collected, the gain and offset (normalization factors) were calculated for each band of each image. Gains and offsets were used to normalize the radiance images.

In order to check the accuracy of the PIF normalization, Equation 19, Equation 20, Equation 21 were implemented in an EXCEL spreadsheet. Table 25 presents the PIF error for Parra study area.

Table 25. PIF Error statistics for Parra study area (SPOT).

		E_{PIF} (%)	
		<i>mean</i>	<i>St. dev</i>
2002	<i>B1</i>	1.0065	0.6107
	<i>B2</i>	1.1126	0.7691
	<i>B3</i>	1.3169	0.6886
2004	<i>B1</i>	0.9902	0.6776
	<i>B2</i>	0.9814	0.5970
	<i>B3</i>	1.1254	0.7189
	<i>B4</i>	1.0363	0.8854
2005	<i>B1</i>	1.0771	0.5385
	<i>B2</i>	1.0325	0.6417
	<i>B3</i>	1.1480	0.5407
	<i>B4</i>	1.3805	0.9747
2006	<i>B1</i>	1.0149	0.4732
	<i>B2</i>	0.7963	0.5908
	<i>B3</i>	0.8510	0.7022
	<i>B4</i>	1.1231	0.7726

As it can be observed all the E_{PIF} are within the range considered as acceptable by other studies, that is, less than 5% (Schott *et al.*, 1998; Martinez *et al.*, 2002).

5.2.3 Mação Study Area

An empirical geometric correction technique was applied in order to relocate as accurately as possible the images in their correct geographic position. An orthophoto was available for geometric correction. Common Ground Control Points between the orthophotos and the images of the datasets were collected on easily identifiable permanent features (cross-roads, buildings, mountain tops,...).

A polynomial model from the ERDAS Image Geometric Correction tool was selected, as the CHRIS-Proba type of image is not an available specific model option. The polynomial

transformation was done with a second polynomial degree for both images of the dataset. The re-sampling technique applied to place the DN of the original image pixels into the geometrically corrected image pixels was the Nearest-Neighbour technique. Table 26 shows the number of GCPs collected and the least squares regression quality of the adjustment (RMSE) achieved for each image.

Table 26. Geometric correction accuracy (Mação-CHRIS-Proba)

Site	Sensor	Acquisition date	Number of GCPs	Quality of the adjustment	Quality of the correction	
				RMSE	Slope	r^2
Mação	CHRIS-Proba	08/06/2005	39	0.6204	1.0071	0.9985
	CHRIS-Proba	19/06/2006	40	0.5801	0.9980	0.9988

As it can be observed, the quality of the adjustment is poor, even with a second polynomial degree transformation. Higher polynomial degree transformations improved the quality of the adjustment, but the image suffered severe deformations. Therefore, it was considered that the results achieved with the second polynomial degree transformation were the most accurate possible ones. In order to check the quality of the correction, several points were identified within the orthophoto and the corrected images and regressed against each other. The slopes and correlation coefficient (r^2) obtained (see Table 26) show how the geometric correction results are not as bad as they could be considering the mentioned problems.

Once the geometric correction of the datasets was finished the absolute atmospheric correction including the haze correction was performed. These images arrive from the image server directly in TOA radiance units. Therefore, only a haze correction, conversion to reflectance units, and atmospheric correction are needed. Also topographic correction would be useful, but unfortunately, no DEM was available for this area.

Concerning the possibility to perform an atmospheric normalization through the mT-nD-PCA PIF selection technique, the same problems were present as for the Parra study area. Visual identification of PIFs was tried, but the spatial resolution of the sensor (18 m) did not allow an accurate identification of PIFs. As a consequence, an absolute atmospheric

correction by means of the COST method was applied to both images of the dataset. The fact that the images were near-anniversary and that the time series was compounded of only two images permitted this approach.

Atmospheric transmittances were computed as stated in section 4.2.6. The optical thickness of Rayleigh dispersion (τ_r) values obtained for CHRIS-Proba sensors are shown in Table 27. The mean exo-atmospheric solar spectral irradiance (E_{λ}^{SUN}) for each band was not available and had to be calculated from the Solar Spectrum database used at the World Radiation Centre. The E_{λ}^{SUN} values of this database are very detailed (one irradiance value per each 0.001 μm), so the mean of the E_{λ}^{SUN} values belonging to the min-max wavelength range of each band of the sensor were extracted (see Table 27).

Table 27. Optical thickness of Rayleigh dispersion and E_{SUN} values for CHRIS-Proba sensor

	Central λ (μm)	τ_r	E_{λ}^{SUN} ($\text{W m}^{-2} \mu\text{m}^{-1}$)
B1	0.4205	0.292727	1874.17
B2	0.4425	0.237156	1910.92
B3	0.4905	0.155324	1890.50
B4	0.5300	0.113147	1864.93
B5	0.5510	0.096557	1843.33
B6	0.5695	0.084401	1666.27
B7	0.6315	0.055452	1538.78
B8	0.6610	0.046079	1515.00
B9	0.6715	0.043228	1423.00
B10	0.6970	0.037172	1398.75
B11	0.7030	0.035905	1379.00
B12	0.7090	0.034691	1284.75
B13	0.7415	0.028940	1259.80
B14	0.7485	0.027862	1184.15
B15	0.7805	0.023527	967.70
B16	0.8720	0.015044	926.30
B17	0.8955	0.013515	876.23
B18	0.9050	0.012953	717.70

Once these variables were defined, the COST method was applied to both images of the dataset, producing absolutely atmospherically corrected reflectance images.

5.3 SPECTRAL ANALYSIS RESULTS

This section presents the results obtained after the application of the spectral analysis techniques. Each sub-section: 5.3.1 Lythrodontas Study Area, 0 Deiva Marina Study Area, 0 Parra Study Area, and 0 Mação Study Area) presents the results for one study area. In the first one, results are thoroughly explained and discussed. As the steps for obtaining results were quite similar between study areas, in order to avoid extreme repetition of results discussion, some arguments have been only inserted in this first sub-section, but they are valid also for the other sub-sections.

5.3.1 Lythrodontas Study Area

5.3.1.1 ENDMEMBER EXTRACTION

Once the atmospheric normalized reflectance images were obtained, the procedure for obtaining image endmembers was applied (see section 4.3.3.2). Principal Component Analysis was performed in order to check the dimensionality of the Landsat images. The eigen-values (E-val) of each image were extracted (see Table 28). As it can be seen, in all of them the first four principal components contain more than 99% of the original variance (V%) of the data. Therefore it was considered that the dimensionality of all images in the dataset was equal to 4. Applying Equation 45 the maximum number of image endmembers to extract from the Landsat images was set to 4 endmembers.

Table 28. Eigen-values and % of variance for Lythrodontas study area (Landsat).

		1999	2000	2001	2002	2003	2004	2005	2006
PC1	<i>E-val</i>	0.007025	0.006342	0.005806	0.006380	0.005084	0.004377	0.004496	0.004835
	<i>V%</i>	84.11	84.42	83.08	81.06	83.85	83.32	83.48	86.69
PC2	<i>E-val</i>	0.000757	0.000657	0.000712	0.000865	0.000511	0.000468	0.000458	0.000447
	<i>V%</i>	9.06	8.75	10.19	10.99	8.43	8.91	8.50	8.01
PC3	<i>E-val</i>	0.000343	0.000321	0.000323	0.000388	0.000260	0.000244	0.000244	0.000207
	<i>V%</i>	4.11	4.27	4.62	4.93	4.29	4.64	4.53	3.71
PC4	<i>E-val</i>	0.000180	0.000155	0.000116	0.000194	0.000160	0.000118	0.000144	0.000049
	<i>V%</i>	2.15	2.06	1.66	2.46	2.64	2.25	2.67	0.89
PC5	<i>E-val</i>	0.000037	0.000028	0.000023	0.000033	0.000032	0.000030	0.000027	0.000024
	<i>V%</i>	0.44	0.37	0.33	0.42	0.53	0.57	0.50	0.43
PC6	<i>E-val</i>	0.000010	0.000009	0.000008	0.000011	0.000016	0.000016	0.000017	0.000015
	<i>V%</i>	0.13	0.13	0.11	0.14	0.26	0.31	0.32	0.27

SMACC was then applied to each image of the dataset. A set of four image endmembers were extracted for each image and their spectral identity was defined. In order to define the latter, their spectral signature was analyzed and NDVI images were produced. The spectral signature of the pixel of each image endmember was extracted and, together with the NDVI value of the pixel, was used to identify the endmember classes. For each one of the eight image endmember sets, a green vegetation class endmember (GV), a soil class endmember (S), a shade class endmember (Sh) and a non photosynthetic vegetation class endmember (NPV) were identified. The endmember classes' reflectance in each band of the eight endmember sets (one for each year) was extracted and put into an EXCEL spreadsheet. Band average reflectance values for each class of endmember (GV, S, Sh, and NPV) were computed, yielding four average endmembers. This was possible because the spectral signatures of the image endmembers of each single class were very similar between them in all the images. This similarity was probably due to the fact that the images were near-anniversary and atmospherically normalized. Table 29 presents the band average reflectance values for each average endmember, and Figure 14 shows their

spectral signatures. This set of average endmembers was then used for the application of the spectral analysis techniques.

Table 29. Average endmember reflectance values (Lythrodontas-Landsat)

	Average Endmember Reflectances			
	GV	S	Sh	NPV
B1	0.029046	0.149809	0.037862	0.055654
B2	0.041257	0.194964	0.044756	0.082107
B3	0.040581	0.243350	0.033295	0.108037
B4	0.261765	0.327605	0.038043	0.194821
B5	0.152510	0.329888	0.021426	0.301091
B7	0.058539	0.222313	0.005303	0.224657

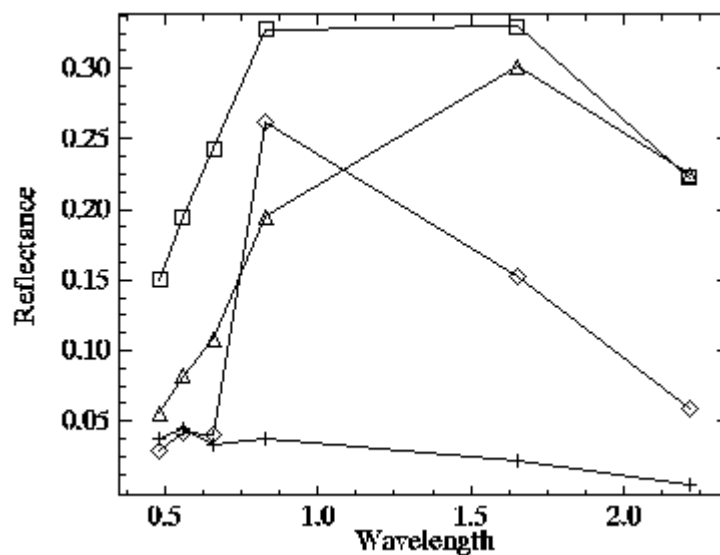


Figure 14. Lythrodontas (Landsat) average endmember spectral signatures: GV ($\diamond$), S ($\square$), Sh (+), and NPV (Δ)

5.3.1.2 SPECTRAL MIXTURE ANALYSIS APPLICATION

SMA was then applied to each image of the dataset in order to obtain the fraction images. SMA was constrained to produce fraction images which sum results 1 in order to produce meaningful fractions. Both the fractional error and the RMSE error were checked for each set of four fraction images in order to assess their accuracy.

Reasonable values for fractions are supposed to be greater than 0 and less than 1. However, negative fractions exist, mainly in roads or buildings. The fraction criterion for SMA accuracy assessment has been introduced by Roberts *et al.* (1998). They argue that a 1% of instrumental noise errors in fractions is permitted, while Souza *et al.* (2003) indicated that an acceptable fractional error is 5% of the fractions. Table 30 shows the fractional errors obtained for the fraction images of each year.

Mean, minimum (min) and maximum (max) RMSE values, together with its standard deviation (st dev) were computed for the SMA results of each image of the dataset (see Table 30). RMSE indicates to what extent the image spectra cannot be explained by the endmembers. In order to get a realistic unmixing model, the mean RMSE has to be below a threshold of less than 0.025 (Roberts *et al.*, 1998; van der Meer & de Jong, 2000).

Table 30. RMSE and Fractional Error values of fraction images (Lythrodontas-Landsat)

	Fractional Error (%)				RMSE			
	GV	S	Sh	NPV	Mean	St.dev	Min	Max
1999	1.69	52.79	1.07	13.25	0.005836	0.002892	0.000133	0.162439
2000	1.06	56.54	1.06	7.18	0.005473	0.002751	0.000180	0.135744
2001	4.90	57.45	1.07	2.73	0.005182	0.002793	0.000118	0.158894
2002	4.80	52.30	0.84	3.46	0.006726	0.003401	0.000123	0.195487
2003	0.46	51.00	1.18	3.53	0.006191	0.003130	0.000188	0.139098
2004	0.41	50.6	1.05	3.56	0.005702	0.002821	0.000125	0.091848
2005	0.34	48.50	1.04	3.88	0.006191	0.003222	0.000138	0.117441
2006	0.74	48.20	0.71	4.23	0.004660	0.002040	0.000103	0.035759

Mean RMSE values obtained (Table 30) are well below the 0.025 threshold. This indicates that the applied unmixing model shows a sufficient fit and, therefore, the set of average endmembers applied is accurate enough as to be used in a multi-temporal study like this one.

Looking at the fractional error values presented in Table 30, it is possible to observe that more than 95% of GV values lay within the required range in each image, remaining the

fractional error GV values under the maximum 5% defined by Souza *et al.* (2003). Also fractional error Sh values are well under 5%. This demonstrates that GV and Sh of each image are well modelled by the average GV and Sh endmembers. However GV fractional error values of 2001 and 2002 are much higher respect to the other values. This can be explained by the fact that these images are immediate post-fire images, and the fire effects are still present in the area (ash, charcoal). In the burned area, vegetation fraction values obtained were quite often negative values, which increased the GV fractional error for these two images. In order to illustrate this, the mean, minimum and maximum GV fraction values, together with the percentage of GV negative fraction values (% Negative GV) for the burned areas for all images were extracted (see Table 31).

Table 31. SMA GV fraction statistics for the burned area (Lythrodontas-Landsat)

	SMA GV fraction statistics				
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>	<i>% Negative GV</i>
1999	0.432322	0.116515	0.049962	0.949297	0
2000	0.407034	0.108017	0.003560	0.944618	0
2001	0.037545	0.138555	-0.277422	0.708879	50.99
2002	0.073615	0.140268	-0.262864	0.792103	32.06
2003	0.241994	0.094262	-0.089641	0.749005	0.07
2004	0.271883	0.089902	0.023469	0.743433	0
2005	0.294477	0.078458	0.016154	0.752085	0
2006	0.326535	0.086920	0.043121	0.738666	0

Regarding soil fraction values (S), the high amount of fractional error can be explained by the high soil variability in the area and the difficulty in modelling with only one endmember this soil variability.

NPV fraction values are below the 5% threshold for 2001, 2002, 2003, 2004, 2005, and 2006 images, but not for 1999 and 2000. Looking at Figure 14, it is possible to observe that the NPV endmember reflectance in band 5 is higher than in band 4, which is a typical post-fire vegetation behaviour linked closely to the exposition of the dry soil layer which has a

pronounced reflectance in the MIR spectral range (Twele, 2003). This influence of soil in the NPV endmember has already been reported by other authors (Roberts *et al.*, 1998). Spectral ambiguity between NPV and soils is an important limitation when trying to define pure material endmembers. Therefore, the high amount of fractional error for NPV in the two pre-fire images can be explained by the absence in these images of post-fire vegetation conditions.

SMA GV fraction images (see Figure 15) were the images used for comparison with the other vegetation fraction extracting techniques. This was done in order to increase the robustness of the comparison, as the other techniques are based in R/NIR indices which are studied to detect green vegetation.

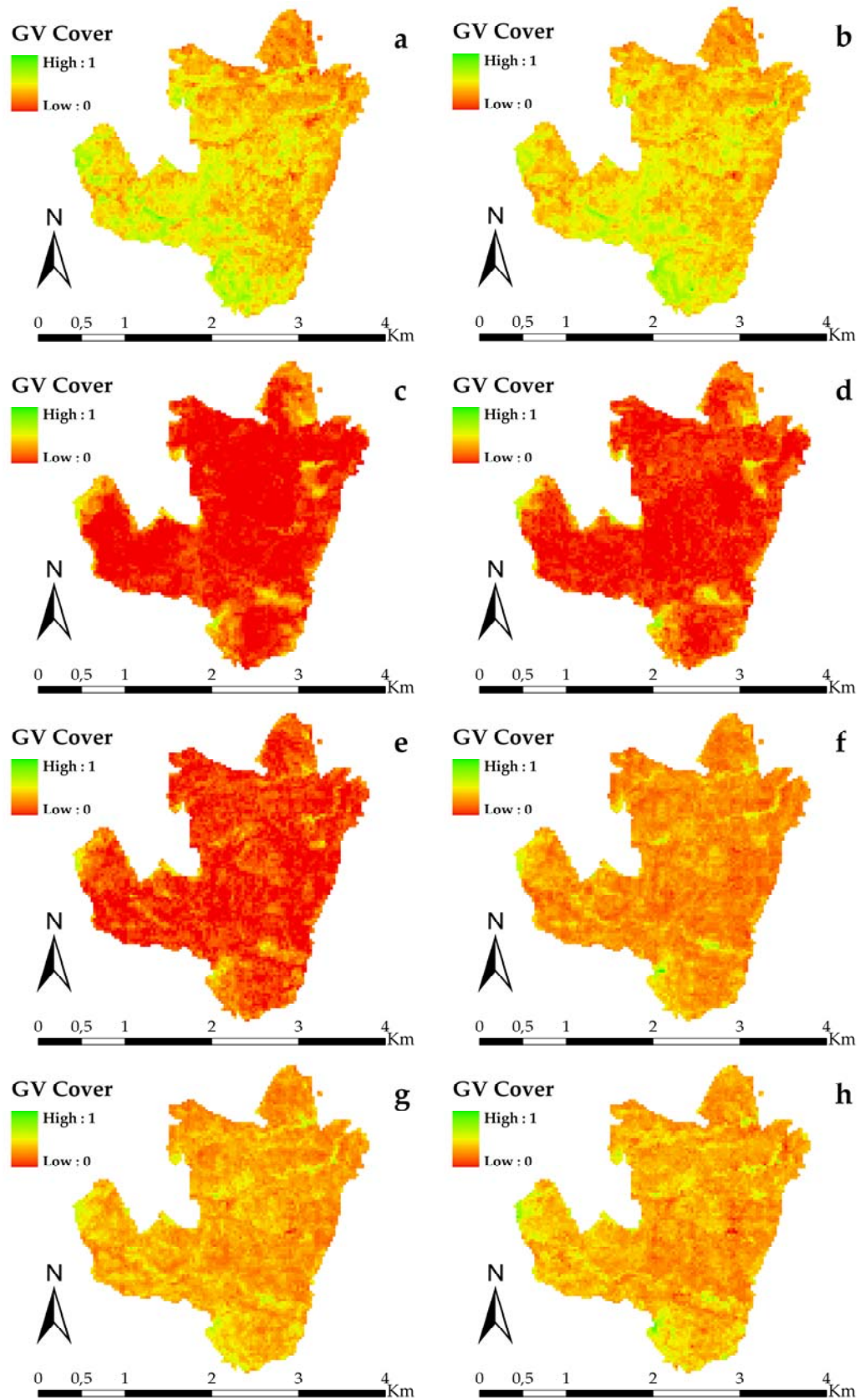


Figure 15. Lythrodontas (Landsat) study area SMA GV fraction images: 1999 (a), 2000 (b), 2001 (c), 2002 (d), 2003 (e), 2004 (f), 2005 (g), and 2006 (h)

As a post-processing step, shade normalization was applied in order to check the need of this last step for a higher accuracy when using SMA. Both the GV fraction images and the shade normalized GV fraction images were used for comparison with the rest of techniques. Table 32 shows the mean and standard deviation values of the burned area for the shade normalized GV (GV_{shn}) fraction images.

Table 32. SMA_{shn} GV fraction statistics for the burned area (Lythrodontas-Landsat)

	SMA_{shn} GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
1999	0.691767	0.210986	0.058801	1.228775
2000	0.672355	0.197778	0.0055141	1.196893
2001	0.055326	0.284532	-0.720721	1.073446
2002	0.121693	0.225890	-0.420190	1.093915
2003	0.373079	0.146224	-0.186094	1.304122
2004	0.407367	0.122793	0.027480	1.026964
2005	0.434911	0.129440	0.026732	1.146917
2006	0.480301	0.124958	0.048053	1.244232

Table 33 shows the percentage of increase ($\Delta GV\%$) that the shade normalization has added to the mean GV fraction values. For the two pre-fire images, the increment is much higher than for the rest of the images. This may be due to the canopy shadowing effect of vegetation. In immediate post-fire images (2001 and 2002) this effect has completely disappeared with vegetation. It only starts to reappear when the burned area starts to recover from the fire, incrementing the vegetation cover and thus, the shadowing effect.

Table 33. Percentages of increase ($\Delta GV\%$) from GV fraction to GV_{shn} fraction

	1999	2000	2001	2002	2003	2004	2005	2006
$\Delta GV\%$	25.94	26.53	1.78	4.81	13.11	13.55	14.04	15.37

Figure 16 shows the shade normalized GV fraction images produced for Lythrodontas study area.

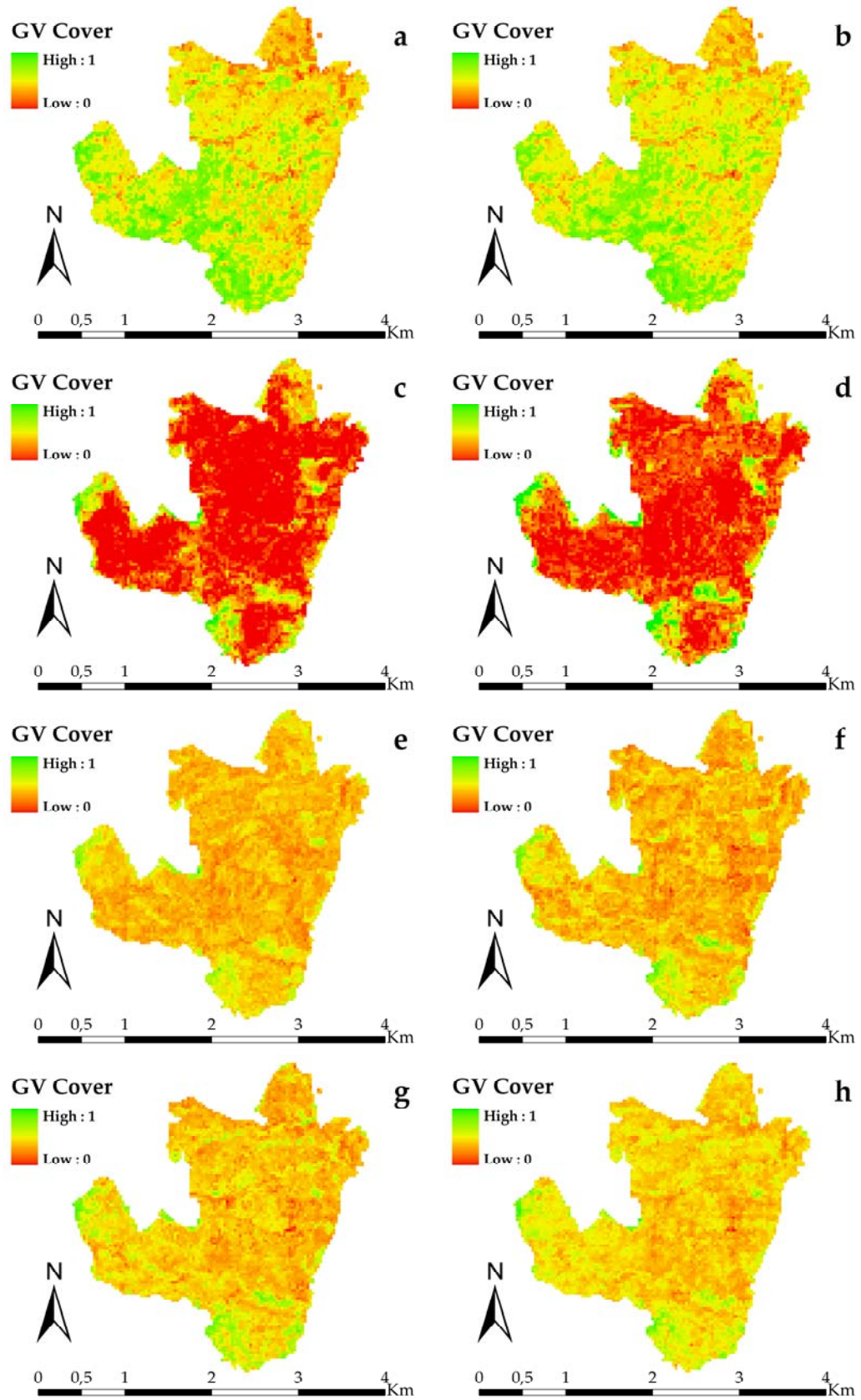


Figure 16. Lythrodontas (Landsat) study area SMA_{shn} GV fraction images: 1999 (a), 2000 (b), 2001 (c), 2002 (d), 2003 (e), 2004 (f), 2005 (g), and 2006 (h)

5.3.1.3 QUANTITATIVE VEGETATION INDICES APPLICATION

Green vegetation fractional cover images were obtained by applying the quantitative vegetation indices (VIs) described in section 4.3.2.

The red (ρ_R) and near-infrared (ρ_{NIR}) reflectance values of the average soil endmember (S) and the average vegetation endmember (GV) were used to scale the vegetation indices (see section 4.3.2 for details). Table 34 presents the ρ_R and ρ_{NIR} reflectance values of these endmembers together with the corresponding NDVI, MSAVI and DVI values.

Table 34. Scaling values for the application of the quantitative VIs (Lythrodontas-Landsat).

	ρ_{NIR}	ρ_{NIR}	NDVI	MSAVI	DVI
GV	0.040581	0.261765	0.731560	0.390392	0.221184
S	0.244450	0.327605	0.147568	0.108981	0.084255

Table 35, Table 36, and Table 37 show the GV fraction statistic values for each year when applying f-NDVI, f-MSAVI, and f-DVI respectively.

Table 35. f- NDVI GV fraction statistics for the burned area (Lythrodontas-Landsat)

	f-NDVI GV fraction statistics			
	Mean	St dev.	Min	Max
1999	0.479690	0.168303	0.016800	1.000000
2000	0.476420	0.162733	0.011025	1.000000
2001	0.172438	0.119722	0.000000	1.000000
2002	0.090418	0.130159	0.000000	1.000000
2003	0.218616	0.096728	0.000000	0.866538
2004	0.249776	0.091665	0.000000	1.000000
2005	0.286281	0.077855	0.000000	0.813222
2006	0.289740	0.086251	0.000000	0.859078

Table 36. f- MSAVI GV fraction statistics for the burned area (Lythrodontas-Landsat)

	f-MSAVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
1999	0.397516	0.144196	0.000000	0.966937
2000	0.367882	0.137129	0.000000	0.995201
2001	0.035791	0.100331	0.000000	0.773888
2002	0.038571	0.110495	0.000000	0.844673
2003	0.139769	0.127542	0.000000	0.835605
2004	0.182577	0.128440	0.000000	0.993588
2005	0.237810	0.099861	0.000000	0.787083
2006	0.257076	0.120906	0.000000	0.776681

Table 37. f- DVI GV fraction statistics for the burned area (Lythrodontas-Landsat)

	f-DVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
1999	0.186995	0.122196	0.000000	0.829919
2000	0.156541	0.115246	0.000000	0.962371
2001	0.010537	0.047156	0.000000	0.515142
2002	0.013942	0.059570	0.000000	0.622319
2003	0.037757	0.077099	0.000000	0.694533
2004	0.053142	0.088437	0.000000	1.000000
2005	0.072819	0.078073	0.000000	0.664113
2006	0.096014	0.097750	0.000000	0.685339

Figure 17, Figure 18, and Figure 19 present the resulting green vegetation cover images for f-NDVI, f-MSAVI, and f-DVI respectively.

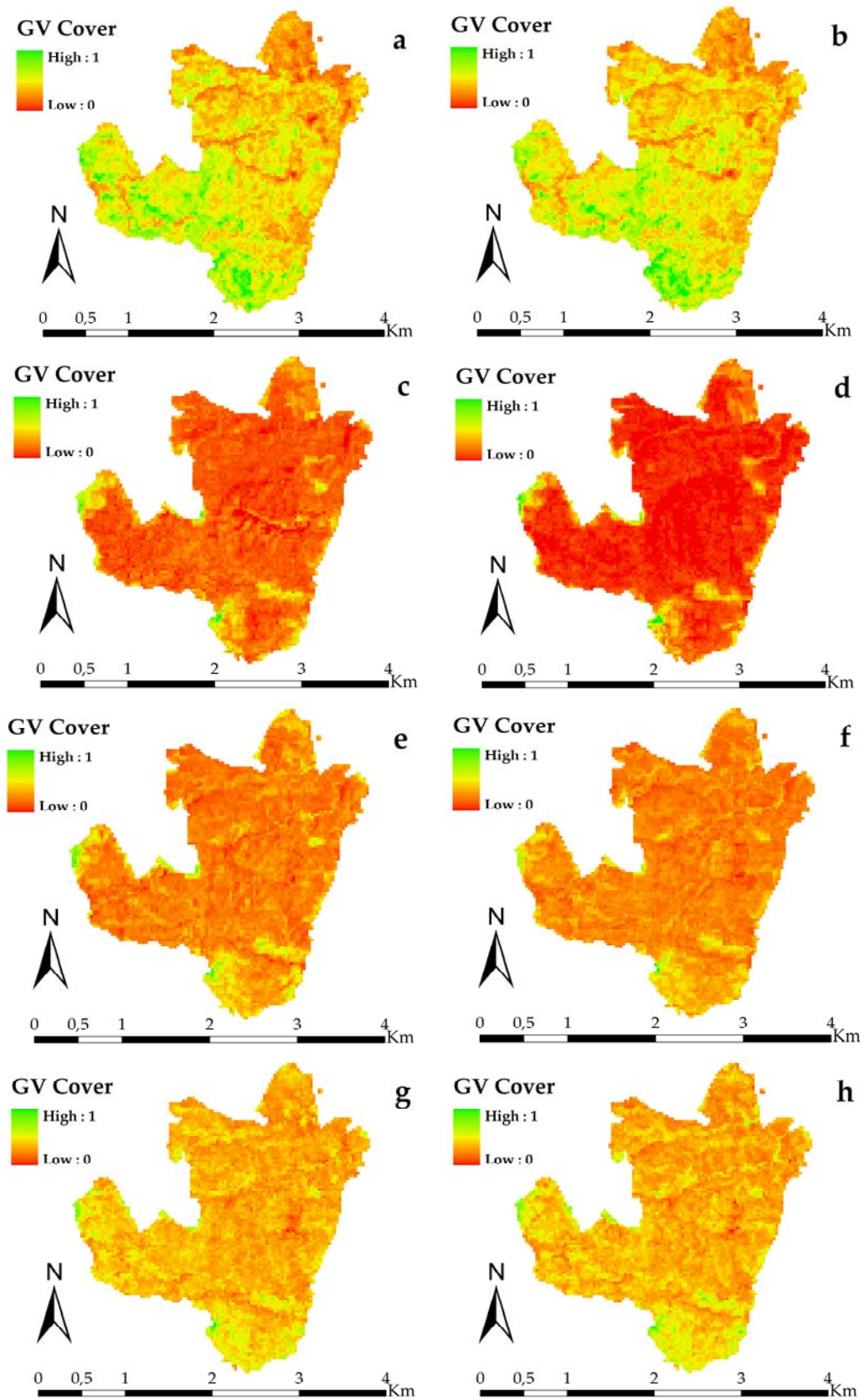


Figure 17. Lythrodontas (Landsat) study area f-NDVI green vegetation cover images: 1999 (a), 2000 (b), 2001 (c), 2002 (d), 2003 (e), 2004 (f), 2005 (g), and 2006 (h)

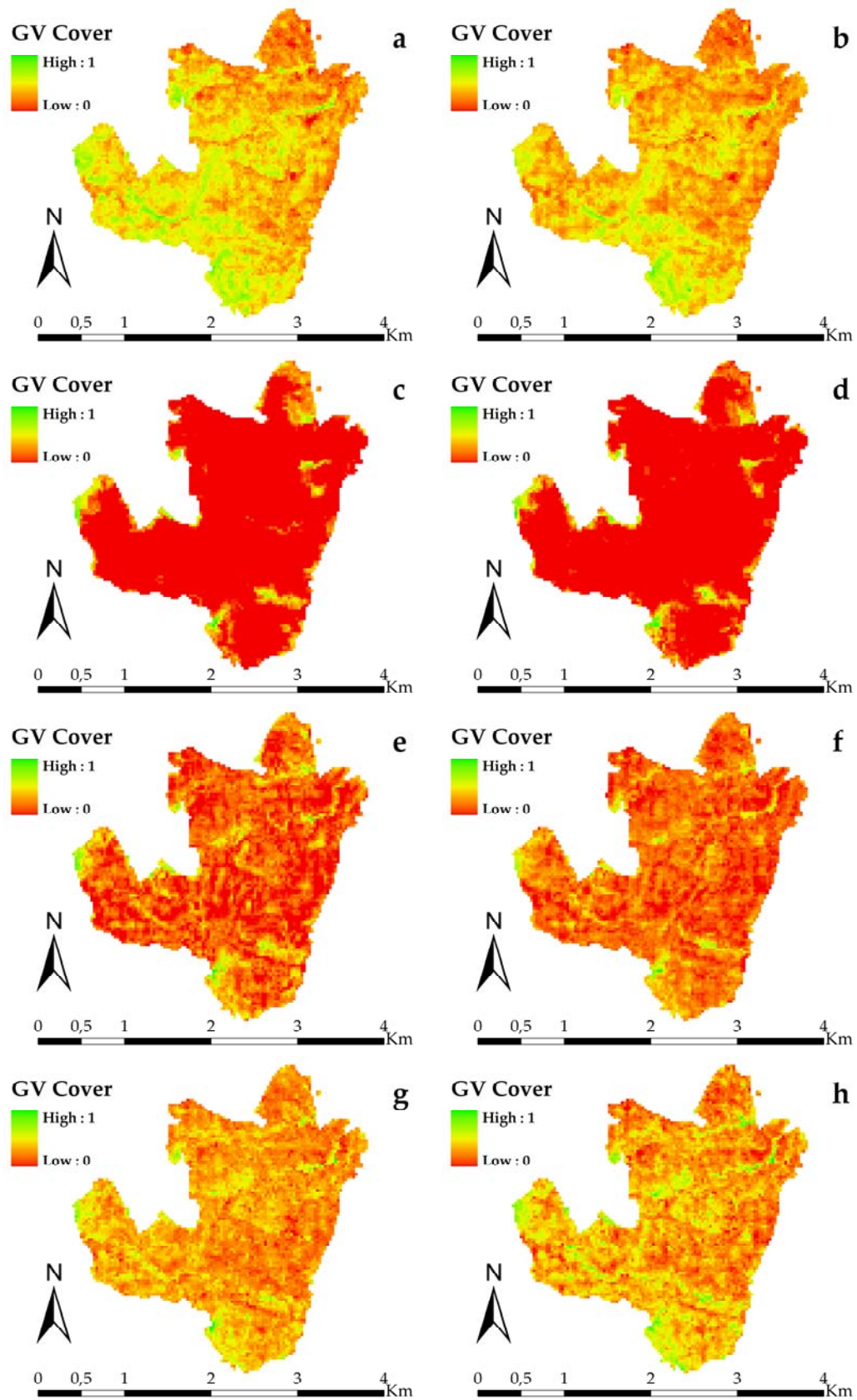


Figure 18. Lythrodontas (Landsat) study area f-MSAVI green vegetation cover images: 1999 (a), 2000 (b), 2001 (c), 2002 (d), 2003 (e), 2004 (f), 2005 (g), and 2006 (h)

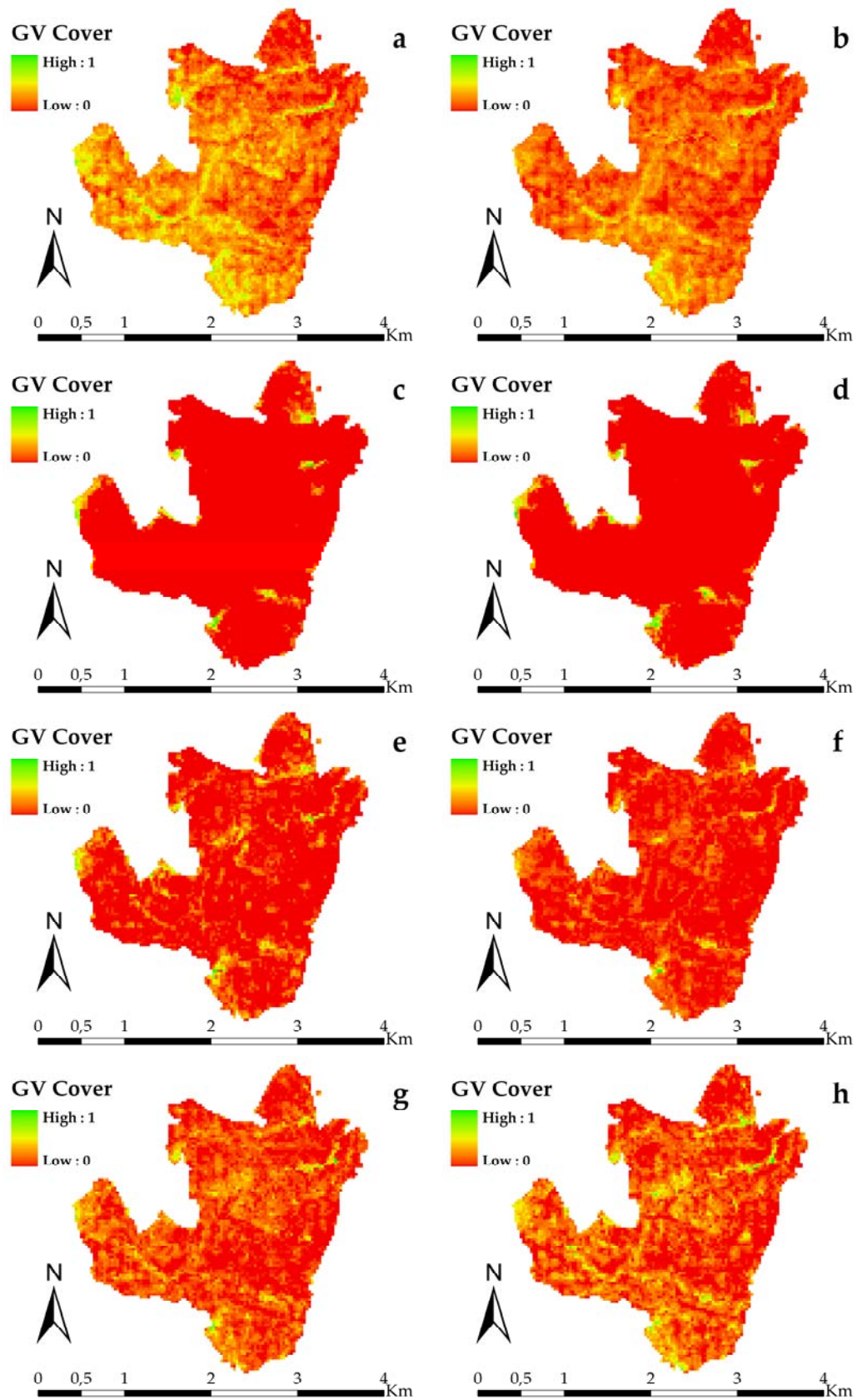


Figure 19. Lythrodontas (Landsat) study area f-DVI green vegetation cover images: 1999 (a), 2000 (b), 2001 (c), 2002 (d), 2003 (e), 2004 (f), 2005 (g), and 2006 (h)

5.3.1.4 ACCURACY AND COMPARISON OF METHODOLOGIES

Table 33 shows the increase of GV cover after the shade normalization of SMA results. As it can be observed, in pre-fire images this increase is the largest, while in immediate post-fire images this increase is almost zero. This suggests that the increase of GV cover due to shade normalization is related to the amount of vegetation present in the area. In order to test this, GV cover increase values between SMA and shade normalized SMA were computed and regressed against the mean GV cover values obtained from the f-NDVI method. The coefficient of correlation obtained was 0.91 demonstrating that the increase of GV cover due to shade normalization of SMA results is closely related to the amount of vegetation present in the area. This can be explained by the canopy shadowing effect, which decreases when vegetation cover is low and increases when vegetation cover increases.

Accuracy of the 2005 and 2006 green vegetation fractional cover resulting images after the application of the five selected methodologies (SMA, SMA shade normalized – SMA_{shn} –, f-NDVI, f-MSAVI, and f-DVI) was checked by regression against the field data collected during the 2005 and 2006 field campaigns.

Accuracy assessment was considered on a 3x3 pixels kernel. The most common source of error when comparing field data and satellite derived data is the geo-location accuracy of the satellite images. However, in this study much care was taken when performing the geometric correction of the images, reaching a geo-location error much lower than 0.5 pixels (from 0.15 to 0.22 pixels, that means converted in meters, an interval from 4.5 to 6.6 m). Giving the size of the field plot (3x3 pixels = 3600 m²), and the high geometric accuracy reached, at least a 2x2 pixels kernel should be considered for accuracy assessment. In order to take into account the still remaining small geo-location error fraction, a 3x3 pixels kernel was defined. A 3x3 average kernel was passed on the GV cover images and 3x3 pixels average GV cover values were extracted from the images at field plots coordinates. Table 38 shows the R² values obtained from the accuracy analysis for 2005 and 2006 GV cover images, and Figure 20 and Figure 21 shows the regression graphics produced for each methodology for 2005 and 2006 respectively.

Table 38. Methodologies accuracy for GV cover retrieval (Lythrodontas-Landsat)

	SMA	SMA_{shn}	f-NDVI	f-MSAVI	f-DVI
R² 2005	0.7798	0.7083	0.8649	0.6962	0.6226
R² 2006	0.7037	0.8174	0.8646	0.6343	0.7177

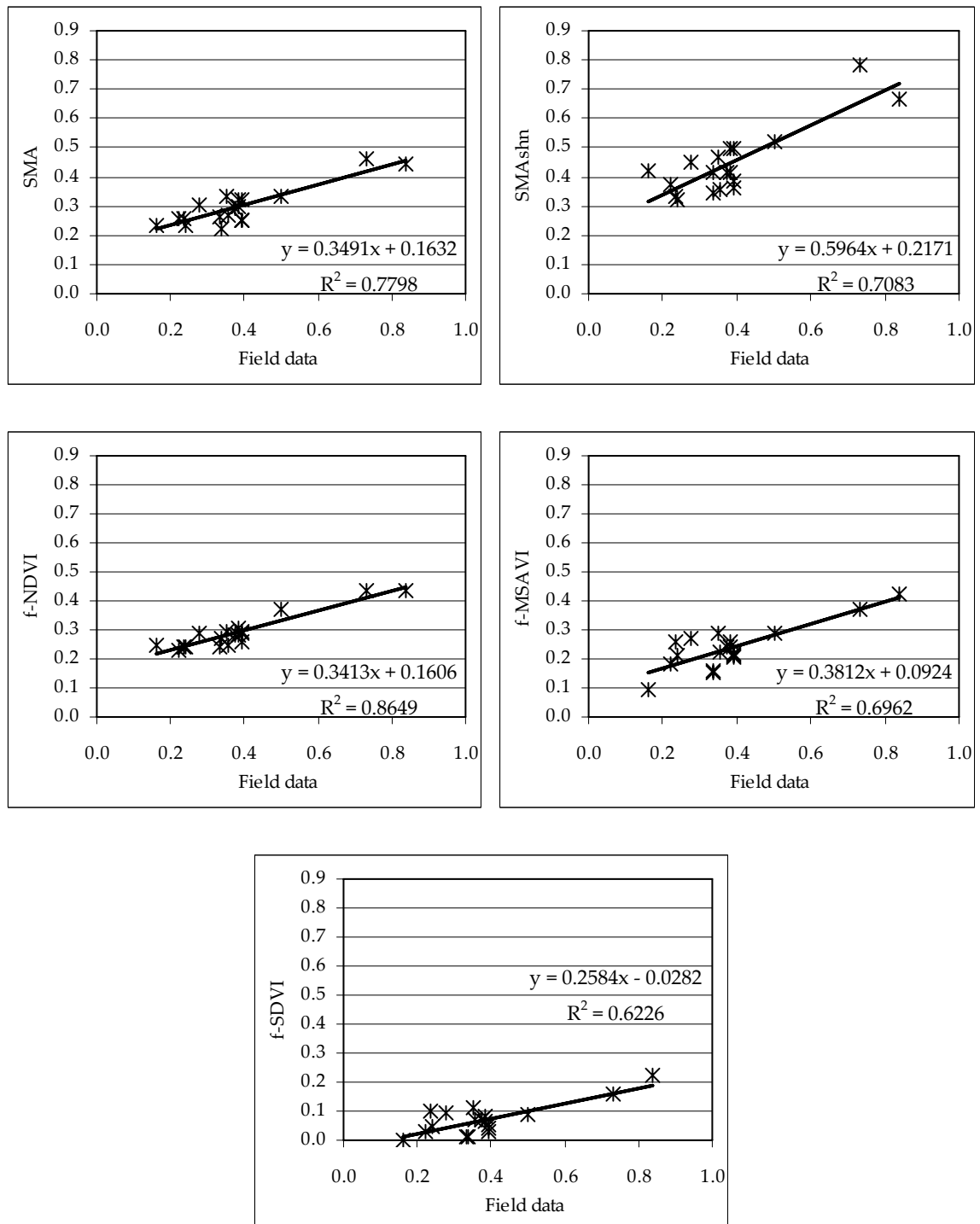


Figure 20. Accuracy regression graphics for the five methodologies (Lythrodontas 2005): SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI.

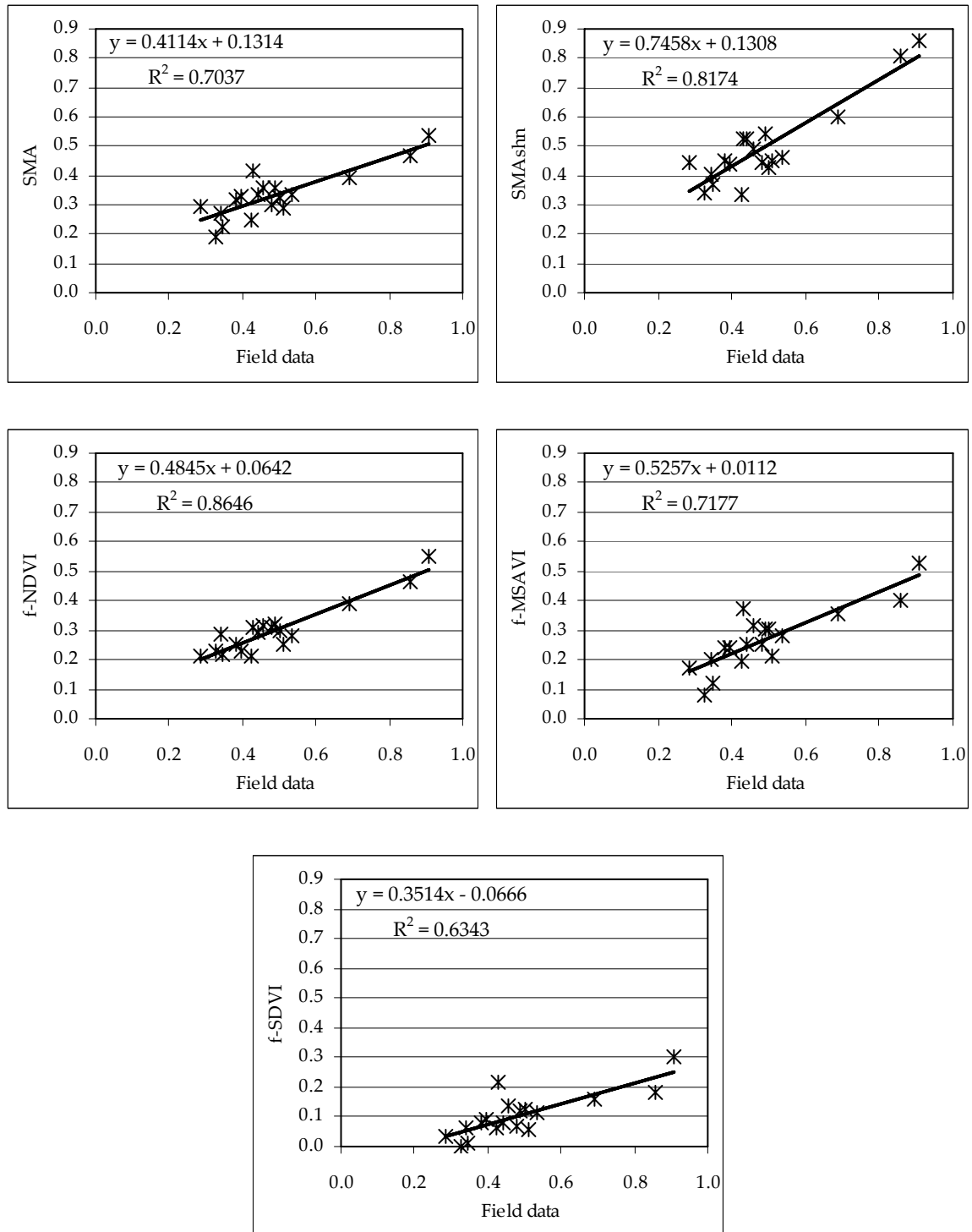


Figure 21. Accuracy regression graphics for the five methodologies (Lythrodontas 2006): SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI.

In both 2005 and 2006 cases, f-NDVI was the best performing methodology, followed by SMA_{shn} in 2005 and by SMA and f-MSAVI in 2006. In order to check thoroughly these results, the mean and standard deviation of GV cover values at the field plots were extracted for each method and compared (see Table 39 and Figure 22).

Table 39. Field plots GV cover mean and standard deviation

		Field data	SMA	SMA _{shn}	f-NDVI	f-MSAVI	f-DVI
2005	<i>Mean</i>	0.383662	0.297150	0.445942	0.291589	0.238631	0.070936
	<i>St dev</i>	0.167776	0.066323	0.118900	0.061581	0.076656	0.054937
2006	<i>Mean</i>	0.489167	0.332670	0.495565	0.301227	0.268387	0.105276
	<i>St dev</i>	0.170669	0.083708	0.140784	0.088919	0.105899	0.075314

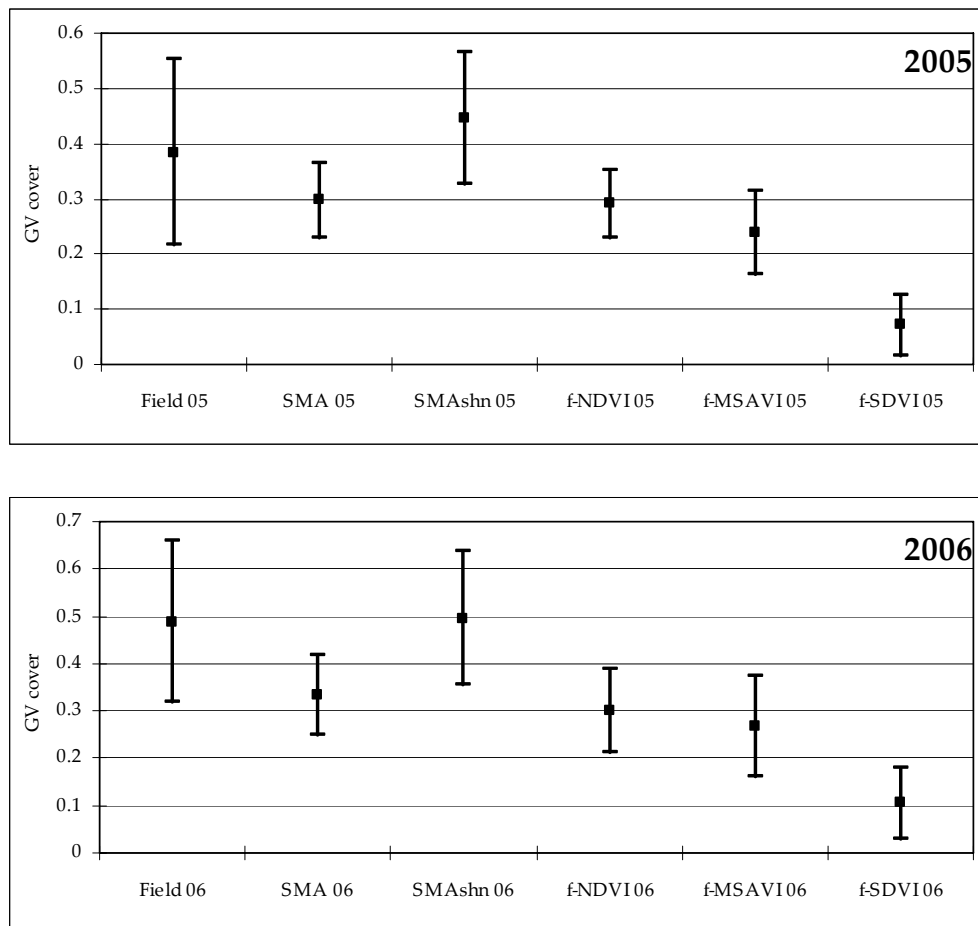


Figure 22. Field plots GV cover mean and standard deviation (2005 and 2006)

As it can be observed, all methodologies except SMA_{shn} underestimate GV cover respect to field 2005 and 2006 data. A possible explanation could be related to the fact that during the field campaigns, not only green vegetation was surveyed, but all the vegetation cover present in the area. All the images of the set were acquired around the end of July, beginning of August, when some vegetation are in a non photosynthetic status (NPV). Therefore, underestimation of GV cover respect field data is expected, as during the field campaigns all vegetation was surveyed.

5.3.1.5 VEGETATION REGROWTH DETECTION

Vegetation regrowth detection was carried out with the GV cover images produced by the best performing GV cover extracting method. For Lythrodontas study area, this best technique was f-NDVI. Figure 23 shows the vegetation regeneration trend within the Lythrodontas burned area when extracting vegetation cover with f-NDVI method. Also, f-NDVI GV cover images were subtracted one to each other in order to produce vegetation regeneration images. Figure 25 shows the regeneration images produced in a year by year interval. In Figure 26 the vegetation cover regeneration map from 2002 until 2006 in Lythrodontas study area is presented. As in 2002 the vegetation has reached its minimum after the fire, this year is taken as reference for the regeneration cover map instead of 2001.

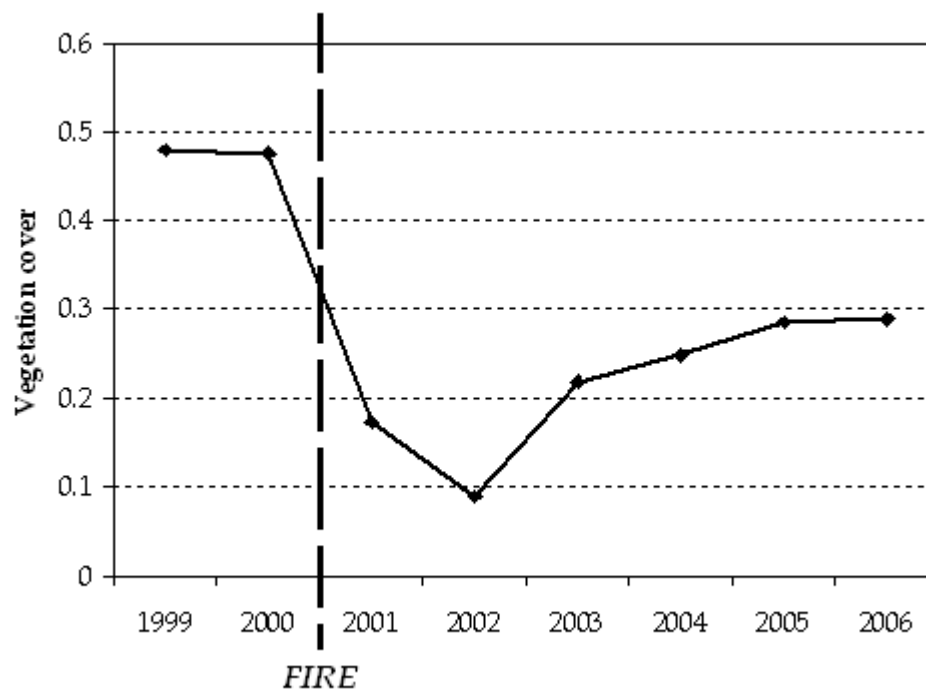


Figure 23. Vegetation regeneration trend in the burned area (Lythrodontas-Landsat)

Figure 23 and Figure 25 show how in the second year after the fire, the regeneration has not yet started. Instead, a further decrease in vegetation cover can be observed. This phenomenon is a consequence of the fire. Sometimes, vegetation that survived the fire, slowly disappear during the other post-fire years. This can happen naturally (vegetation dies due to the fire effects) or by anthropic causes (vegetation is extracted from the area in order to facilitate re-vegetation programs). During the third year, the increase of vegetation is the maximum registered of the time series, while in the remaining post-fire images this vegetation increase is lower, tending to reach an horizontal behaviour (see Figure 23). It seems that this horizontal maximum does not equal the pre-fire vegetation cover, but more images would be necessary to confirm that post-fire vegetation does not reach pre-fire conditions. Figure 24 shows the vegetation cover trend outside the Lythrodontas burned area. It shows how the amount of vegetation is decreasing. Climatic conditions in Cyprus during last years may have affected vegetation response during summer. Possibly the amount of NPV has increased due to the lack of rainfall and high temperatures suffered, while GV has decreased progressively. More images before 1999

and 2006 would be needed to confirm the role of local climate on vegetation cover behaviour. This local climate role should be beard in mind when analysing vegetation cover regrowth rates in the burned area.

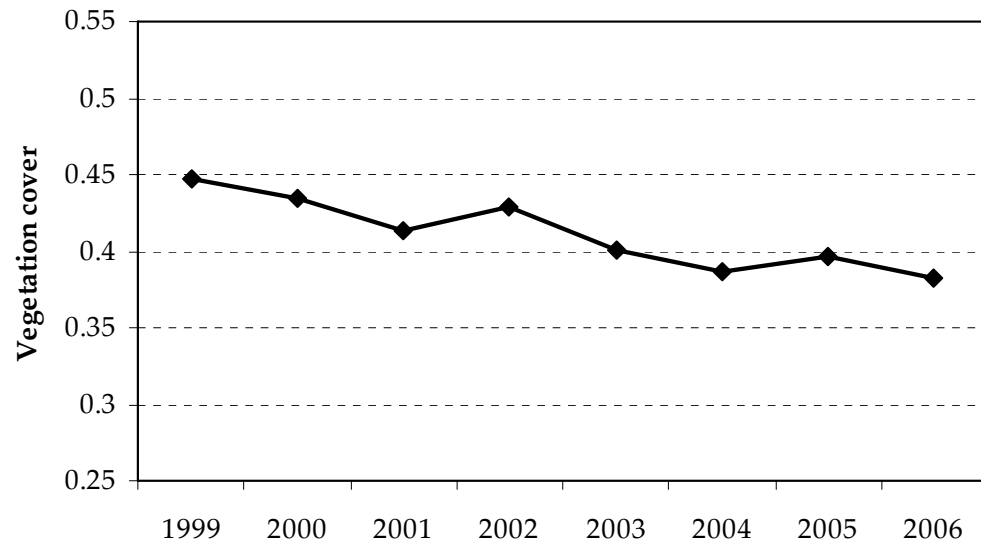


Figure 24. Vegetation regeneration trend outside the burned area (Lythrodontas-Landsat).

The general GV recovery of the site between 2002 (the lowest vegetation cover after the fire) and 2006 (last image of the series) can be observed in Figure 26. This figure shows how the whole area is recovering from the fire, with a mean recovery rate of 20%. However, certain areas show a vegetation cover decrease (blue pixels). Looking at the f-NDVI immediate post-fire images (Figure 17) it is evident that these areas are the ones where vegetation has survived after the fire. The vegetation in these areas have slowly disappeared due to fire effects or to anthropic interventions.

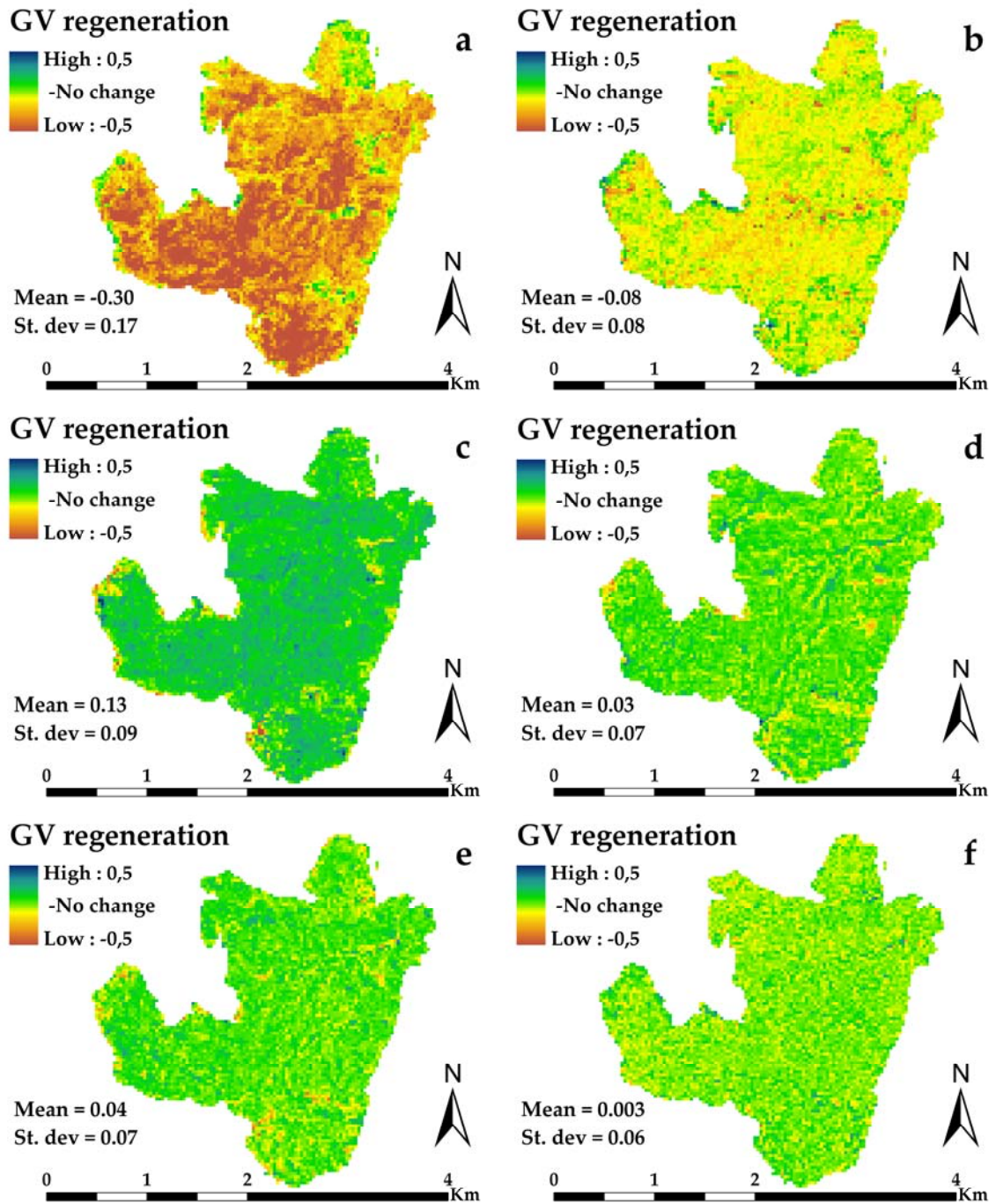


Figure 25. Regeneration images for Lythrodontas (Landsat) study area: 2000-2001 (a), 2001-2002 (b), 2002-2003 (c), 2003-2004 (d), 2004-2005 (e), and 2005-2006 (f)

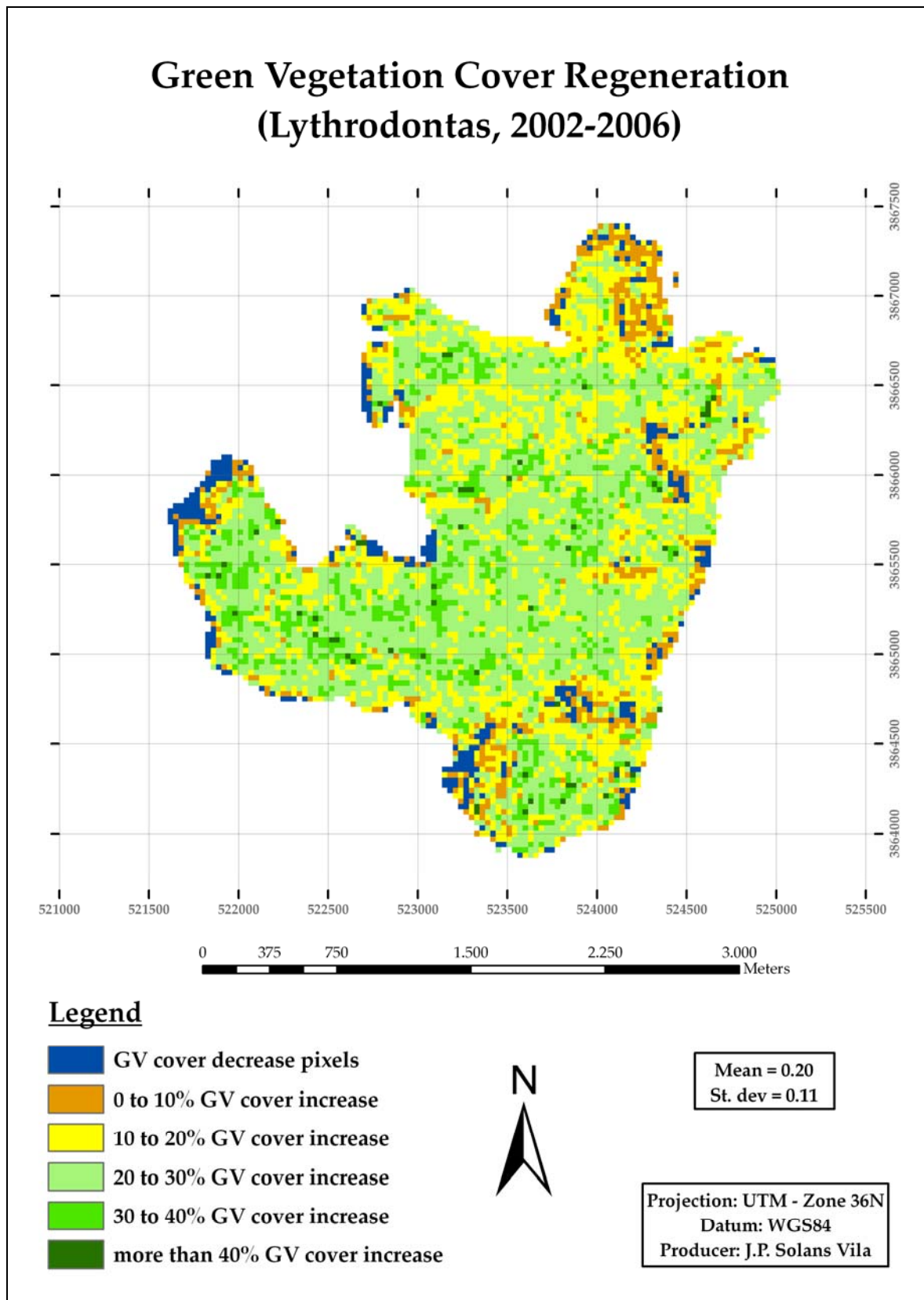


Figure 26. GV cover regeneration quantities (%) for Lythrodontas site (Landsat) between 2002 and 2006

5.3.2 Deiva Marina Study Area

5.3.2.1 ENDMEMBER EXTRACTION

As in the previous study area, once the atmospheric normalized reflectance images were obtained, image endmembers were extracted following the procedure described in section 4.3.3.2. Principal Component Analysis was performed in order to check the dimensionality of the Landsat images. Table 40 shows the extracted eigen-values (E-val) for each image. As it can be seen, in all of them the first four principal components contain more than 99% of the original variance (V%) of the data. Therefore it was considered that the dimensionality of all images in the dataset was equal to 4. Applying Equation 45 the maximum number of image endmembers to extract from the Landsat images was set to 4 endmembers.

Table 40. Eigen-values and % of variance for Deiva Marina study area (Landsat).

		1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
PC1	E-val	0.005513	0.007399	0.005386	0.004973	0.004711	0.005197	0.005355	0.005499	0.005196	0.005376
	V%	75.54	75.25	67.45	65.14	63.65	66.78	69.02	63.28	64.63	61.22
PC2	E-val	0.001569	0.002216	0.002322	0.002423	0.002469	0.002342	0.002127	0.002769	0.002542	0.003079
	V%	21.50	22.54	29.08	31.74	33.36	30.10	27.41	31.86	31.63	35.06
PC3	E-val	0.000139	0.000129	0.000190	0.000178	0.000156	0.000178	0.000195	0.000318	0.000206	0.000229
	V%	1.91	1.31	2.38	2.34	2.11	2.29	2.51	3.66	2.56	2.61
PC4	E-val	0.000047	0.000057	0.000051	0.000034	0.000038	0.000033	0.000045	0.000058	0.000051	0.000065
	V%	0.64	0.58	0.64	0.44	0.51	0.42	0.58	0.67	0.63	0.74
PC5	E-val	0.000019	0.000020	0.000023	0.000015	0.000016	0.000019	0.000020	0.000028	0.000025	0.000018
	V%	0.26	0.20	0.29	0.20	0.22	0.24	0.26	0.32	0.31	0.21
PC6	E-val	0.000011	0.000012	0.000013	0.000011	0.000011	0.000013	0.000017	0.000018	0.000019	0.000014
	V%	0.15	0.12	0.16	0.14	0.15	0.17	0.22	0.21	0.24	0.16

SMACC was then applied to each image of the dataset. A set of four image endmembers were extracted for each image and their spectral identity was defined. In order to define the latter, their spectral signature was analyzed and NDVI images were produced. The spectral signature of the pixel of each image endmember was extracted and, together with the, NDVI value of the pixel, was used to identify the endmember classes. For each one of

the ten image endmembers sets, a green vegetation class endmember (GV), a soil class endmember (S), a shade class endmember (Sh) and a non photosynthetic vegetation class endmember (NPV) were identified. The endmbemner classes' reflectance in each band of the ten endmember sets (one for each year) was extracted and put into an EXCEL spreadsheet. Band average reflectance values for each class of endmember (GV, S, Sh, and NPV) were computed, yielding four average endmembers. Table 41 presents the band average reflectance values for each average endmember, and Figure 27 shows their spectral signatures. This set of average endmembers was then used for the application of the spectral analysis techniques.

Table 41. Average endmember reflectance values (Deiva Marina-Landsat)

	Average Endmember Reflectances			
	GV	S	Sh	NPV
B1	0.035948	0.101293	0.026551	0.070771
B2	0.052871	0.131184	0.025235	0.112846
B3	0.036457	0.175174	0.022436	0.099077
B4	0.507609	0.228444	0.045698	0.208494
B5	0.179608	0.346223	0.010732	0.330003
B7	0.158435	0.274934	0.009891	0.168660

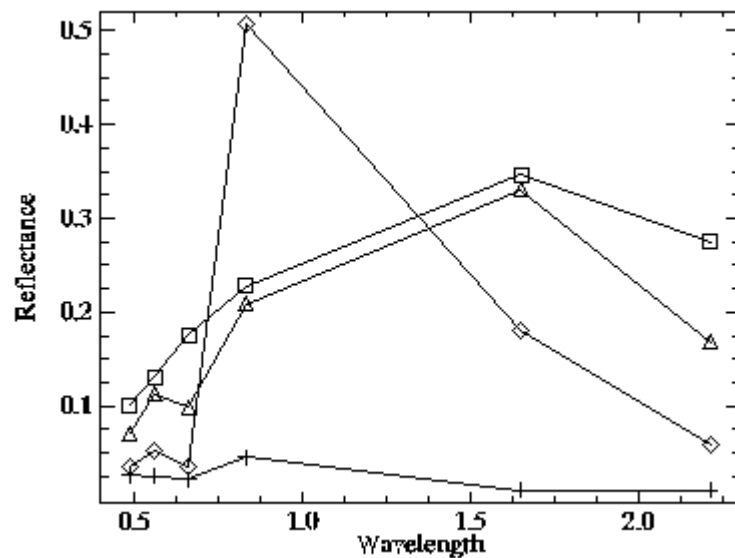


Figure 27. Deiva Marina (Landsat) average endmember spectral signatures: GV (◇), S (□), Sh (+), and NPV (Δ)

5.3.2.2 SPECTRAL MIXTURE ANALYSIS APPLICATION

SMA was then applied to each image of the dataset in order to obtain the fraction images. Cloud masks were constructed for some of the images of the dataset (1999, 2002, 2003, and 2006), as cloudy pixels introduce a certain amount of error into the analysis results. SMA was constrained to produce fraction images which sum results 1 in order to produce meaningful fractions. Both the fractional error and the RMSE error were checked for each set of four fraction images in order to assess their accuracy. Table 42 shows the fractional errors obtained for the fraction images of each year. Mean, minimum (min) and maximum (max) RMSE values, together with its standard deviation (st dev) were also computed for the SMA results of each image of the dataset (see Table 42).

Table 42. RMSE and Fractional Error values of fraction images (Deiva Marina-Landsat)

	Fractional Error (%)				RMSE			
	GV	S	Sh	NPV	Mean	St.dev	Min	Max
1997	0.15	62.63	0.01	15.15	0.004387	0.002689	0.000094	0.047028
1998	6.98	60.67	0.11	13.64	0.004525	0.002826	0.000145	0.037705
1999	3.76	55.63	0.003	14.40	0.004713	0.003226	0.000116	0.076497
2000	1.04	55.55	0.007	14.32	0.004362	0.003182	0.000065	0.049039
2001	0.45	57.41	0.02	13.57	0.004359	0.002936	0.000024	0.060674
2002	0.89	54.87	0.14	15.45	0.004443	0.003520	0.000049	0.071664
2003	0.31	59.96	0.12	15.15	0.004676	0.003013	0.000126	0.054229
2004	0.64	62.73	0.22	14.77	0.004800	0.002997	0.000097	0.046545
2005	1.94	62.44	0.39	14.72	0.005182	0.003294	0.000065	0.048774
2006	0.66	61.12	0.07	14.72	0.004632	0.003561	0.000056	0.071466

Mean RMSE values obtained (Table 42) are well below the 0.025 threshold. This indicates that the applied unmixing model shows a sufficient fit and, therefore, the set of average endmembers applied is accurate enough as to be used in a multi-temporal study like this one.

Looking at the fractional error values presented in Table 42, it is possible to observe that more than 95% of Sh values lay within the required range in each image, remaining the fractional error Sh values well under the maximum 5%. Also almost all GV fractional

error values are well below the 5% threshold, with the only exception of 1998 that is higher than the threshold. As explained in section 5.3.1.2 for the Lythrodontas area, GV fractional error values of immediate post-fire images are higher due to the presence of the fire effects in the area (ash, charcoal). Table 43 shows the mean, minimum and maximum GV fraction values, together with the percentage of GV negative fraction values (% Negative GV) for the burned area.

Table 43. SMA GV fraction statistics for the burned area (Deiva Marina-Landsat)

	SMA GV fraction statistics				
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>	<i>% Negative GV</i>
1997	0.247031	0.124044	-0.065228	0.884727	0.32
1998	0.028433	0.113833	-0.182934	0.608073	49.85
1999	0.082308	0.111470	-0.144549	0.767241	25.29
2000	0.142585	0.108385	-0.136592	0.737559	6.05
2001	0.176828	0.111547	-0.071204	0.792897	2.62
2002	0.191401	0.124397	-0.128082	0.759826	4.12
2003	0.241769	0.117615	-0.096931	0.927483	1.18
2004	0.227275	0.132583	-0.130059	0.782531	2.32
2005	0.215146	0.129241	-0.136626	0.812070	2.46
2006	0.232632	0.129522	-0.130300	0.987533	1.57

Regarding soil fraction values (S), the high amount of fractional error can be explained by the high soil variability in the area and the difficulty in modelling with only one endmember this soil variability.

NPV fraction values are well above the 5% threshold for all images. Looking at Figure 27, it is possible to observe that the NPV endmember reflectance in band 5 is higher than in band 4, which is a typical post-fire vegetation behaviour linked closely to the exposition of the dry soil layer which has a pronounced reflectance in the MIR spectral range. Spectral ambiguity between NPV and soils is an important limitation when trying to define pure material endmembers. And the spectral signatures of S and NPV endmembers demonstrate it. This high level of confusion between these two endmembers may have affected the NPV fraction results, introducing a certain amount of error.

GV fraction images produced with SMA and used for comparison with the other vegetation fraction extracting techniques results are presented in Figure 28. As a cloud mask was applied to cloudy images, some areas are missing in *f*, *g*, and *i* images (2002, 2003, and 2005).

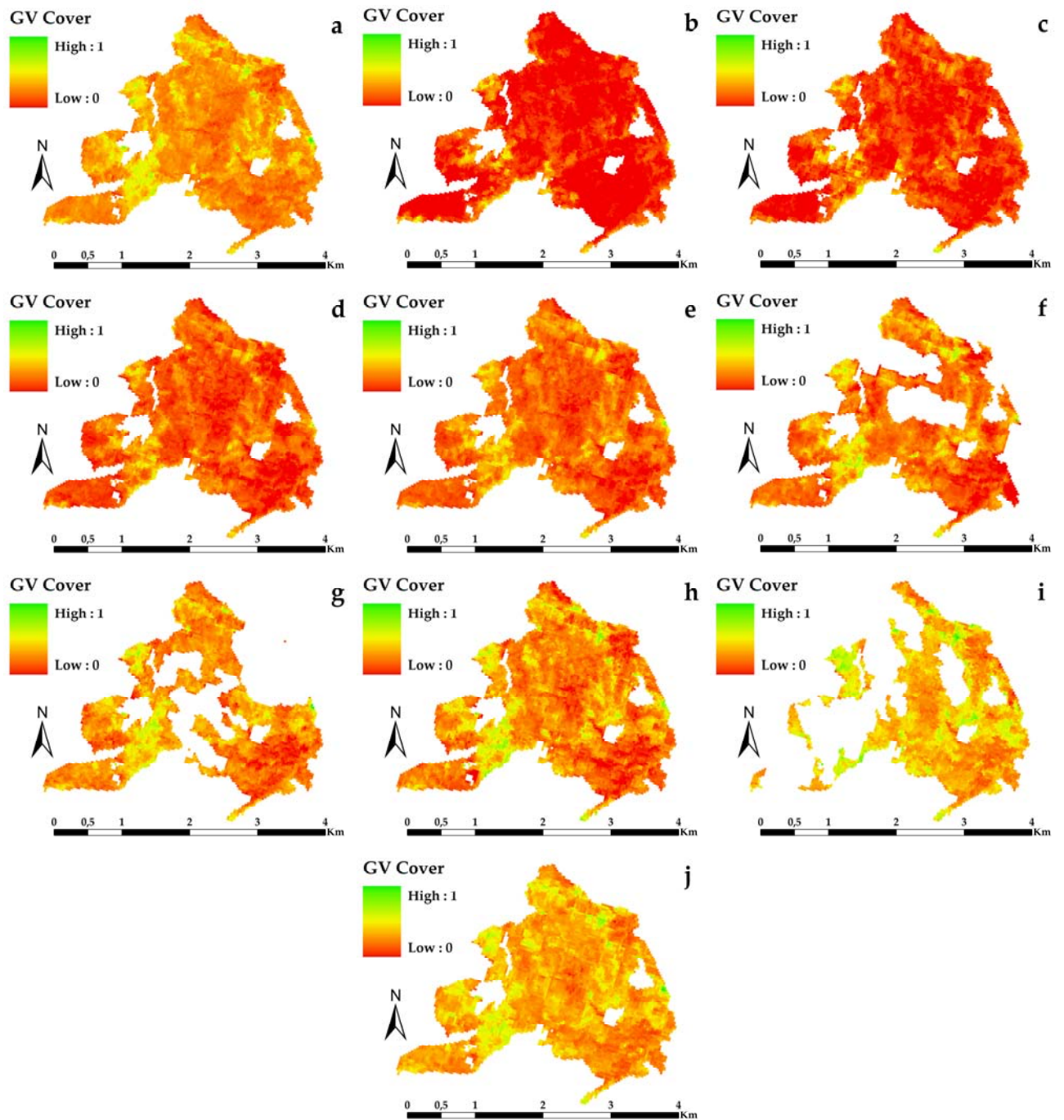


Figure 28. Deiva Marina (Landsat) study area SMA GV fraction images: 1997 (a), 1998 (b), 1999 (c), 2000 (d), 2001 (e), 2002 (f), 2003 (g), 2004 (h), 2005 (i), and 2006 (j)

As a post-processing step, shade normalization was applied. Both the GV fraction images and the shade normalized GV fraction images were used for comparison with the rest of techniques. Table 44 shows the mean and standard deviation values of the burned area for the shade normalized GV (GV_{shn}) fraction images.

Table 44. SMA_{shn} GV fraction statistics for the burned area (Deiva Marina-Landsat)

	SMA_{shn} GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
1997	0.651041	0.245548	-0.192834	1.630297
1998	0.031576	0.338719	-2.916397	1.138536
1999	0.188499	0.252351	-0.487084	1.075022
2000	0.320293	0.229290	-0.382967	1.266490
2001	0.378160	0.219521	-0.307856	1.386211
2002	0.414296	0.286384	-1.781492	1.859205
2003	0.476057	0.207192	-0.355786	1.132028
2004	0.457079	0.242264	-0.306778	1.573754
2005	0.478700	0.323604	-0.634098	2.265122
2006	0.490093	0.245370	-0.375093	1.633538

Table 45 shows the percentage of increase ($\Delta GV\%$) that the shade normalization has added to the mean GV fraction values. For the pre-fire image, the increment is much higher than for the rest of the images. This may be due, as explained in section 5.3.1.2, to the canopy shadowing effect of vegetation. In the immediate post-fire image (1998) this effect has completely disappeared with vegetation. It only starts to reappear when the burned area starts to recover from the fire, incrementing the vegetation cover and thus, the shadowing effect.

Table 45. Percentages of increase ($\Delta GV\%$) from GV fraction to GV_{shn} fraction

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
$\Delta GV\%$	40.40	0.31	10.62	17.77	20.13	22.29	23.43	22.98	26.35	25.74

Figure 29 shows the shade normalized GV fraction images produced for Deiva Marina study area.

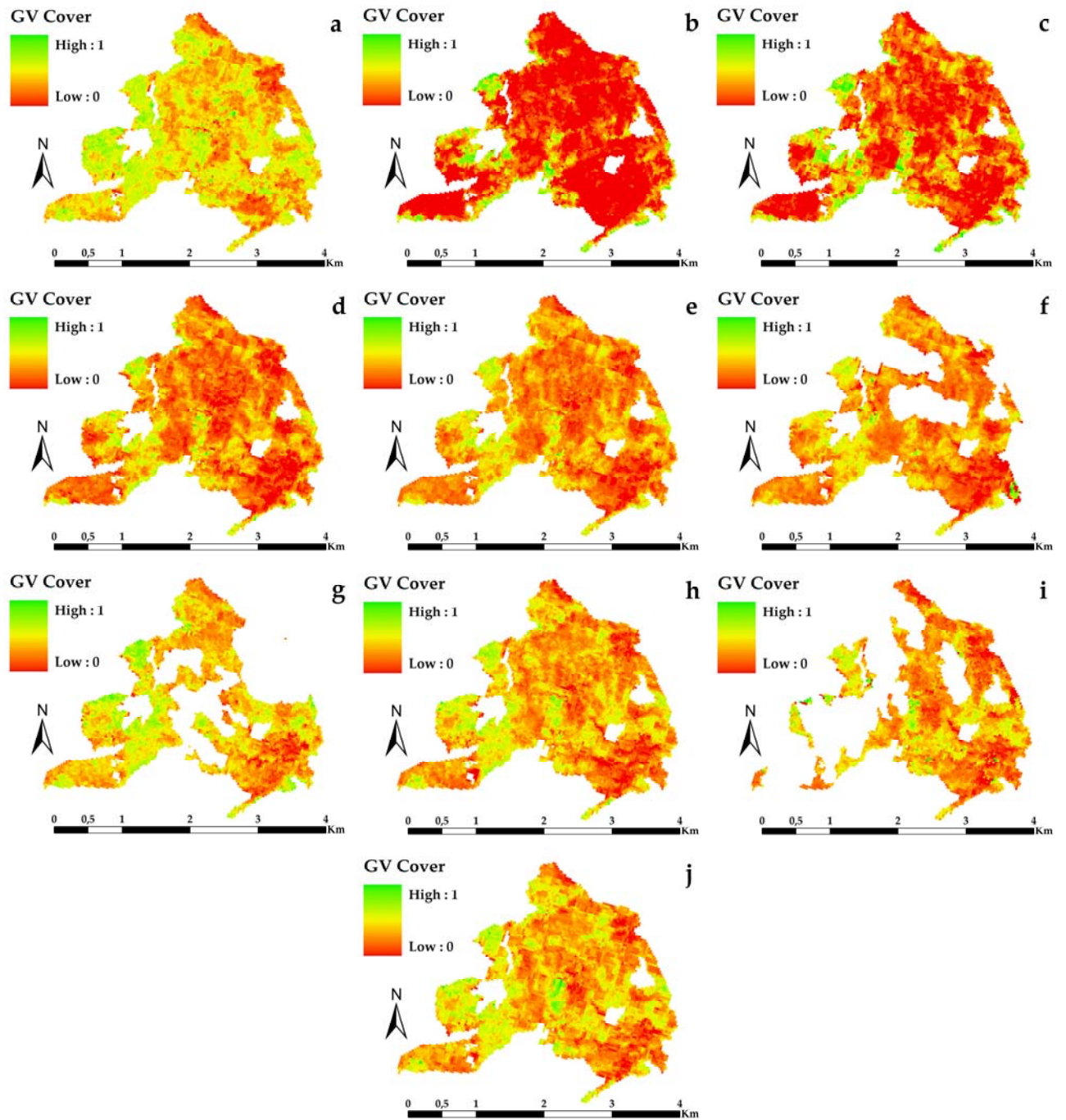


Figure 29. Deiva Marina (Landsat) study area SMA_{shn} GV fraction images: 1997 (a), 1998 (b), 1999 (c), 2000 (d), 2001 (e), 2002 (f), 2003 (g), 2004 (h), 2005 (i), and 2006 (j)

5.3.2.3 QUANTITATIVE VEGETATION INDICES APPLICATION

Green vegetation fractional cover images were obtained by applying the quantitative vegetation indices (VIs) described in section 4.3.2.

The red (ρ_R) and near-infrared (ρ_{NIR}) reflectance values of the average soil endmember (S) and the average vegetation endmember (GV) were used to scale the vegetation indices (see section 4.3.2 for details). Table 46 presents the ρ_R and ρ_{NIR} reflectance values of these endmembers together with the corresponding NDVI, MSAVI and DVI values.

Table 46. Scaling values for the application of the quantitative VIs (Deiva Marina-Landsat).

	ρ_R	ρ_{NIR}	NDVI	MSAVI	DVI
GV	0.036457	0.507609	0.865983	0.737476	0.471152
S	0.175174	0.228444	0.131981	0.077221	0.053270

Table 47, Table 48, and Table 49 show the GV fraction statistic values for each year when applying f-NDVI, f-MSAVI, and f-DVI respectively.

Table 47. f-NDVI GV fraction statistics for the burned area (Deiva Marina-Landsat)

	f-NDVI GV fraction statistics			
	Mean	St dev.	Min	Max
1997	0.499933	0.164378	0.000000	1.000000
1998	0.189165	0.145751	0.000000	0.829734
1999	0.215463	0.185739	0.000000	0.935231
2000	0.311294	0.170432	0.000000	0.973256
2001	0.364869	0.165951	0.000000	1.000000
2002	0.368431	0.181961	0.000000	0.927336
2003	0.424434	0.151388	0.000000	0.966381
2004	0.440159	0.164656	0.000000	1.000000
2005	0.438073	0.155928	0.000000	0.981511
2006	0.447668	0.176208	0.000000	1.000000

Table 48. f-MSAVI GV fraction statistics for the burned area (Deiva Marina-Landsat)

	f-MSAVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
1997	0.350269	0.176151	0.000000	1.000000
1998	0.086615	0.136053	0.000000	0.813919
1999	0.128407	0.157444	0.000000	0.924679
2000	0.214131	0.161488	0.000000	0.929242
2001	0.270252	0.164838	0.000000	0.972823
2002	0.280686	0.180722	0.000000	0.933281
2003	0.350362	0.161359	0.000000	0.981187
2004	0.350234	0.178014	0.000000	0.954861
2005	0.338121	0.172174	0.000000	0.953609
2006	0.349435	0.180636	0.000000	1.000000

Table 49. f-DVI GV fraction statistics for the burned area (Deiva Marina-Landsat)

	f-DVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
1997	0.210512	0.130653	0.000000	1.000000
1998	0.045602	0.087866	0.000000	0.627794
1999	0.071280	0.101796	0.000000	0.761418
2000	0.123728	0.109212	0.000000	0.750995
2001	0.161319	0.115258	0.000000	0.821091
2002	0.171101	0.127135	0.000000	0.769802
2003	0.221141	0.119374	0.000000	0.910541
2004	0.218396	0.131736	0.000000	0.785883
2005	0.208127	0.126992	0.000000	0.811654
2006	0.216621	0.132112	0.000000	0.945023

Figure 30, Figure 31, and Figure 32 present the resulting green vegetation cover images for f-NDVI, f-MSAVI, and f-DVI respectively.

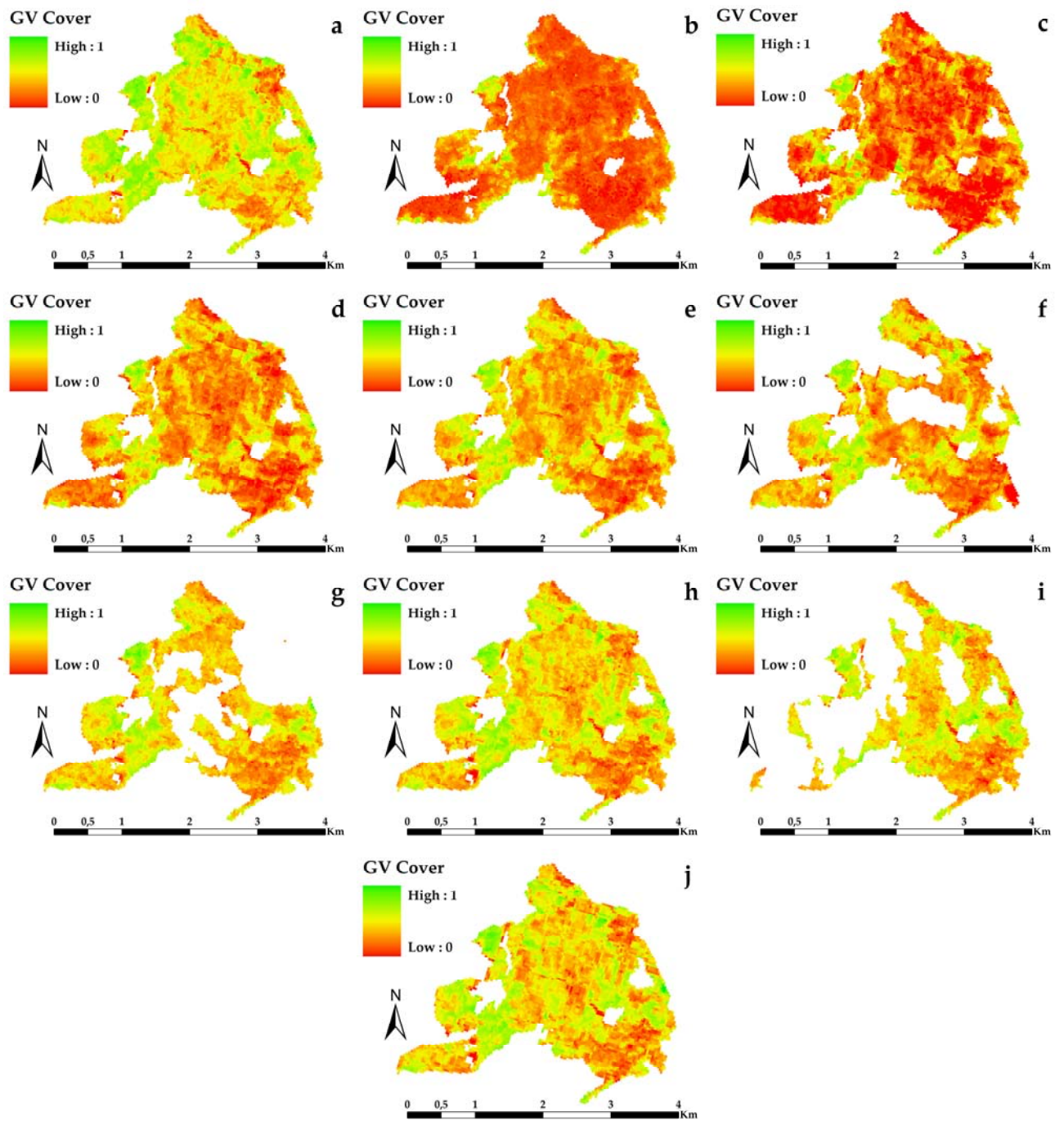


Figure 30 . Deiva Marina (Landsat) study area f-NDVI GV fraction images: 1997 (a), 1998 (b), 1999 (c), 2000 (d), 2001 (e), 2002 (f), 2003 (g), 2004 (h), 2005 (i), and 2006 (j)

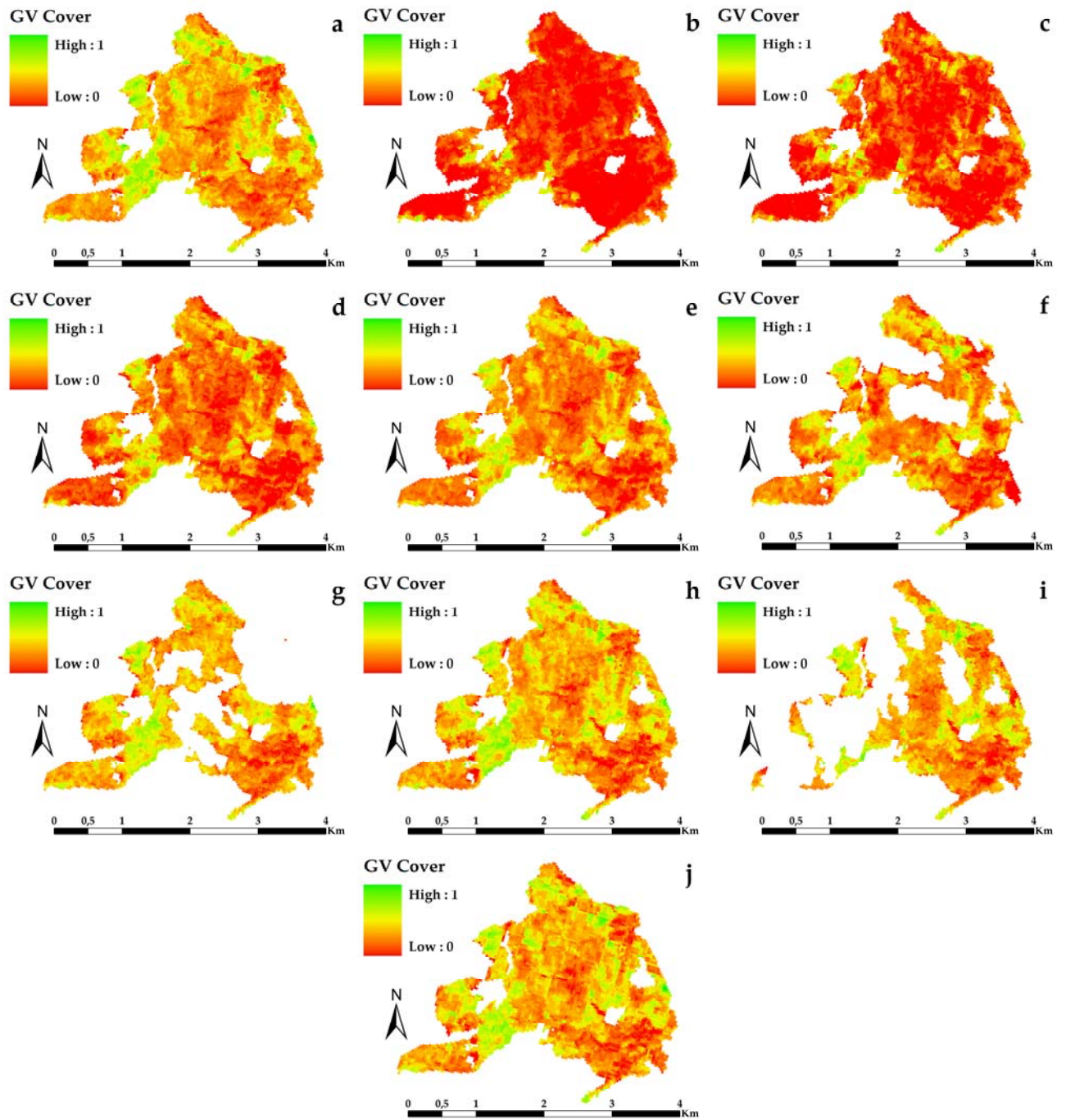


Figure 31. Deiva Marina (Landsat) study area f-MSAVI GV fraction images: 1997 (a), 1998 (b), 1999 (c), 2000 (d), 2001 (e), 2002 (f), 2003 (g), 2004 (h), 2005 (i), and 2006 (j)

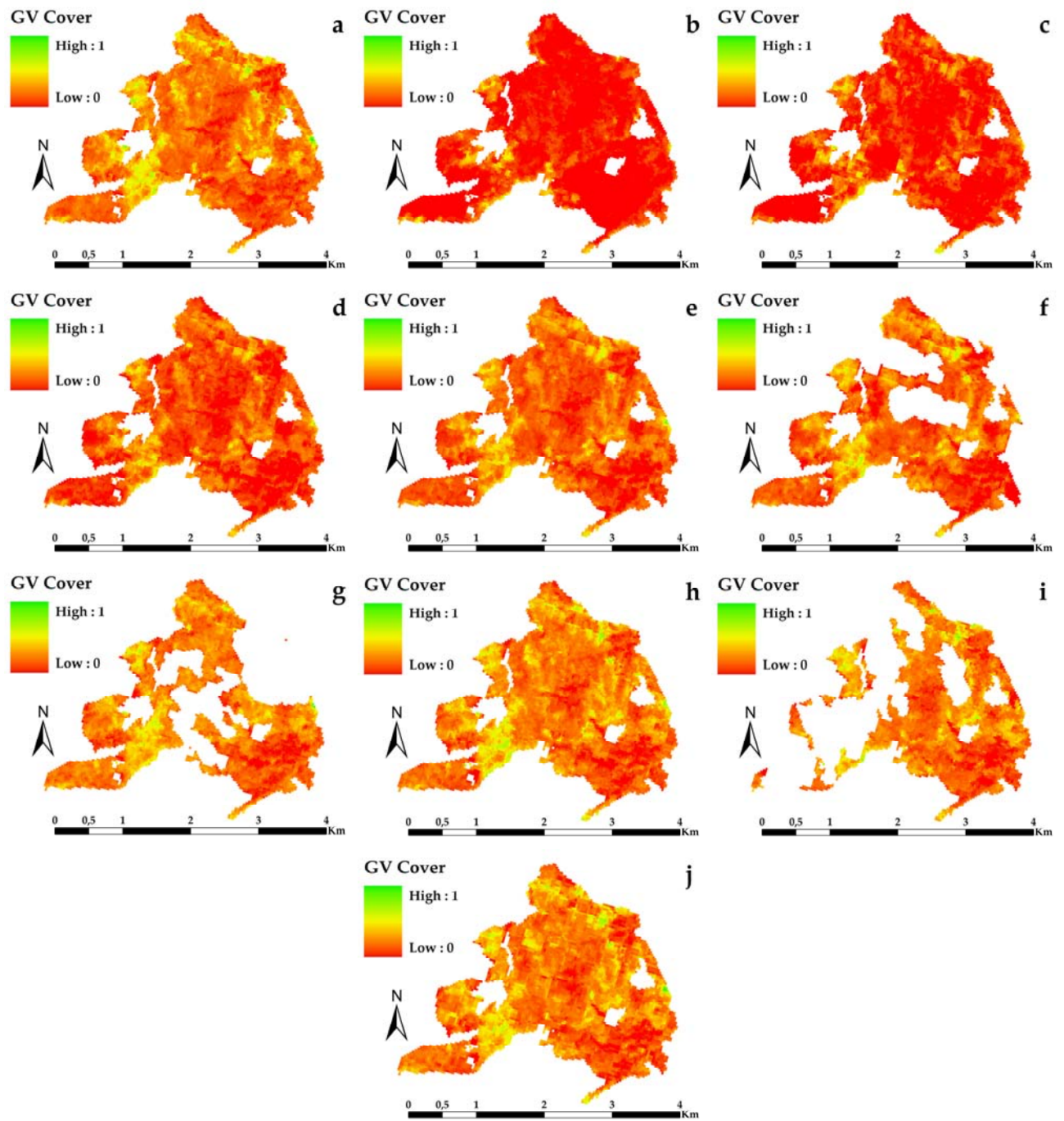


Figure 32. Deiva Marina (Landsat) study area f-DVI GV fraction images: 1997 (a), 1998 (b), 1999 (c), 2000 (d), 2001 (e), 2002 (f), 2003 (g), 2004 (h), 2005 (i), and 2006 (j)

5.3.2.4 ACCURACY AND COMPARISON OF METHODOLOGIES

Table 45 shows the increase of GV cover after the shade normalization of SMA results. As it can be observed, in the pre-fire image this increase is the largest, while in immediate post-fire images this increase is almost zero. This suggests that the increase of GV cover due to shade normalization is related to the amount of vegetation present in the area. In order to test this, GV cover increase values between SMA and shade normalized SMA were computed and regressed against the mean GV cover values obtained from the f-NDVI method. The coefficient of correlation obtained was 0.87 demonstrating that the increase of GV cover due to shade normalization of SMA results is closely related to the amount of vegetation present in the area. This can be explained by the canopy shadowing effect, which decreases when vegetation cover is low and increases when vegetation cover increases.

Accuracy of the 2006 green vegetation fractional cover resulting images after the application of the five selected methodologies was checked by regression against the field data collected during the 2006 field campaigns.

Accuracy assessment was considered on a 3x3 pixels kernel as for the Lythrodontas study area. Table 50 shows the R^2 values obtained from the accuracy analysis for 2006 GV cover images, and Figure 33 shows the regression graphics produced for each methodology for 2006.

Table 50. Methodologies accuracy for GV cover retrieval (Deiva Marina-Landsat)

	SMA	SMA _{shn}	f-NDVI	f-MSAVI	f-DVI
R² 2006	0.8145	0.6753	0.8919	0.8209	0.7799

The best performing methodology was f-NDVI, followed by f-MSAVI and SMA. In order to check thoroughly these results, the mean and standard deviation of GV cover values at the field plots were extracted for each method and compared (see Table 51 and Figure 34).

Table 51. Field plots GV cover mean and standard deviation

		Field data	SMA	SMA _{shn}	f-NDVI	f-MSAVI	f-DVI
2006	<i>Mean</i>	0.602411	0.293547	0.612606	0.536924	0.430629	0.273142
	<i>St dev</i>	0.134337	0.112341	0.157194	0.127037	0.151469	0.151469

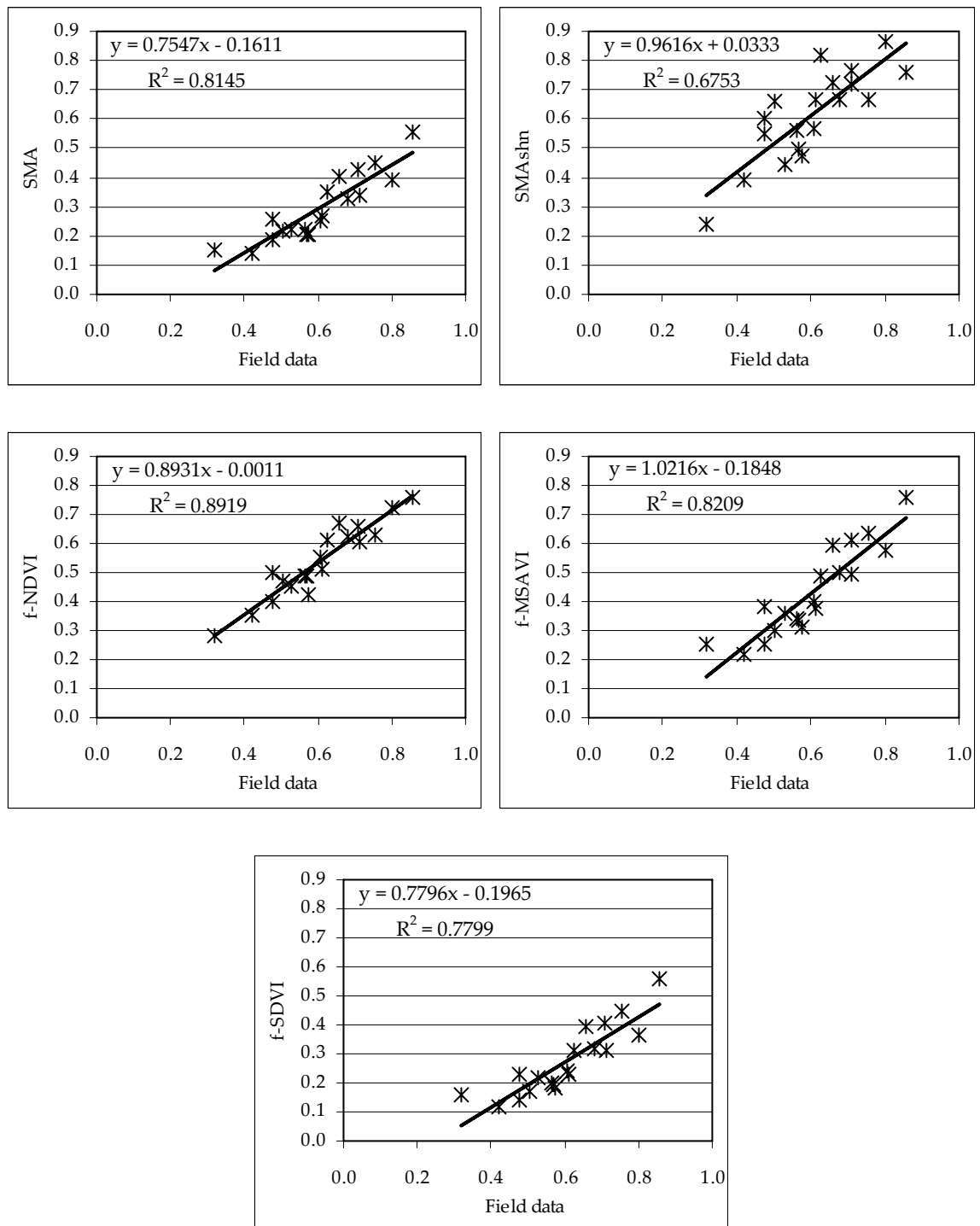


Figure 33. Accuracy regression graphics for the five methodologies (Deiva Marina 2006): SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI

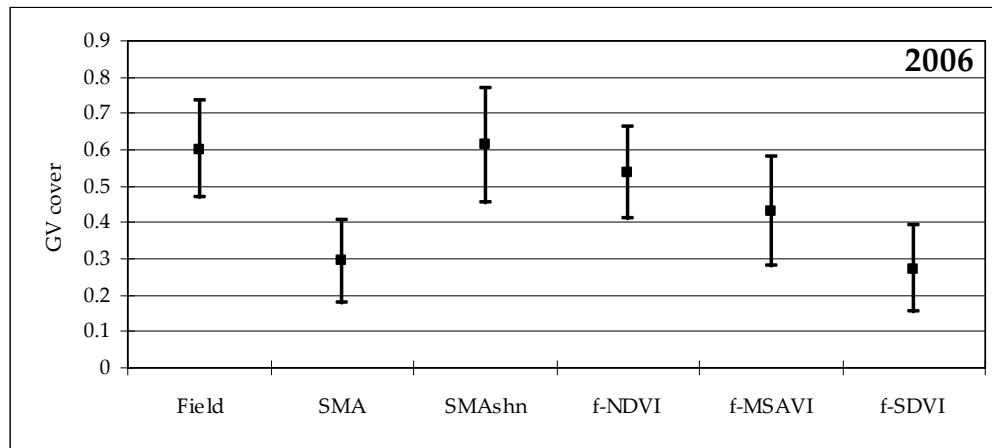


Figure 34. Field plots GV cover mean and standard deviation (2006)

As it can be observed, all methodologies except SMA_{shn} underestimate GV cover respect to field 2006 data. A possible explanation could be related to the fact that during the field campaigns, not only green vegetation was surveyed, but all the vegetation cover present in the area. All the images of the set were acquired around the end of July, beginning of August, when some vegetation are in a non photosynthetic status (NPV). Therefore, underestimation of GV cover respect field data is expected, as during the field campaigns all vegetation was surveyed.

5.3.2.5 VEGETATION REGROWTH DETECTION

Vegetation regrowth detection was carried out with the GV cover images produced by the best performing GV cover extracting method. For Deiva Marina study area, this best technique was f-NDVI. Figure 35 shows the vegetation regeneration trend for Deiva Marina study area when extracting vegetation cover with f-NDVI method. Also, f-NDVI GV cover images were subtracted one to each other in order to produce vegetation regeneration images. Figure 37 shows the regeneration images produced.

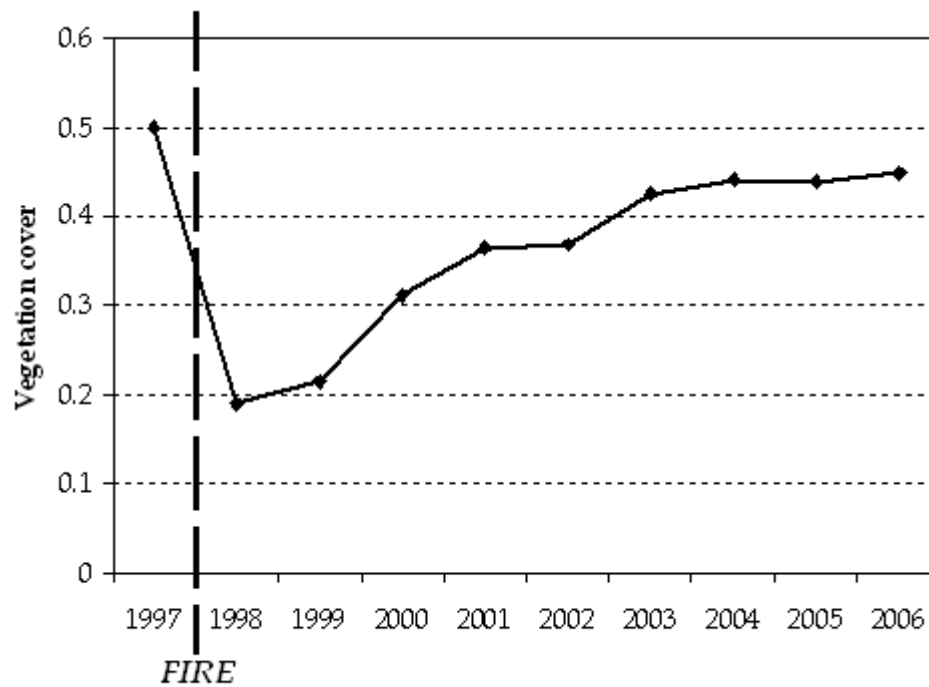


Figure 35. Vegetation regeneration trend in the burned area (Deiva Marina-Landsat)

Figure 35 shows how in this study area, in the second year after the fire, the regeneration already starts to recover, even if very slowly. But Figure 37b shows how this recovery is not general over the area. Some areas start to recover, while other areas are still regressing and vegetation cover is still decreasing. This recalls what explained in section 5.3.1.5 about this phenomenon. During the third year, the increase of vegetation is the maximum registered of the time series, while in the remaining post-fire images this vegetation increase is lower, tending to reach an horizontal behaviour (see Figure 35). However, 2002 image shows a slight decrease in this trend. A possible reason for this could be the highly different radiometric asset of this image. The radiometric band gains of this Landsat image were all set to LOW, while in the rest of the images almost all radiometric band gains were set to HIGH. This could have introduced a different radiometric response. Despite this different behaviour of 2002 image, it seems that the horizontal maximum does not equal the pre-fire vegetation cover, but more images would be necessary to confirm that post-fire vegetation does not reach pre-fire conditions. Figure 36 shows the vegetation cover trend outside the burned area. It is possible to observe how the

vegetation response remains quite constant along the time series with slight variations, which are possibly due to driest conditions in these particular years or to differences in the radiometric asset of the images (as explained above for the 2002 image).

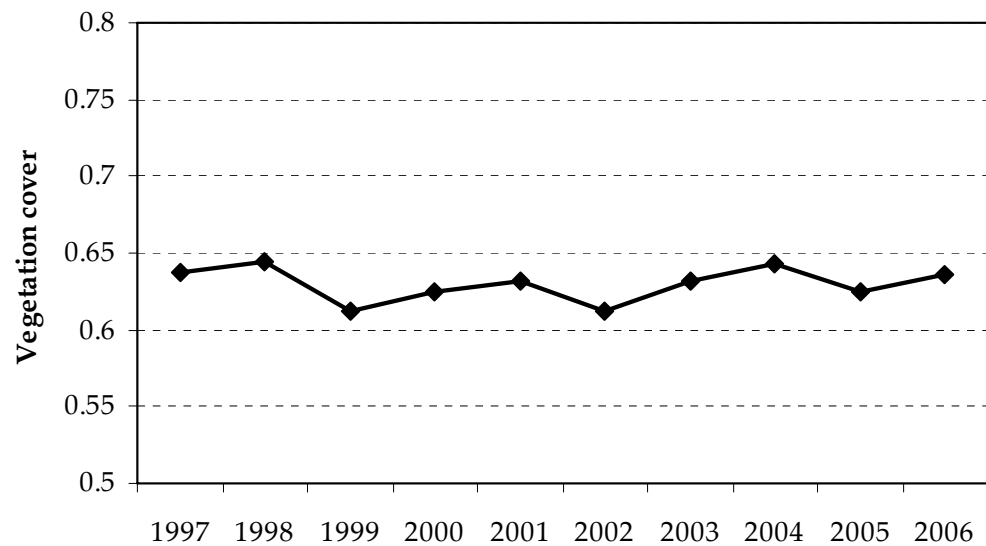


Figure 36. Vegetation regeneration trend outside the burned area (Deiva Marina-Landsat)

The general GV recovery of the site between 1998 (the lowest vegetation cover after the fire) and 2006 (last image of the series) can be observed in Figure 38. This figure shows how the whole area is recovering from the fire, with a mean recovery rate of 26%. However, certain areas show a vegetation cover decrease (blue pixels). Looking at the f-NDVI immediate post-fire images (Figure 30) it is evident that these areas are the ones where vegetation has survived after the fire. The vegetation in these areas have slowly disappeared due to fire effects or to anthropic interventions.

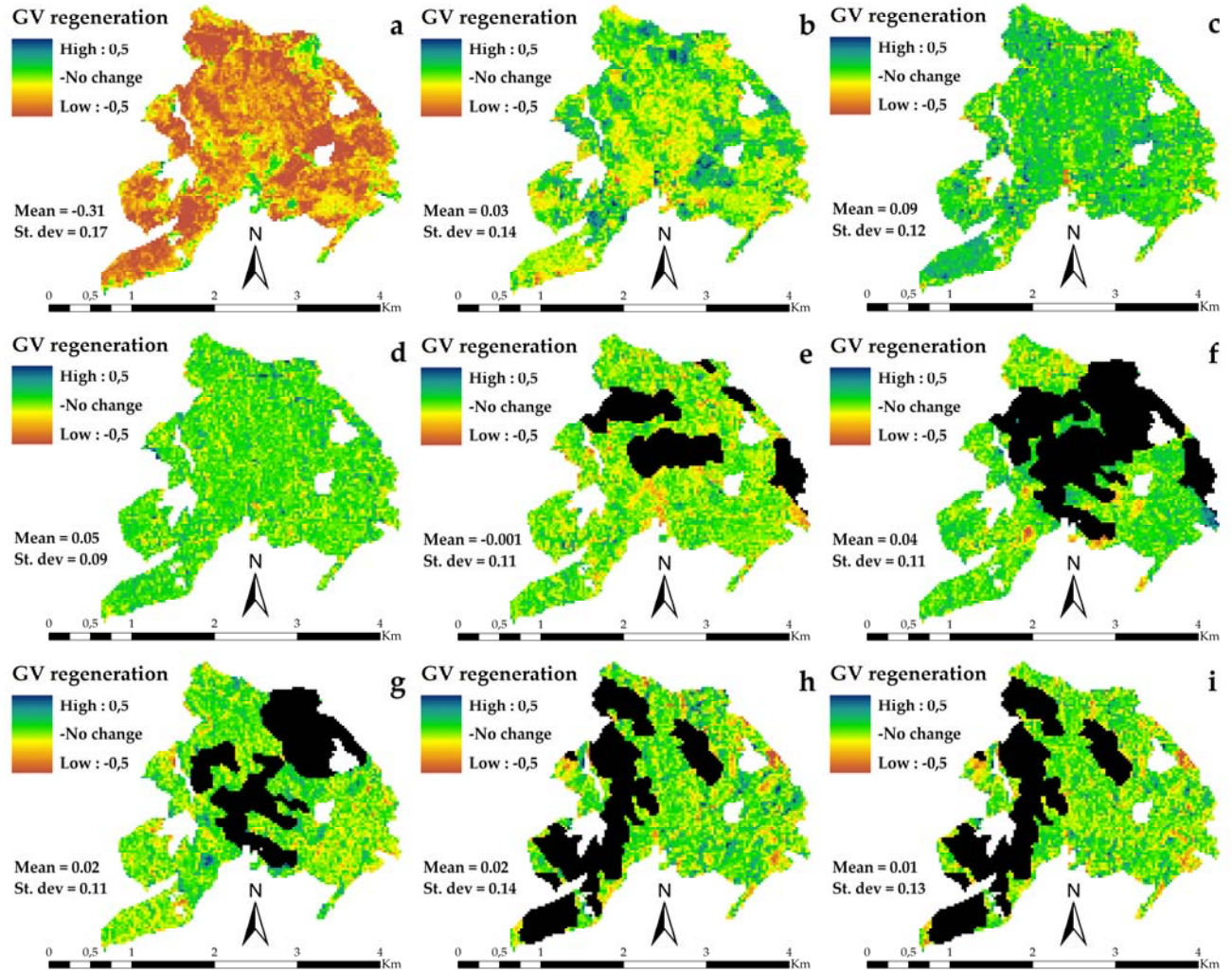


Figure 37. Regeneration images for Deiva Marina (Landsat) study area: 1997-1998 (a), 1998-1999 (b), 1999-2000 (c), 2000-2001 (d), 2001-2002 (e), 2002-2003 (f), 2003-2004 (g), 2004-2005 (h), and 2005-2006 (i).

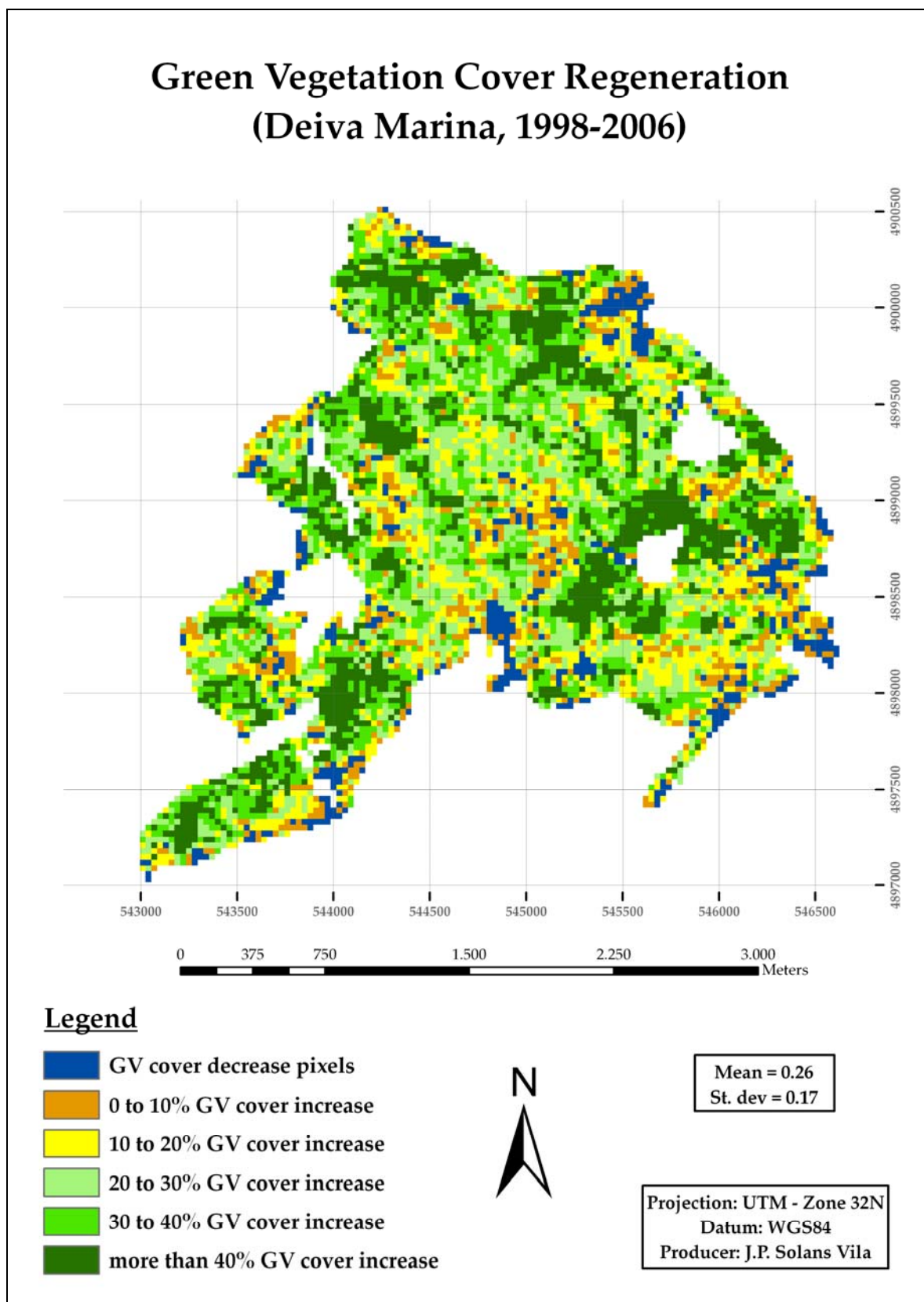


Figure 38. GV cover regeneration quantities (%) for Deiva Marina site (Landsat) between 1998 and 2006

5.3.3 Parra Study Area

5.3.3.1 ENDMEMBER EXTRACTION

As in the previous study area, once the atmospheric normalized reflectance images were obtained, image endmembers were extracted following the procedure described in section 4.3.3.2. Principal Component Analysis was performed in order to check the dimensionality of the SPOT images. Table 52 shows the extracted eigen-values (E-val) for each image. As it can be seen, in all SPOT 5 images the first three principal components contain more than 99% of the original variance (V%) of the data. For SPOT 2 image (2002) the first two principal components contain more than 99% of the original variance. Therefore it was considered that the dimensionality of all SPOT 5 images in the dataset was equal to 3, and the dimensionality of SPOT 2, was equal to 2. Applying Equation 45 the maximum number of image endmembers to extract from the SPOT images was set to 3 endmembers. However, when a set of 2 endmembers for SPOT 2 and a set of 3 endmembers for SPOT 5 were applied with SMA, the RMSE was well above the accepted threshold. Therefore, it was decided to try with one more endmember per set (3 endmembers for SPOT 2 and 4 endmembers for SPOT 5). RMSE resulted below the threshold. Considering that Equation 45 is not only referred to the dimensionality of the data, but also to the number of spectral channels, the solution accepted was acceptable.

Table 52. Eigen-values and % of variance for Parra (SPOT) study area

		2002	2003	2004	2005	2006
PC1	<i>E-val</i>	0.001056	0.001962	0.000921	0.002053	0.000755
	<i>V%</i>	67.73	74.88	68.99	81.59	73.02
PC2	<i>E-val</i>	0.000495	0.000558	0.000288	0.000325	0.000201
	<i>V%</i>	31.75	21.30	21.57	12.92	19.44
PC3	<i>E-val</i>	0.000008	0.000093	0.000117	0.000132	0.000074
	<i>V%</i>	0.52	3.55	8.76	5.25	7.15
PC4	<i>E-val</i>	----	0.000007	0.000009	0.000006	0.000004
	<i>V%</i>	----	0.27	0.68	0.24	0.39

SMACC was then applied to each image of the dataset. A set of four image endmembers were extracted for each SPOT 5 image and a set of three endmembers was extracted from the SPOT 2 image. Their spectral identity was defined by analyzing their spectral signature and NDVI images. The spectral signature of the pixel of each image endmember was extracted and, together with the, NDVI value of the pixel, was used to identify the endmember classes. For each one of the five image endmember sets, a green vegetation class endmember (GV), a soil class endmember (S), a shade class endmember (Sh) and a non photosynthetic vegetation class endmember (NPV) were identified (for SPOT 2 image, the identified endmember classes were GV, S, and Sh). The endmember classes reflectance in each band of the five endmember sets (one for each year) was extracted and put into an EXCEL spreadsheet. Band average reflectance values for each class of endmember (GV, S, Sh, and NPV) were computed, yielding four average endmembers. Table 53 presents the band average reflectance values for each average endmember, and Figure 39 shows their spectral signatures. This set of average endmembers was then used for the application of the spectral analysis techniques. When applying it to the SPOT 2 image, the NPV endmember was eliminated and only the remaining three endmembers were used.

Table 53. Average endmember reflectance values (Parra-SPOT)

	Average Endmember Reflectances			
	GV	S	Sh	NPV
B1	0.020509	0.129447	0.014197	0.047477
B2	0.015252	0.186331	0.013245	0.066367
B3	0.274537	0.230890	0.001868	0.088623
B4	0.076318	0.222149	0.012317	0.184839

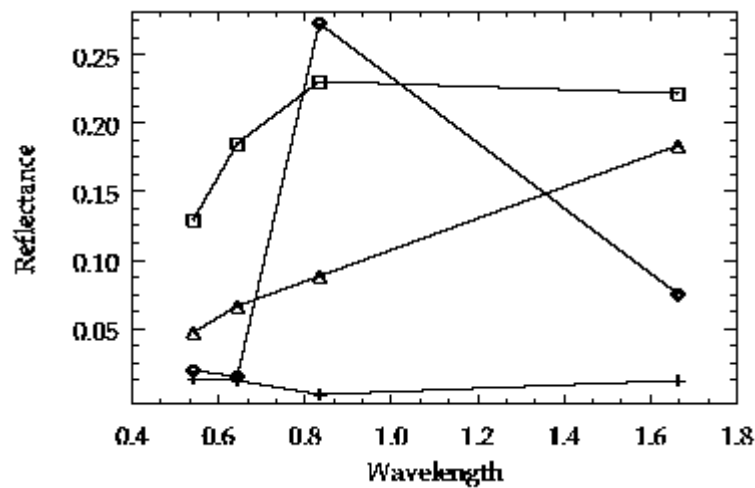


Figure 39. Parra (SPOT) average endmember spectral signatures: GV (♦), S (□), Sh (+), and NPV (Δ)

5.3.3.2 SPECTRAL MIXTURE ANALYSIS APPLICATION

SMA was then applied to each image of the dataset in order to obtain the fraction images. SMA was constrained to produce fraction images which sum results 1 in order to produce meaningful fractions. Both the fractional error and the RMSE error were checked for each set of four fraction images in order to assess their accuracy. Table 54 shows the fractional errors obtained for the fraction images of each year. Mean, minimum (min) and maximum (max) RMSE values, together with its standard deviation (st dev) were also computed for the SMA results of each image of the dataset (see Table 54).

Table 54. RMSE and Fractional Error values of fraction images (Parra-SPOT)

	Fractional Error (%)				RMSE			
	GV	S	Sh	NPV	Mean	St.dev	Min	Max
2002	0.57	22.19	0.01	----	0.001508	0.001374	0.000000	0.019371
2003	0.18	12.31	0.89	4.85	0.001839	0.001222	0.000000	0.009206
2004	0.19	7.55	0.61	0.73	0.002330	0.001267	0.000000	0.013406
2005	0.29	47.52	1.42	3.76	0.002261	0.001016	0.000000	0.013527
2006	0.50	6.42	0.40	0.28	0.002427	0.000832	0.000000	0.008190

Mean RMSE values obtained (Table 54) are well below the 0.025 threshold. This indicates that the applied unmixing model shows a sufficient fit and, therefore, the set of average

endmembers applied is accurate enough as to be used in a multi-temporal study like this one.

Looking at the fractional error values presented in Table 54, it is possible to observe that more than 95% of the GV, NPV and Sh values lay within the required range in each image. The low accuracy of the soil fraction values has several explanations. For the 2003, 2004 and 2006 images the high fractional error can be explained by the high soil variability in the area and the difficulty in modelling it with only one endmember. The 2002 image is a pre-fire image with high vegetation coverage. Therefore, in addition to the effect of soil variability, it could be considered normal that soil fractions become negative when dealing with a highly vegetated pixel. Soil fractional error from 2005 has a more difficult explanation. This image was acquired the latest in the time series (end of September). Its sun elevation angle is the lowest of the time series. This quite different angle, even if the pre-processing has been applied accurately, may leave some permanent effects on the image, increasing the effect of the soil variability due to the use of average endmembers and not image specific endmembers. On top of that, the rain that fell during the last days of September may have even more increased the soil variability.

Table 55 shows the mean, minimum and maximum GV fraction values, for the burned area.

Table 55. SMA GV fraction statistics for the burned area (Parra-SPOT)

	SMA GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2002	0.275562	0.120752	-0.226092	0.991423
2003	0.103290	0.083199	-0.153613	1.051698
2004	0.151303	0.087068	-0.150014	1.074787
2005	0.165527	0.082112	-0.117930	1.025761
2006	0.221201	0.086830	-0.211705	0.864402

GV fraction images produced with SMA and used for comparison with the other vegetation fraction extracting techniques results are presented in Figure 40.

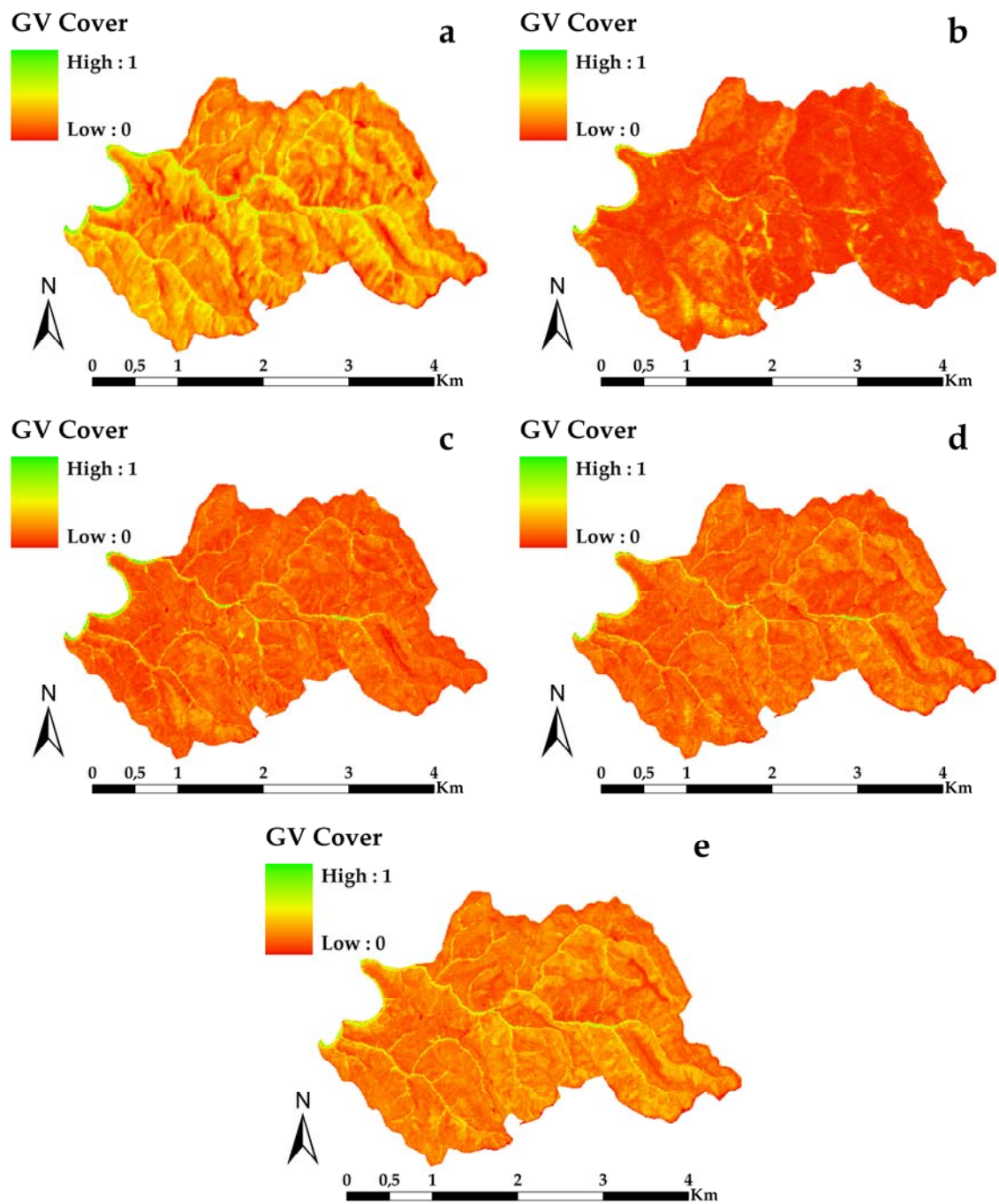


Figure 40. Parra (SPOT) study area SMA GV fraction images: 2002 (a), 2003 (b), 2004 (c), 2005 (d), and 2006 (e)

As a post-processing step, shade normalization was applied. Both the GV fraction images and the shade normalized GV fraction images were used for comparison with the rest of techniques. Table 56 shows the mean and standard deviation values of the burned area for the shade normalized GV (GV_{shn}) fraction images.

Table 56. SMA_{shn} GV fraction statistics for the burned area (Parra-SPOT)

	SMA_{shn} GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2002	0.737134	0.173397	-0.503679	1.388175
2003	0.221297	0.135435	-0.250555	1.340348
2004	0.222299	0.142725	-0.460840	1.251649
2005	0.332377	0.143780	-0.190349	1.404487
2006	0.308734	0.128995	-0.307081	1.013428

Table 57 shows the percentage of increase ($\Delta GV\%$) that the shade normalization has added to the mean GV fraction values. For the pre-fire image, the increment is much higher than for the rest of the images. This may be due, as explained in section 5.3.1.2, to the canopy shadowing effect of vegetation. In the immediate post-fire image (2003) this effect has been highly reduced due to the fire.

Table 57. Percentages of increase ($\Delta GV\%$) from GV fraction to GV_{shn} fraction

	2002	2003	2004	2005	2006
$\Delta GV\%$	46.16	11.80	7.10	16.68	8.75

Figure 41 shows the shade normalized GV fraction images produced for Parra study area.

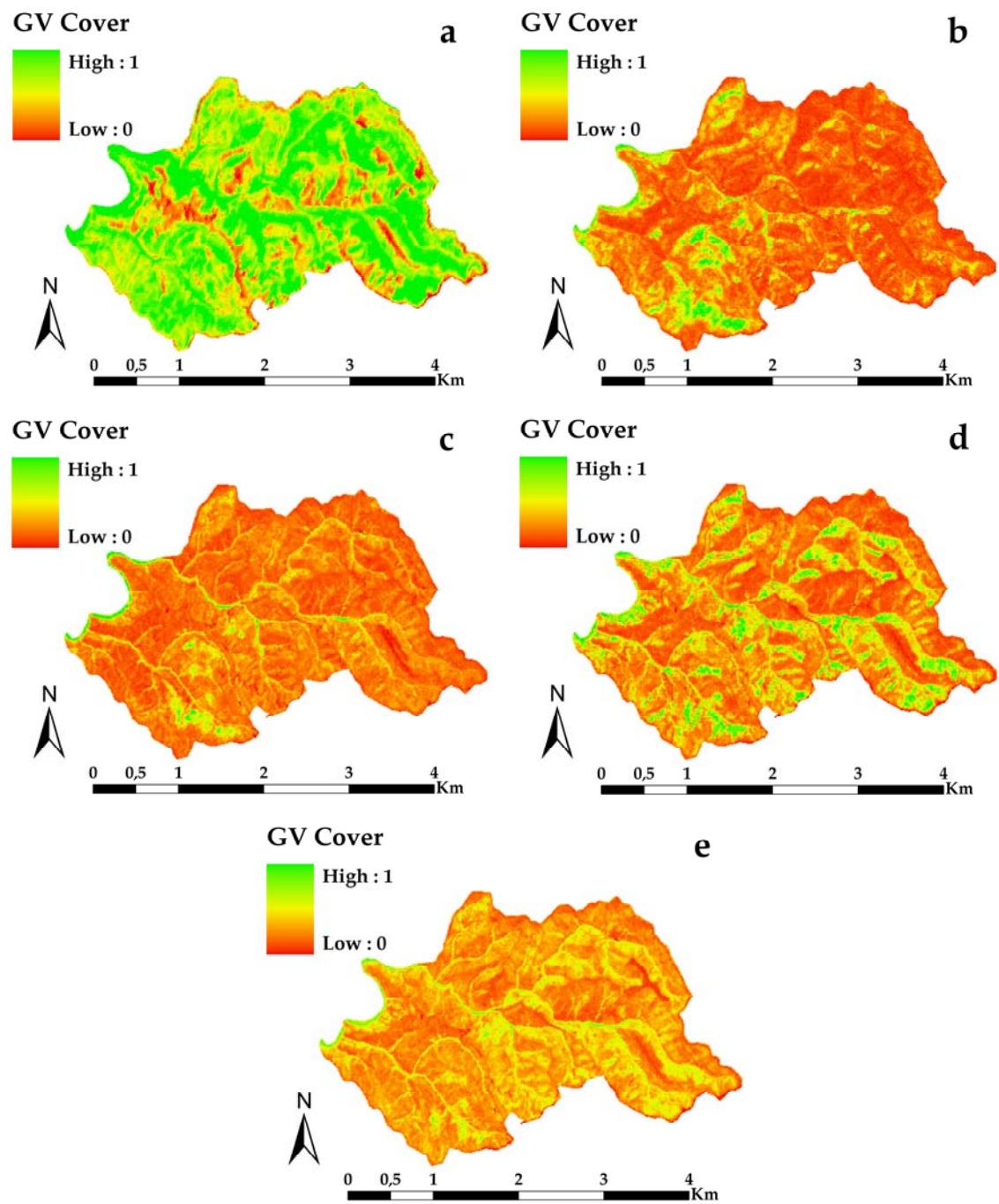


Figure 41. Parra (SPOT) study area SMA_{shn} GV fraction images: 2002 (a), 2003 (b), 2004 (c), 2005 (d), and 2006 (e)

5.3.3.3 QUANTITATIVE VEGETATION INDICES APPLICATION

Green vegetation fractional cover images were obtained by applying the quantitative vegetation indices (VIs) described in section 4.3.2.

The red (ρ_R) and near-infrared (ρ_{NIR}) reflectance values of the average soil endmember (S) and the average vegetation endmember (GV) were used to scale the vegetation indices (see section 4.3.2 for details). Table 58 presents the ρ_R and ρ_{NIR} reflectance values of these endmembers together with the corresponding NDVI, MSAVI and DVI values.

Table 58. Scaling values for the application of the quantitative VIs (Parra-SPOT).

	ρ_R	ρ_{NIR}	NDVI	MSAVI	DVI
GV	0.015252	0.274537	0.894737	0.978679	0.259285
S	0.186331	0.230890	0.106799	0.127490	0.044559

Table 59, Table 60, and Table 61 show the GV fraction statistic values for each year when applying f-NDVI, f-MSAVI, and f-DVI respectively.

Table 59. f-NDVI GV fraction statistics for the burned area (Parra-SPOT)

	f-NDVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2002	0.420001	0.264641	0.000000	1.000000
2003	0.101110	0.198573	0.000000	0.894039
2004	0.151908	0.118814	0.000000	1.000000
2005	0.237227	0.162045	0.000000	1.000000
2006	0.229020	0.108882	0.000000	0.821796

Table 60. f-MSAVI GV fraction statistics for the burned area (Parra-SPOT)

	f-MSAVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2002	0.209114	0.161901	0.000000	1.000000
2003	0.032722	0.088453	0.000000	1.000000
2004	0.074110	0.108659	0.000000	1.000000
2005	0.079719	0.100412	0.000000	1.000000
2006	0.168995	0.111015	0.000000	0.911806

Table 61. f-DVI GV fraction statistics for the burned area (Parra-SPOT)

	f-DVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2002	0.120699	0.121731	0.000000	0.978376
2003	0.017550	0.063166	0.000000	1.000000
2004	0.035674	0.081641	0.000000	1.000000
2005	0.033475	0.069054	0.000000	1.000000
2006	0.097375	0.086667	0.000000	0.851183

Figure 42, Figure 43, and Figure 44 present the resulting green vegetation cover images for f-NDVI, f-MSAVI, and f-DVI respectively.

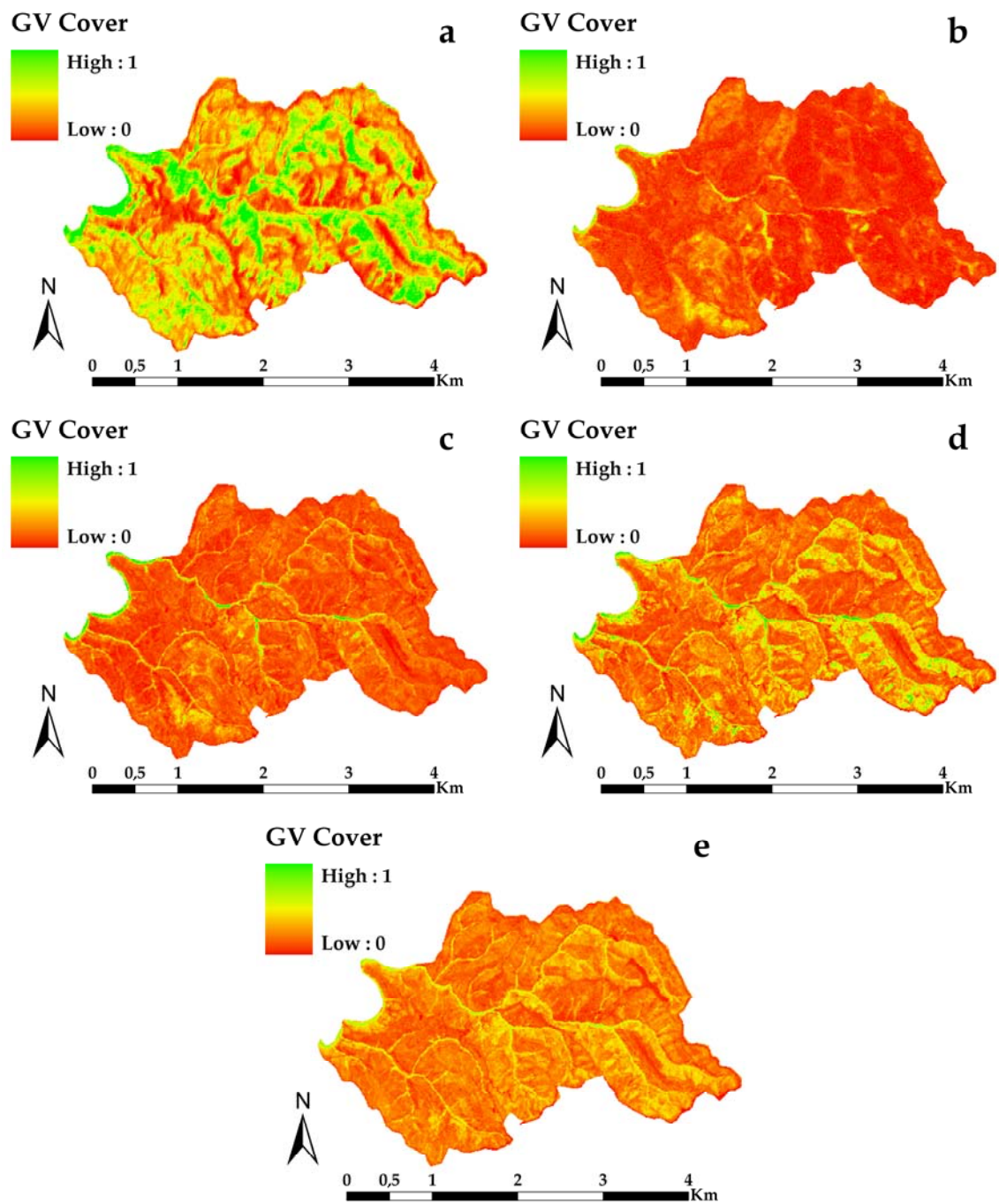


Figure 42. Parra (SPOT) study area f-NDVI GV fraction images: 2002 (a), 2003 (b), 2004 (c), 2005 (d), and 2006 (e)

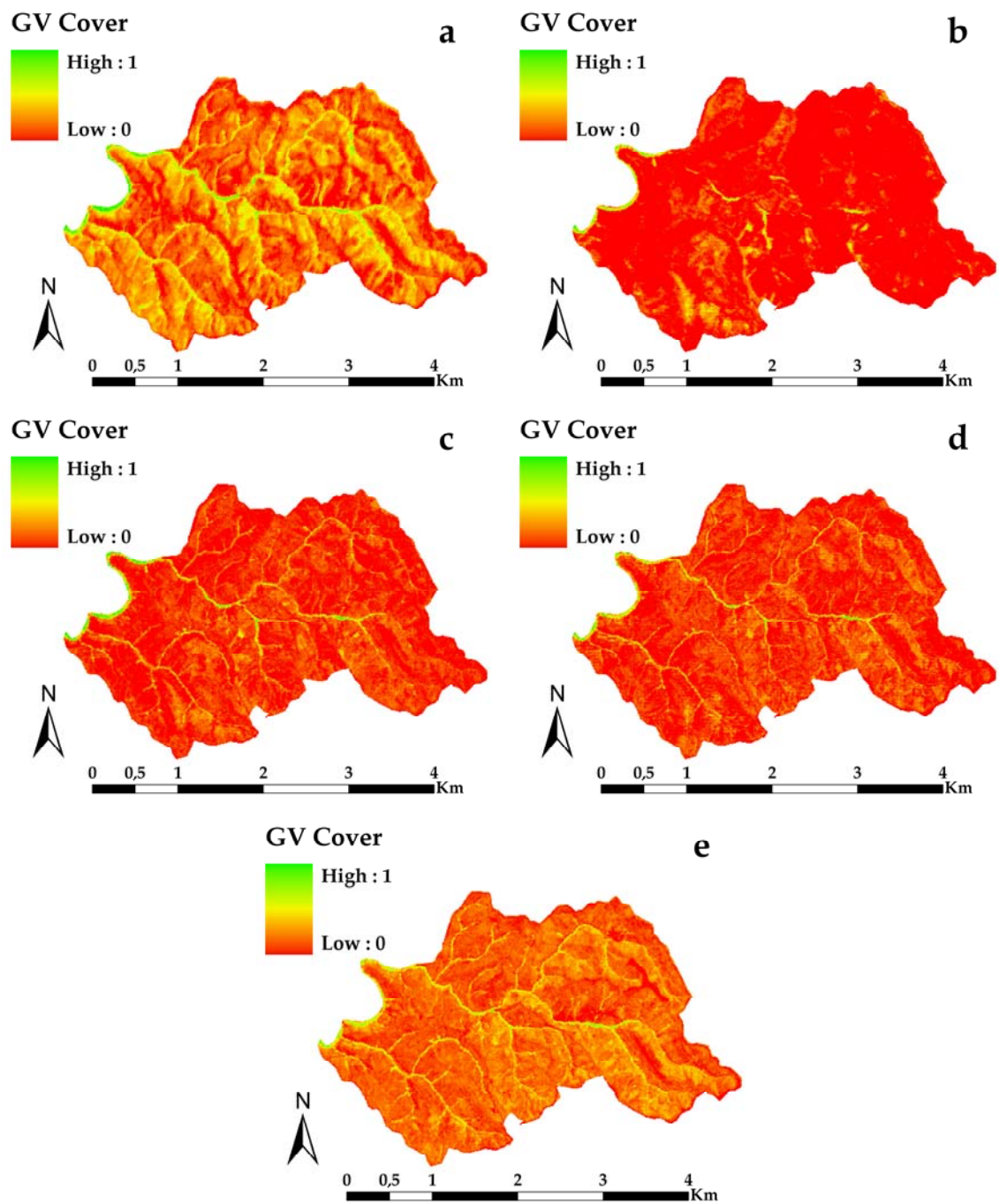


Figure 43. Parra (SPOT) study area f-MSAVI GV fraction images: 2002 (a), 2003 (b), 2004 (c), 2005 (d), and 2006 (e)

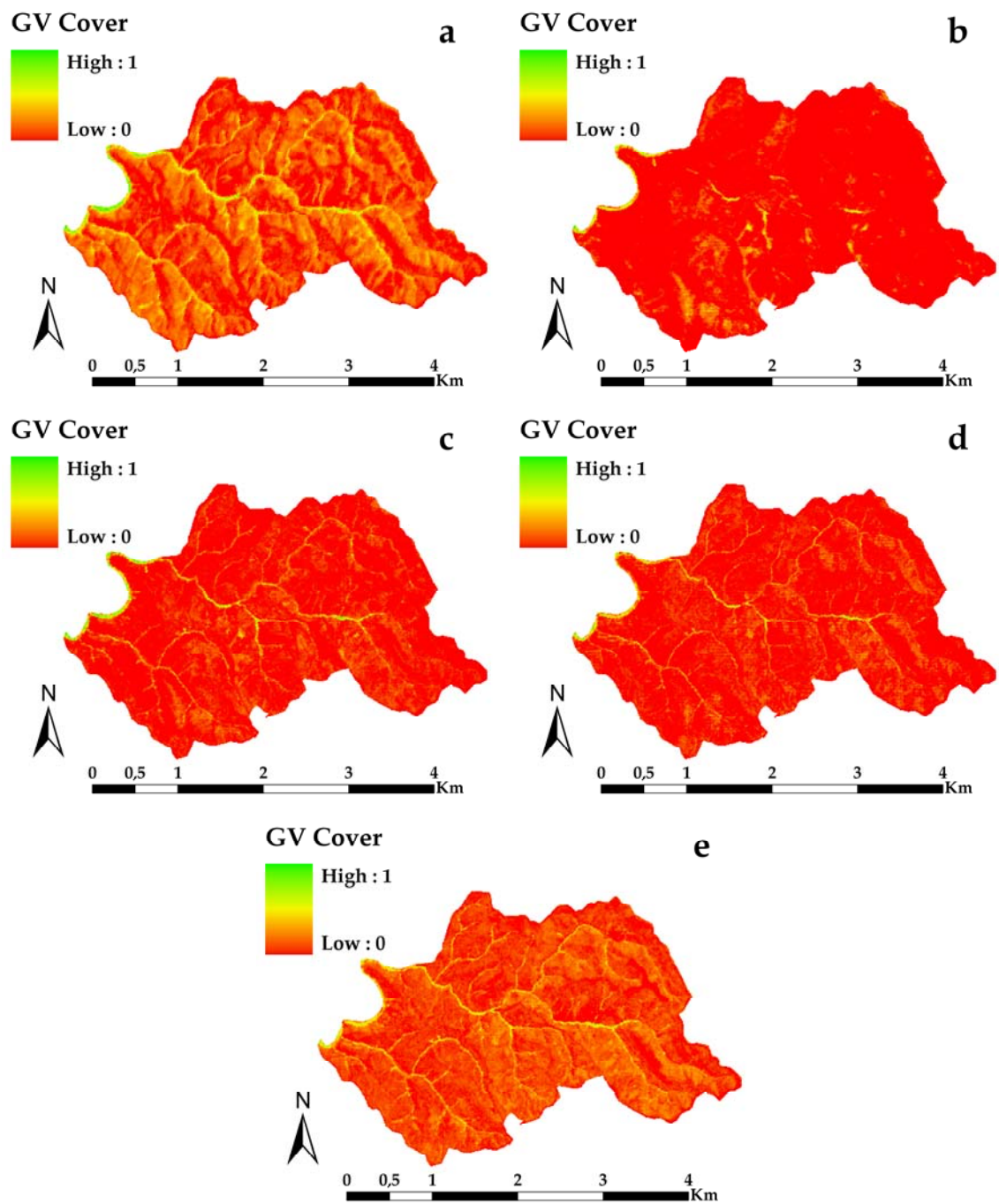


Figure 44. Parra (SPOT) study area f-DVI GV fraction images: 2002 (a), 2003 (b), 2004 (c), 2005 (d), and 2006 (e)

5.3.3.4 ACCURACY AND COMPARISON OF METHODOLOGIES

Table 57 shows the increase of GV cover after the shade normalization of SMA results. As it can be observed, in the pre-fire image this increase is the largest, while in immediate post-fire images this increase is much lower. This suggests that the increase of GV cover due to shade normalization is related to the amount of vegetation present in the area. In order to test this, GV cover increase values between SMA and shade normalized SMA were computed and regressed against the mean GV cover values obtained from the f-NDVI method. The coefficient of correlation obtained was 0.80 demonstrating that the increase of GV cover due to shade normalization of SMA results is related to the amount of vegetation present in the area. This can be explained by the canopy shadowing effect, which decreases when vegetation cover is low and increases when vegetation cover increases.

Accuracy of the 2005 and 2006 green vegetation fractional cover images obtained after application of the five selected methodologies (SMA, SMA shade normalized – SMA_{shn} –, f-NDVI, f-MSAVI, and f-DVI) was checked by regression against the field data collected during the 2005 and 2006 field campaigns.

Accuracy assessment was considered on a 3x3 pixels kernel. Table 62 shows the R² values obtained from the accuracy analysis for 2005 and 2006 GV cover images, and Figure 45 and Figure 46 shows the regression graphics produced for each methodology for 2005 and 2006 respectively.

Table 62. Methodologies accuracy for GV cover retrieval (Parra-SPOT)

	SMA	SMA _{shn}	f-NDVI	f-MSAVI	f-DVI
R² 2005	0.7461	0.8709	0.9153	0.4560	0.3672
R² 2006	0.8678	0.8616	0.9215	0.7771	0.7255

In both 2005 and 2006 cases, f-NDVI was the best performing methodology, followed by SMA_{shn} in 2005 and by SMA and SMA_{shn} in 2006. In order to check thoroughly these results, the mean and standard deviation of GV cover values at the field plots were extracted for each method and compared (see Table 63 and Figure 47).

Table 63. Field plots GV cover mean and standard deviation

		Field data	SMA	SMA_{shn}	f-NDVI	f-MSAVI	f-DVI
2005	<i>Mean</i>	0.279038	0.185252	0.394886	0.269297	0.093275	0.034403
	<i>St dev</i>	0.113415	0.052734	0.221228	0.119579	0.049226	0.030122
2006	<i>Mean</i>	0.423565	0.233878	0.332639	0.247047	0.172377	0.106378
	<i>St dev</i>	0.104161	0.056110	0.101966	0.076466	0.069153	0.053472

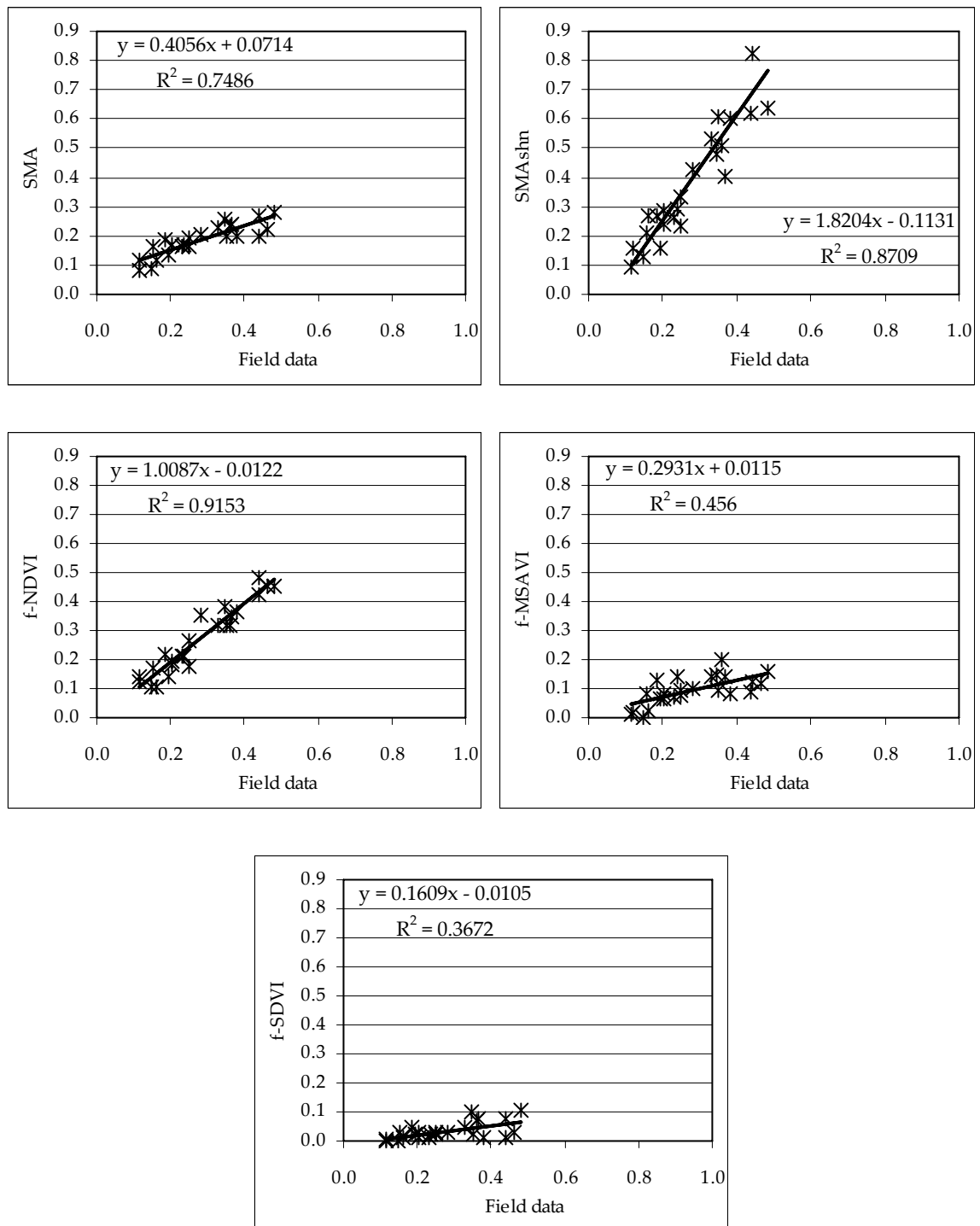


Figure 45. Accuracy regression graphics for the five methodologies (Parra 2005):
SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI

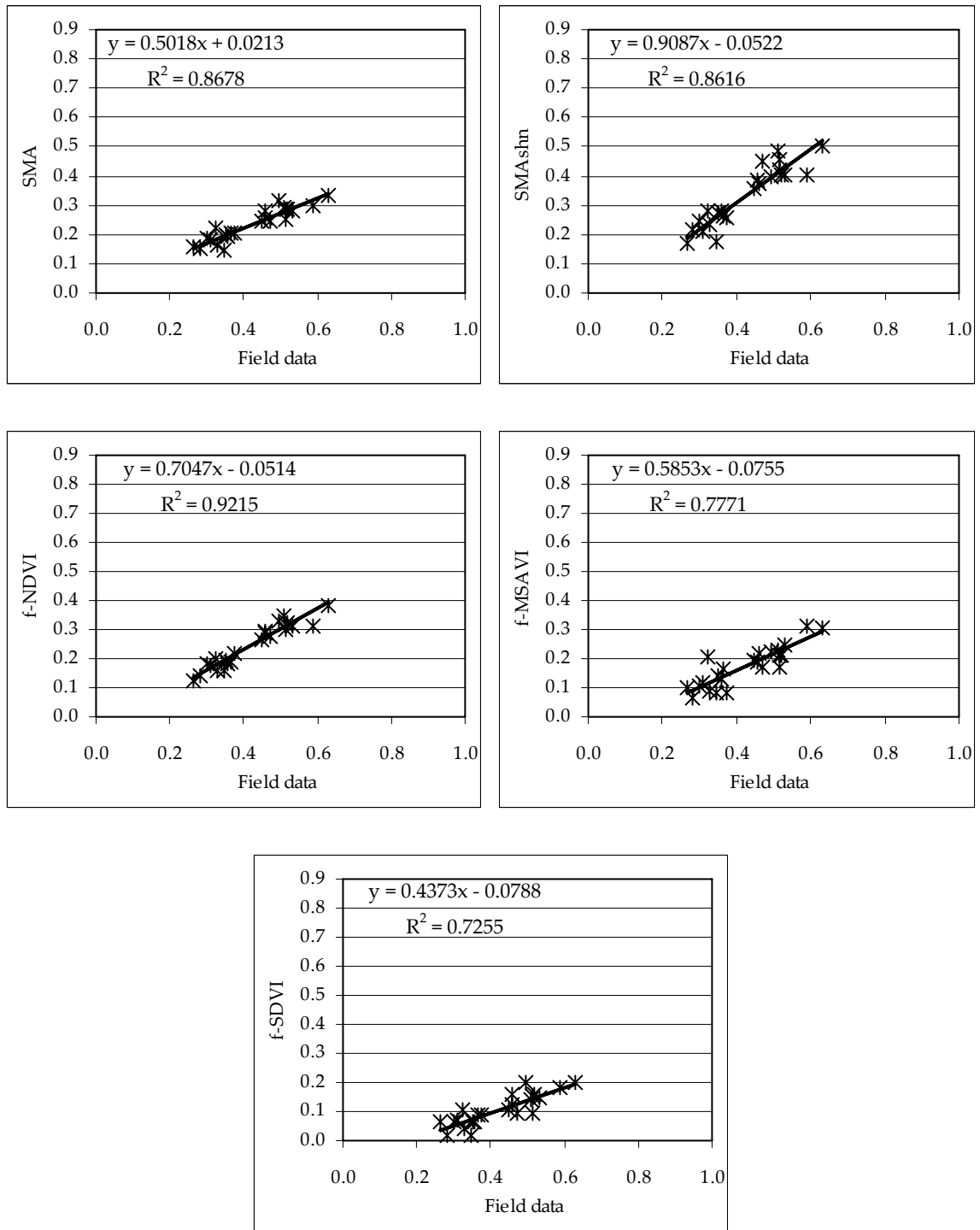


Figure 46. Accuracy regression graphics for the five methodologies (Parra 2006):
SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI

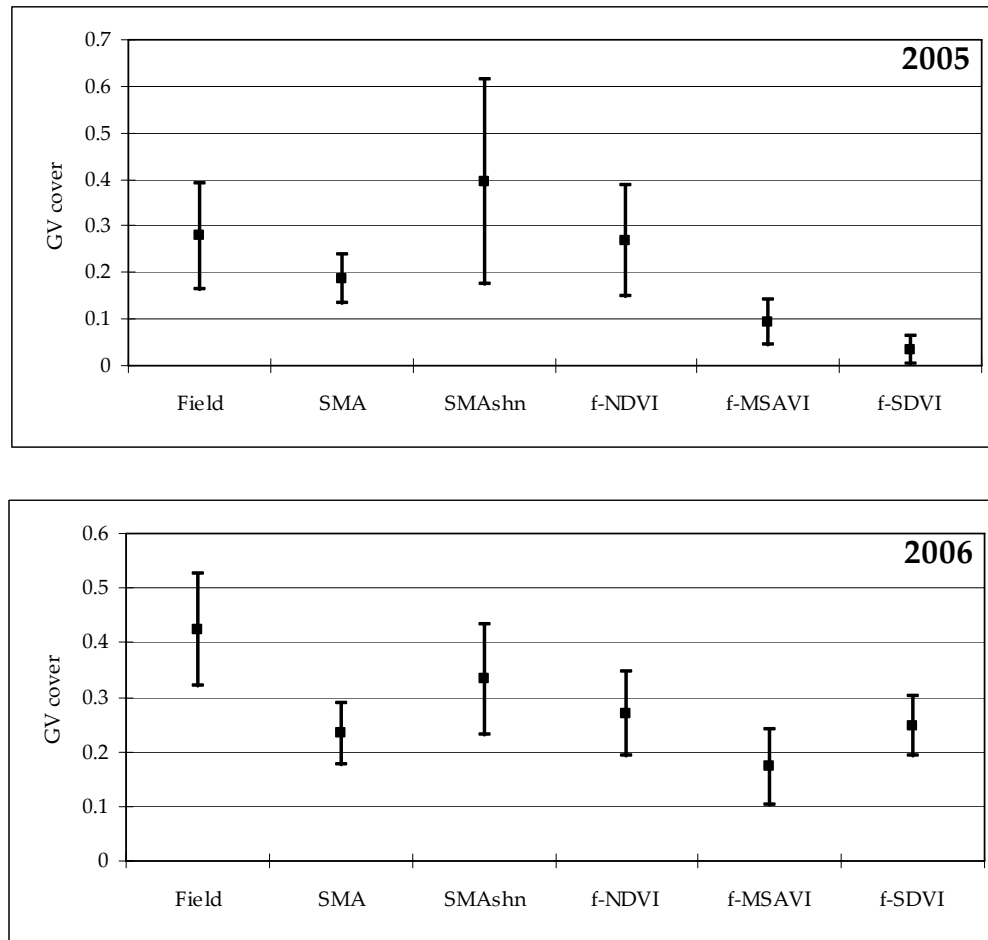


Figure 47. Field plots GV cover mean and standard deviation (2005 and 2006)

As it can be observed, in 2005 SMA_{shn} overestimates GV cover, f-NDVI is very close to field data, and the rest of methodologies underestimate GV cover. A possible explanation could be related to the fact that 2005 image was acquired the latest respect the year period (acquisition on 30th September 2005). During that month the vegetation that has reduced or stopped their photosynthetic activity (NPV) during summer due to extreme temperatures started to be photosynthetically active due to the decrease of temperatures and the beginning of the rainfall season (small rainfalls fell during the last days of September). This increased the amount of GV detected by the methodologies without increasing the vegetation cover. During the field work campaigns, not only green

vegetation was surveyed, but all the vegetation cover present in the area. Therefore, 2005 amount of GV detected by sensors was close to that surveyed in the field.

When analyzing the 2005 SMA_{shn} statistics, the large standard deviation surprises. The normalization of shade in the 2005 image created some artificial peaks. Solar elevation of 2005 image was the lowest of the image dataset, and therefore shadows due to topography were more abundant than in other images. In order to check for this, the orientation of each field plot was checked. All plots which have suffered an extreme increase on GV cover were western orientated (2005 image was acquired before noon). This suggests that shade normalization on SMA has to be applied with care and taking into account the acquisition conditions of the image.

In 2006 all methodologies underestimate GV cover. This image was acquired on 22nd July, when NPV has not yet modified its status, and therefore it is not detected as GV by the sensors as it happened in 2005. Therefore, underestimation of GV cover respect field data is expected, as during the field campaigns all vegetation was surveyed.

5.3.3.5 VEGETATION REGROWTH DETECTION

Vegetation regrowth detection was carried out with the GV cover images produced by the best performing GV cover extracting method. For Parra study area, this best technique was f-NDVI. Figure 48 shows the vegetation regeneration trend for Parra study area when extracting vegetation cover with f-NDVI method. Also, f-NDVI GV cover images were subtracted one to each other in order to produce vegetation regeneration images. Figure 49 shows the regeneration images produced.

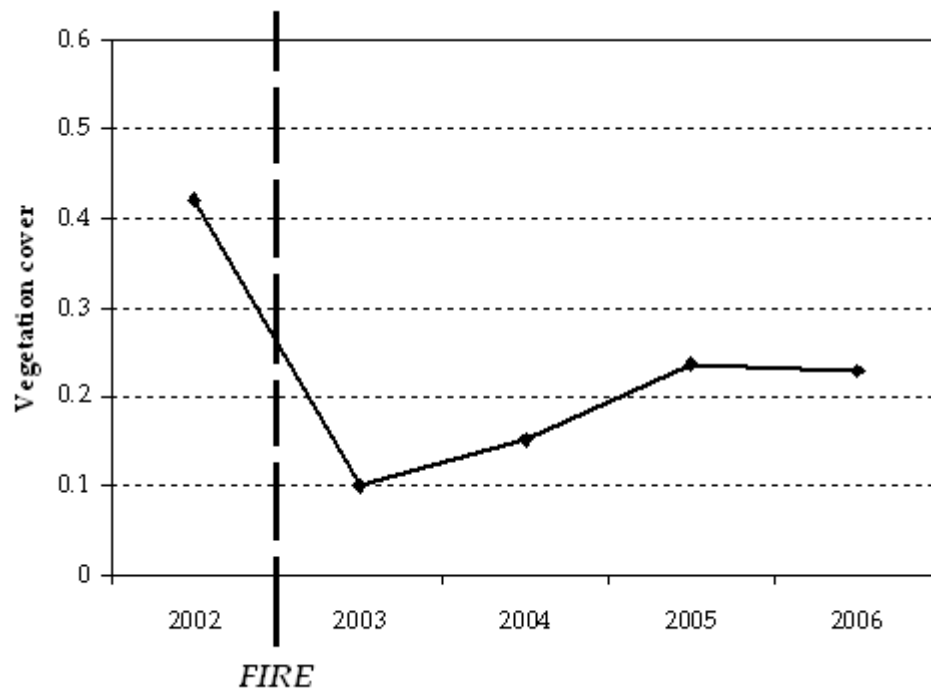


Figure 48. Vegetation regeneration trend (Parra-SPOT)

Figure 35 shows how in this study area, in the second year after the fire, the regeneration already starts to recover, even if very slowly. But Figure 37 shows how this recovery is not general over the area. Some areas start to recover, while other areas are still regressing and vegetation cover is still decreasing. The recovery is mainly located in the valley bottoms and in northern facing slopes. This could be explained by the fact that image from 2002 was acquired in July, while image from 2003 was acquired in September. Therefore the different phenological states of vegetation between these two images could introduce some recovery variations that are not only due to the increase in vegetation cover, but also to the activation of photosynthesis of NPV in valley bottoms and northern facing slopes. During the third year, the increase of vegetation is the maximum registered of the time series, but again some variation of recovery could have been introduced due to the phenological differences between images as 2004 image was acquired in July. Even though, the increase between this two years remains the maximum registered of the time series. From 2004 to 2005 the increase of vegetation seems to be also high, but again the differences in the phenological state of vegetation may have introduced variations, as

2005 image was acquired in September. Therefore this recovery could be lower if near-anniversary images were compared. The same problem remains between the two last images, as 2006 image was acquired during July. The vegetation cover decrease between this two images is mainly located in valley bottoms and northern slopes, that is, where phenological differences between vegetation are more evident. Despite these different phenological behaviours between images, a general trend could be observed. During the first year after the fire, the recovery is low, while in the third after the fire the recovery rate is the maximum registered. After this high recovery, the regeneration trend enters into a near horizontal behaviour, without reaching the pre-fire conditions. However, more images would be necessary to confirm that post-fire vegetation does not reach pre-fire conditions.

In this study area, the study of the trend of vegetation outside the burned area was not possible, as the whole area around the study area burned during the same fire in 2003.

The general GV recovery of the site between 2003 (the lowest vegetation cover after the fire) and 2006 (last image of the series) can be observed in Figure 50. This figure shows how the whole area is recovering from the fire, with a mean recovery rate of 13%. However, certain areas show a vegetation cover decrease (blue pixels). Looking at the f-NDVI immediate post-fire images (Figure 42) it is evident that these areas are the ones where vegetation has survived after the fire. The vegetation in these areas has slowly disappeared due to fire effects or to anthropic interventions.

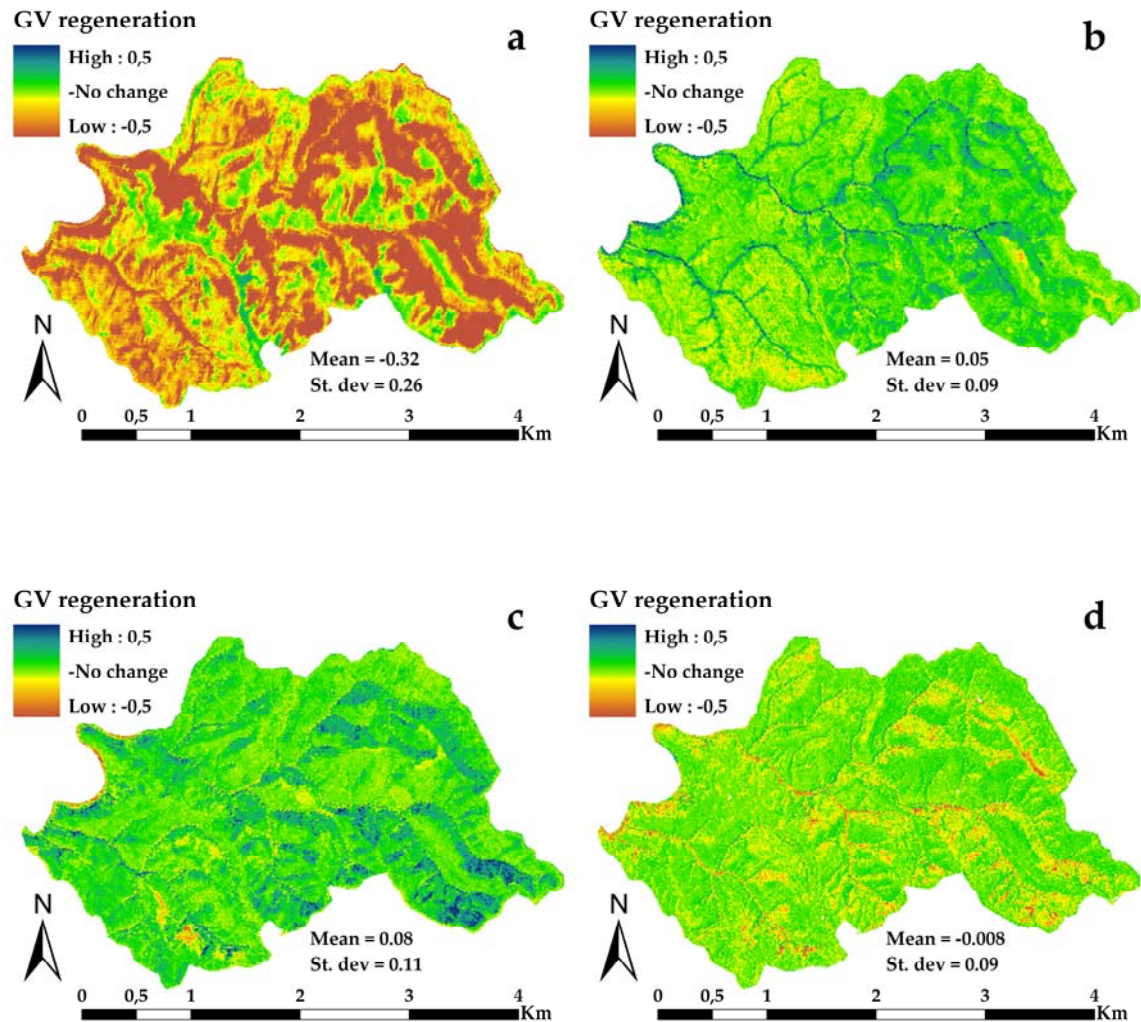


Figure 49. Regeneration images for Parra (SPOT) study area: 2002-2003 (a), 2003-2004 (b), 2004-2005 (c), and 2005-2006 (d)

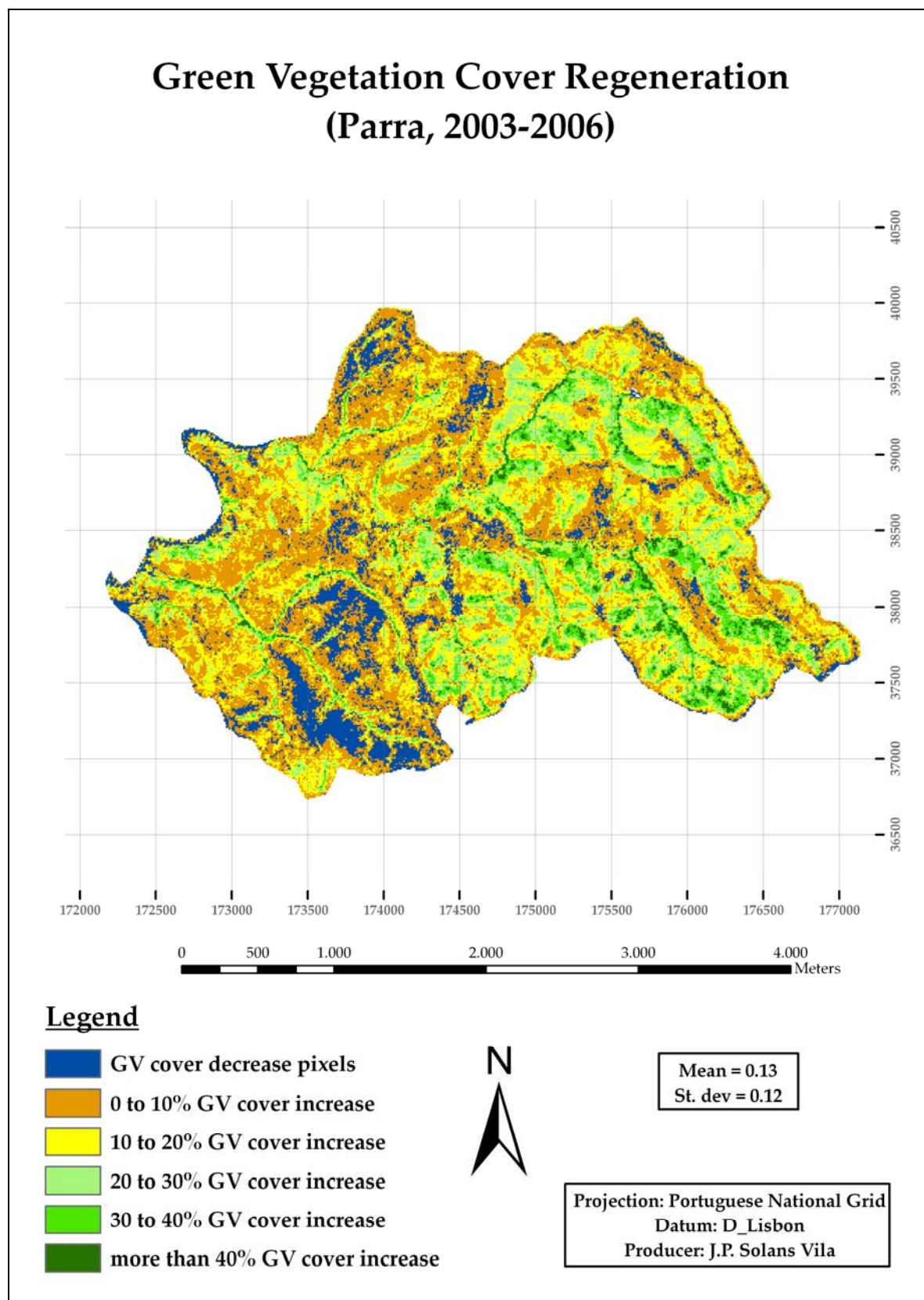


Figure 50. GV cover regeneration quantities (%) for Parra site (SPOT) between 2003 and 2006

5.3.4 Mação Study Area

5.3.4.1 ENDMEMBER EXTRACTION

Once the atmospheric normalized reflectance images were obtained, image endmembers were extracted following the procedure described in section 4.3.3.2. Principal Component Analysis was performed in order to check the dimensionality of the CHRIS-Proba images. Table 64 shows the extracted eigen-values (E-val) for each image. As it can be seen, in both images the first four principal components contain more than 99% of the original variance (V%) of the data. Therefore it was considered that the dimensionality of both CHRIS-Proba images was equal to 4. Applying Equation 45 the maximum number of image endmembers to extract from the images was set to 4 endmembers.

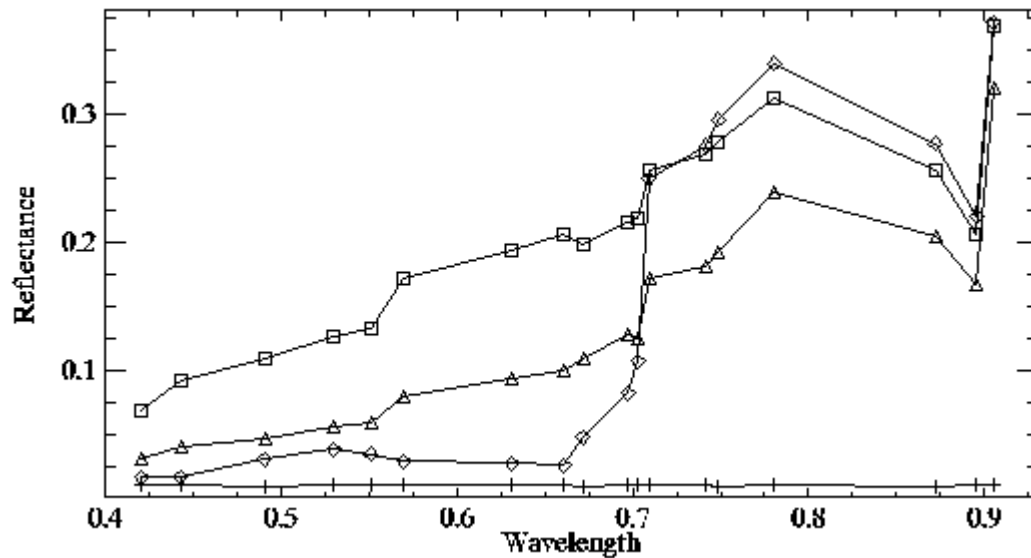
Table 64. Eigen-values and % of variance for Mação (CHRIS-Proba) study area

		2005	2006
PC1	<i>E-val</i>	0.010807	0.011901
	<i>V%</i>	85.54	86.93
PC2	<i>E-val</i>	0.001565	0.001672
	<i>V%</i>	12.32	12.21
PC3	<i>E-val</i>	0.000063	0.000055
	<i>V%</i>	0.50	0.40
PC4	<i>E-val</i>	0.000021	0.000024
	<i>V%</i>	0.17	0.17
PC5	<i>E-val</i>	0.000010	0.000018
	<i>V%</i>	0.08	0.13
PC6	<i>E-val</i>	0.000005	0.000005
	<i>V%</i>	0.04	0.04
PC7	<i>E-val</i>	0.000004	0.000004
	<i>V%</i>	0.03	0.03
PC8	<i>E-val</i>	0.000003	0.000003
	<i>V%</i>	0.02	0.02
PC9	<i>E-val</i>	0.000003	0.000002
	<i>V%</i>	0.02	0.01
PC10	<i>E-val</i>	0.000002	0.000002
	<i>V%</i>	0.02	0.01
PC11	<i>E-val</i>	0.000001	0.000001
	<i>V%</i>	0.01	0.01
PC12	<i>E-val</i>	0.000001	0.000001
	<i>V%</i>	0.01	0.01
PC13	<i>E-val</i>	0.000001	0.000001
	<i>V%</i>	0.01	0.01
PC14	<i>E-val</i>	0.000001	0.000001
	<i>V%</i>	0.01	0.01
PC15	<i>E-val</i>	0.000001	0.000000
	<i>V%</i>	0.01	0.00
PC16	<i>E-val</i>	0.000000	0.000000
	<i>V%</i>	0.00	0.00
PC17	<i>E-val</i>	0.000000	0.000000
	<i>V%</i>	0.00	0.00
PC18	<i>E-val</i>	0.000000	0.000000
	<i>V%</i>	0.00	0.00

SMACC was then applied to both images of the dataset. In order to take advantage of the hyper-spectral character of this sensor, the maximum number of endmembers to be extracted from each image with the SMACC tool was set equal to the number of spectral channels. SMACC finds the first extreme pixel and continuous to identify extreme pixels until it returns to the first pixel found. For 2005 image a set of 7 endmembers was obtained, and for 2006 a set of 5 endmembers was obtained. Their spectral identity was defined by analyzing their spectral signature and NDVI images. The spectral signature of the pixel of each image endmember was extracted and, together with the, NDVI value of the pixel, was used to identify the endmember classes. Once endmembers were identified, they were grouped in order to form a set of four endmembers classes (green vegetation endmember (GV), soil endmember (S), shade endmember (Sh) and non photosynthetic vegetation endmember (NPV)). The endmember classes reflectance in each band was extracted and put into an EXCEL spreadsheet. Band average reflectance values for each endmember class (GV, S, Sh, and NPV) were computed, yielding four average endmembers. Table 65 presents the band average reflectance values for each average endmember, and Figure 51 shows their spectral signatures. This set of average endmembers was then used for the application of the spectral analysis techniques.

Table 65. Average endmember reflectance values (Mação-CHRIS-Proba)

	Average Endmember Reflectances			
	GV	S	Sh	NPV
B1	0.017311	0.069589	0.011300	0.030872
B2	0.017305	0.091924	0.011082	0.040661
B3	0.031094	0.109506	0.010267	0.047494
B4	0.038862	0.127505	0.010384	0.056524
B5	0.034824	0.132786	0.010512	0.059193
B6	0.029766	0.171766	0.010686	0.080240
B7	0.027741	0.193967	0.010497	0.093555
B8	0.026305	0.206117	0.010437	0.099939
B9	0.048318	0.199383	0.010185	0.109228
B10	0.082542	0.216597	0.011109	0.128299
B11	0.107483	0.218623	0.010634	0.125120
B12	0.249756	0.255911	0.010458	0.171684
B13	0.275605	0.269016	0.010915	0.181417
B14	0.296246	0.277832	0.010245	0.193135
B15	0.340157	0.312821	0.010493	0.239267
B16	0.277623	0.256586	0.010278	0.204543
B17	0.220830	0.207159	0.010860	0.167198
B18	0.372099	0.369910	0.011337	0.320264

**Figure 51.** Mação (CHRIS-Proba) average endmember spectral signatures: GV ($\diamond$), S ($\square$), Sh (+), and NPV (Δ)

5.3.4.2 SPECTRAL MIXTURE ANALYSIS APPLICATION

SMA was then applied to each image in order to obtain the fraction images. SMA was constrained to produce fraction images which sum results 1 in order to produce meaningful fractions. Both the fractional error and the RMSE error were checked for each set of four fraction images in order to assess their accuracy. Table 66 shows the fractional errors obtained for the fraction images of each year. Mean, minimum (min) and maximum (max) RMSE values, together with its standard deviation (st dev) were also computed for the SMA results of each image of the dataset (see Table 66).

Table 66. RMSE and Fractional Error values of fraction images (Mação-CHRIS-Proba)

	Fractional Error (%)				RMSE			
	<i>GV</i>	<i>S</i>	<i>Sh</i>	<i>NPV</i>	<i>Mean</i>	<i>St.dev</i>	<i>Min</i>	<i>Max</i>
2005	16.24	6.82	0.23	1.05	0.002030	0.000675	0.000000	0.015065
2006	7.15	10.06	0.15	1.14	0.002593	0.000753	0.000299	0.018077

Mean RMSE values obtained (Table 66) are well below the 0.025 threshold. This indicates that the applied unmixing model shows a sufficient fit and, therefore, the set of average endmembers applied is accurate enough as to be used in a multi-temporal study like this one.

Looking at the fractional error values presented in Table 66, it is possible to observe that more than 95% of the NPV and Sh values lay within the required range in each image. The high soil fractional error can be explained by the high soil variability in the area and the difficulty in modelling it with only one endmember.

However GV fractional error values are higher than the 5% threshold. This can be explained by the fact that these images are immediate post-fire images, and the fire effects are still present in the area (ash, charcoal). Unfortunately, no pre-fire image was available for this study area in order to compare it with the post-fire images. In the burned area, vegetation fraction values obtained were quite often negative values, which increased the GV fractional error for these two images. In order to illustrate this, the mean, minimum

and maximum GV fraction values, together with the percentage of GV negative fraction values (% Negative GV) for the burned areas for all images were extracted (see Table 68).

Table 67. SMA GV fraction statistics for the burned area (Mação-CHRIS-Proba)

	SMA GV fraction statistics				
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>	<i>% Negative GV</i>
2005	0.108699	0.122545	-0.156813	1.059507	14.72
2006	0.219380	0.139869	-0.147608	0.973303	5.37

GV fraction images produced with SMA and used for comparison with the other vegetation fraction extracting techniques results are presented in Figure 52.

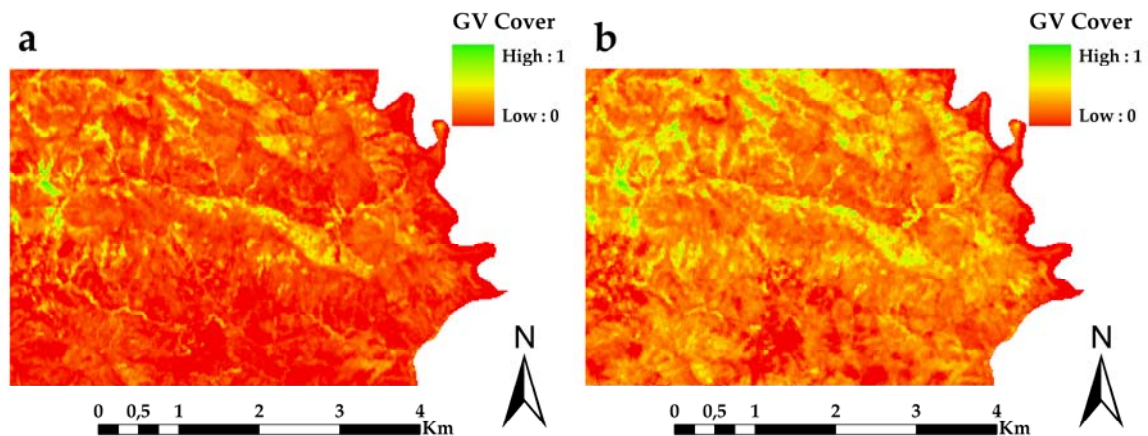


Figure 52. Mação (CHRIS-Proba) study area SMA GV fraction images: 2005 (a), and 2006 (b)

As a post-processing step, shade normalization was applied. Both the GV fraction images and the shade normalized GV fraction images were used for comparison with the rest of techniques. Table 68 shows the mean and standard deviation values of the burned area for the shade normalized GV (GV_{shn}) fraction images.

Table 68. SMA_{shn} GV fraction statistics for the burned area (Mação-CHRIS-Proba)

	SMA_{shn} GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2005	0.157773	0.201044	-2.926710	1.103202
2006	0.303340	0.230159	-2.481814	1.281335

Table 69 shows the percentage of increase ($\Delta GV\%$) that the shade normalization has added to the mean GV fraction values. As both images are post-fire images, the increase amount is quite low due to the absence of vegetation in the area (no canopy shadowing effect).

Table 69. Percentages of increase ($\Delta GV\%$) from GV fraction to GV_{shn} fraction

	2005	2006
$\Delta GV\%$	4.91	8.39

Figure 53 shows the shade normalized GV fraction images produced for Mação study area.

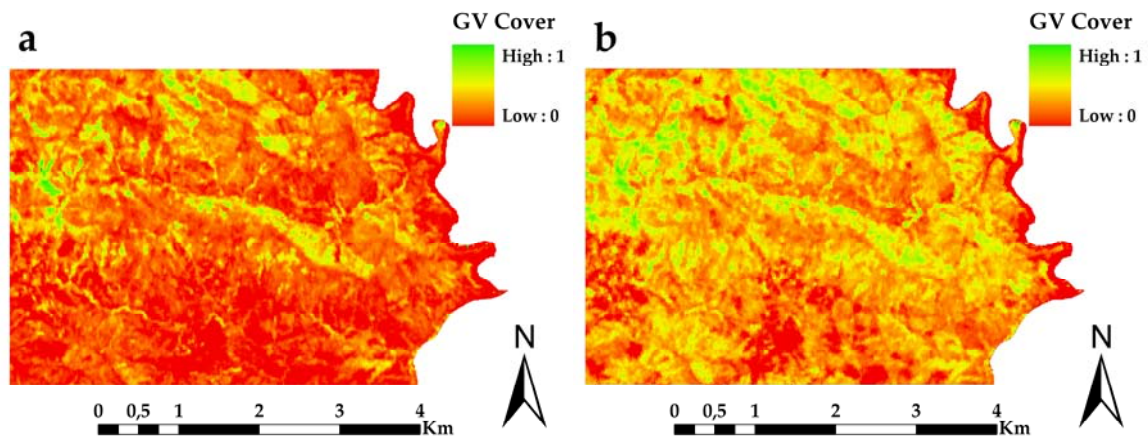


Figure 53. Mação (CHRIS-Proba) study area SMA_{shn} GV fraction images: 2005 (a), and 2006 (b)

5.3.4.3 QUANTITATIVE VEGETATION INDICES APPLICATION

Green vegetation fractional cover images were obtained by applying the quantitative vegetation indices (VIs) described in section 4.3.2.

The red (ρ_R) and near-infrared (ρ_{NIR}) reflectance values of the average soil endmember (S) and the average vegetation endmember (GV) were used to scale the vegetation indices (see section 4.3.2 for details). Being CHRIS-Proba a hyperspectral sensor, several bands are available within the red and NIR spectral ranges. Thus the ρ_R and ρ_{NIR} reflectance values for the scaling of the indices were computed as follows:

$$\rho_R = \frac{B6 + B7 + B8}{3} \quad \text{and} \quad \rho_{NIR} = \frac{B14 + B15 + B16}{3}$$

Table 70 presents the computed ρ_R and ρ_{NIR} reflectance values of these endmembers together with the corresponding NDVI, MSAVI and DVI values.

Table 70. Scaling values for the application of the quantitative VIs (Mação-CHRIS-Proba).

	ρ_R	ρ_{NIR}	NDVI	MSAVI	DVI
GV	0.027937	0.304675	0.832014	0.996077	0.276738
S	0.190616	0.282413	0.194062	0.255511	0.091797

Table 71, Table 72, and Table 73 show the GV fraction statistic values for each year when applying f-NDVI, f-MSAVI, and f-DVI respectively.

Table 71. f-NDVI GV fraction statistics for the burned area (Mação-CHRIS-Proba)

	f-NDVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2005	0.195329	0.120235	0.000000	0.972627
2006	0.299129	0.138278	0.000000	1.000000

Table 72. f-MSAVI GV fraction statistics for the burned area (Mação-CHRIS-Proba)

	f-MSAVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2005	0.109577	0.148064	0.000000	1.000000
2006	0.251746	0.175728	0.000000	0.998848

Table 73. f-DVI GV fraction statistics for the burned area (Mação-CHRIS-Proba)

	f-DVI GV fraction statistics			
	<i>Mean</i>	<i>St dev.</i>	<i>Min</i>	<i>Max</i>
2005	0.048224	0.102857	0.000000	1.000000
2006	0.134496	0.140754	0.000000	0.984246

Figure 54, Figure 55, and Figure 56 present the resulting green vegetation cover images for f-NDVI, f-MSAVI, and f-DVI respectively.

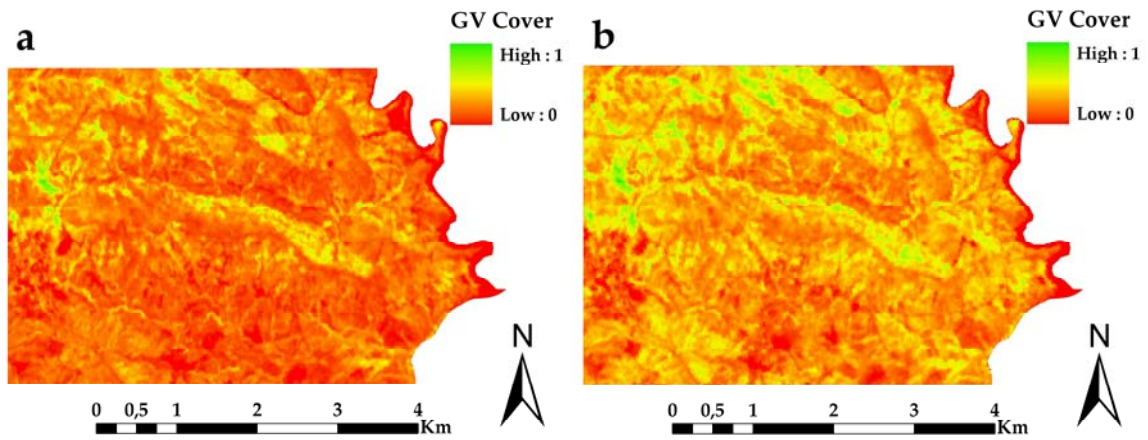


Figure 54. Mação (CHRIS-Proba) study area f-NDVI GV fraction images: 2005 (a), and 2006 (b)

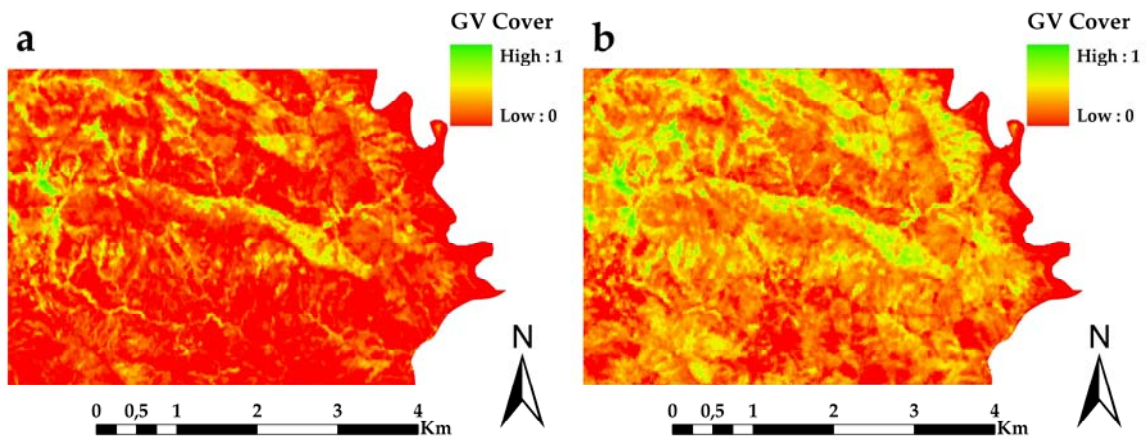


Figure 55. Mação (CHRIS-Proba) study area f-MSAVI GV fraction images: 2005 (a), and 2006 (b)

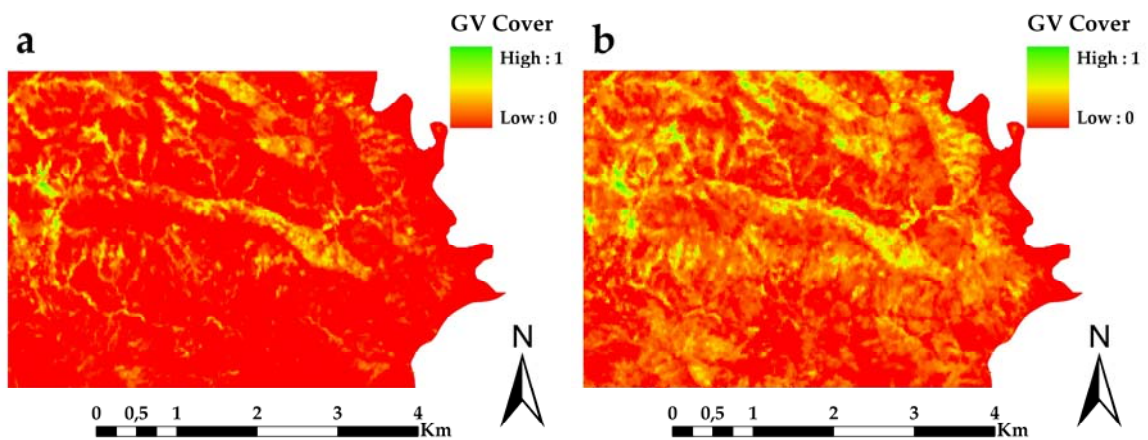


Figure 56. Mação (CHRIS-Proba) study area f-DVI GV fraction images: 2005 (a), and 2006 (b)

5.3.4.4 ACCURACY AND COMPARISON OF METHODOLOGIES

Accuracy of the 2005 and 2006 green vegetation fractional cover images obtained after application of the five selected methodologies (SMA, SMA shade normalized – SMA_{shn} –, f-NDVI, f-MSAVI, and f-DVI) was checked by regression against the field data collected during the 2005 and 2006 field campaigns.

Accuracy assessment was considered on a 3x3 pixels kernel. Table 74 shows the R² values obtained from the accuracy analysis for 2005 and 2006 GV cover images, and Figure 57 and Figure 58 shows the regression graphics produced for each methodology for 2005 and 2006 respectively.

Table 74. Methodologies accuracy for GV cover retrieval (Mação-CHRIS-Proba)

	SMA	SMA _{shn}	f-NDVI	f-MSAVI	f-DVI
R² 2005	0.8771	0.8686	0.9178	0.9080	0.8444
R² 2006	0.7366	0.8562	0.8856	0.7358	0.6452

In both 2005 and 2006 cases, f-NDVI was the best performing methodology, followed by f-MSAVI in 2005 and by SMA_{shn} in 2006. In order to check thoroughly these results, the mean and standard deviation of GV cover values at the field plots were extracted for each method and compared (see Table 75 and Figure 59). Standard deviation values obtained are much higher than in the other study areas. This high value of standard deviation may be due to high landscape variability. However, one of the characteristic effects of fire in landscape is the homogenization of the areas burned. This homogenized landscape slowly increases its variability with time, when vegetation starts to create different associations and structures. This is a long-term process that may take decades, and therefore is not possible that it is the cause of the high standard deviation values found. The latter are most probably due to a high level of noise of the sensor. Several studies that have used CHRIS-Proba data have already reported this high noise level in this sensor (Garcia & Moreno, 2004; Guanter *et al.*, 2004).

Table 75. Field plots GV cover mean and standard deviation

		Field data	SMA	SMA _{shn}	f-NDVI	f-MSAVI	f-DVI
2005	<i>Mean</i>	0.405432	0.242384	0.330514	0.303539	0.270956	0.164623
	<i>St dev</i>	0.201017	0.149041	0.186317	0.149138	0.201808	0.152703
2006	<i>Mean</i>	0.494296	0.336744	0.430281	0.389046	0.405188	0.267593
	<i>St dev</i>	0.163407	0.133155	0.140231	0.137020	0.183327	0.168982

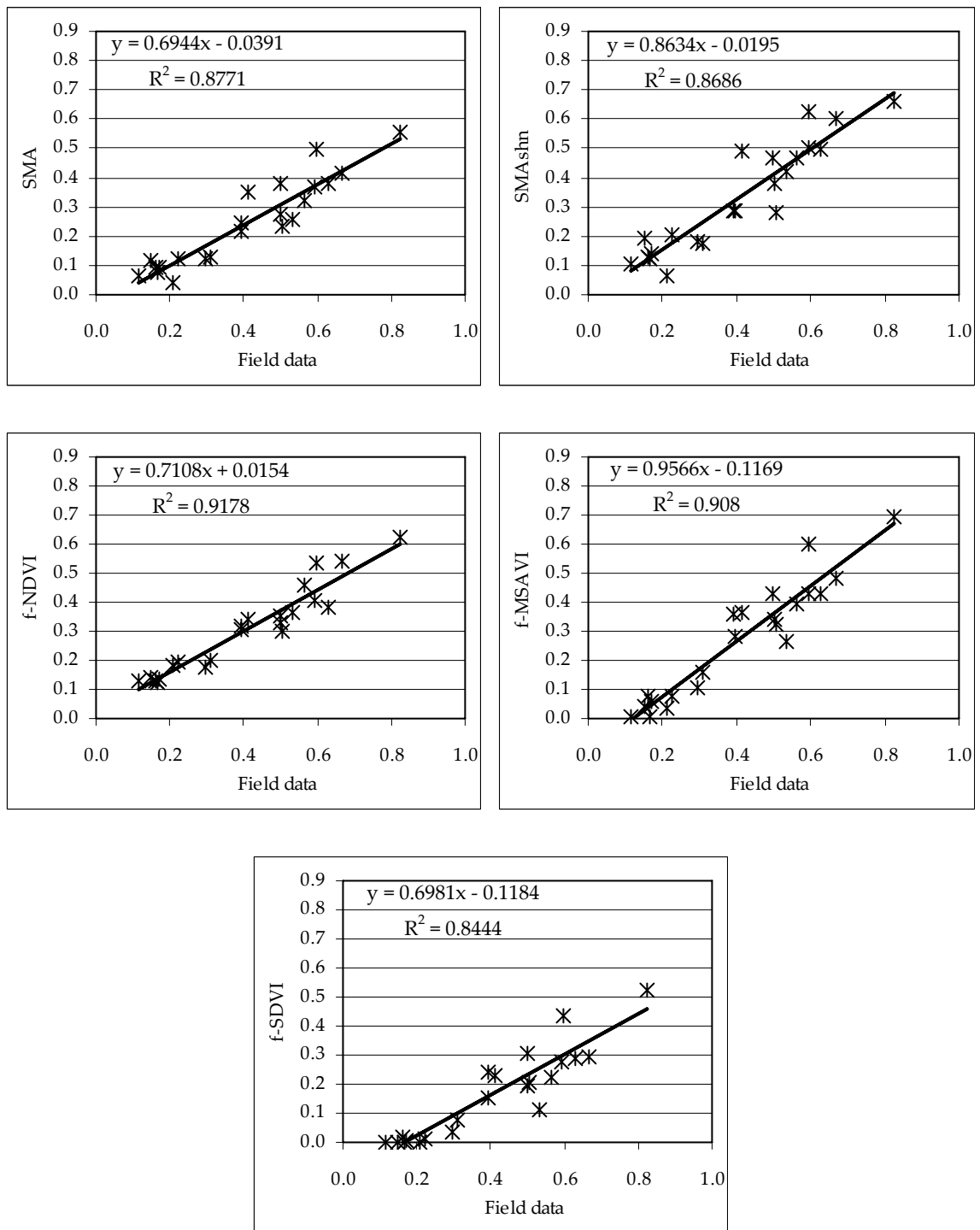


Figure 57. Accuracy regression graphics for the five methodologies (Mação 2005):
SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI

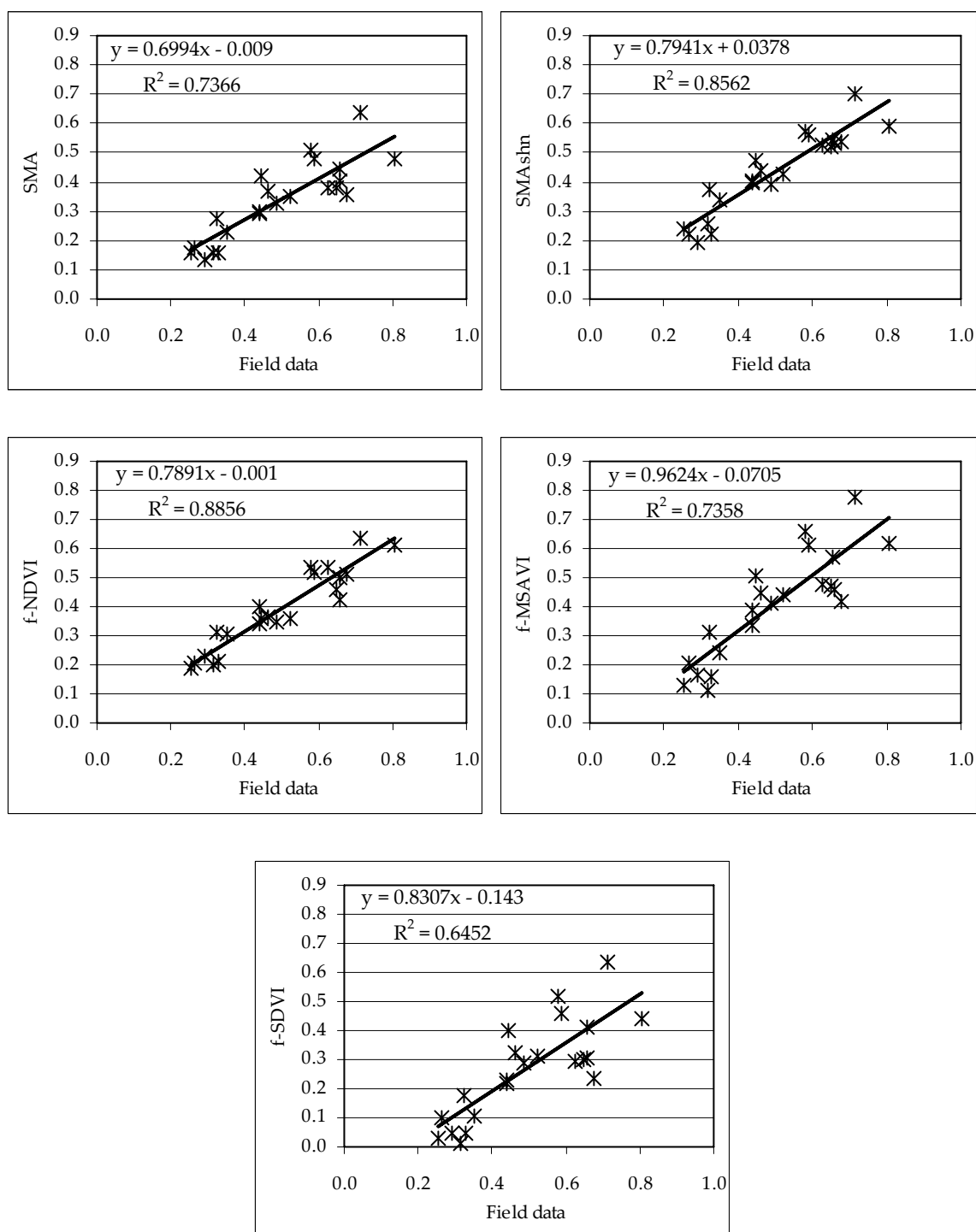


Figure 58. Accuracy regression graphics for the five methodologies (Mação 2006): SMA, SMA_{shn}, f-NDVI, f-MSAVI, and f-DVI

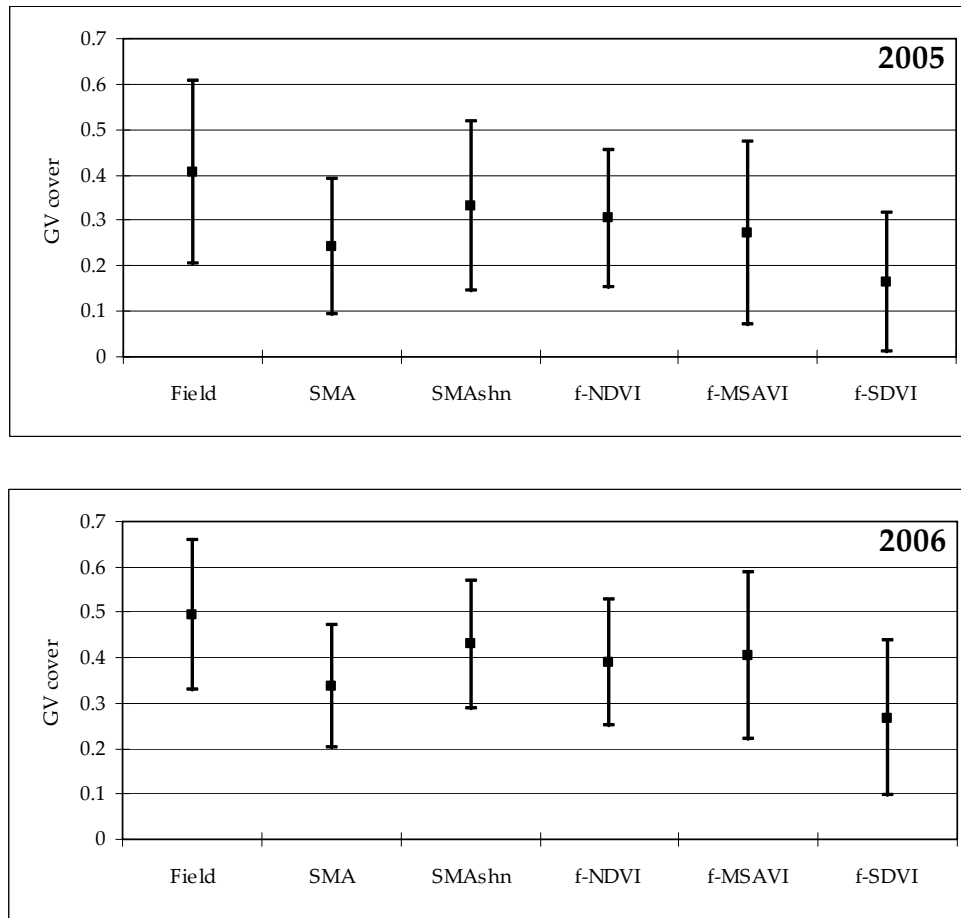


Figure 59. Field plots GV cover mean and standard deviation (2005 and 2006)

As it can be observed, both in 2005 and 2006 all methodologies underestimate field data. Both images were acquired on June, when NPV has not yet modified its status, and therefore it is not detected as GV by the sensors. Therefore, underestimation of GV cover respect field data is expected, as during the field campaigns all vegetation was surveyed.

5.3.4.5 VEGETATION REGROWTH DETECTION

Vegetation regrowth detection was carried out with the GV cover images produced by the best performing GV cover extracting method. For Mação study area, this best technique was f-NDVI. Figure 60 shows the vegetation regeneration trend for Mação study area when extracting vegetation cover with f-NDVI method. Also, f-NDVI GV cover images

were subtracted one to each other in order to produce vegetation regeneration images. Figure 61 shows the regeneration image produced.

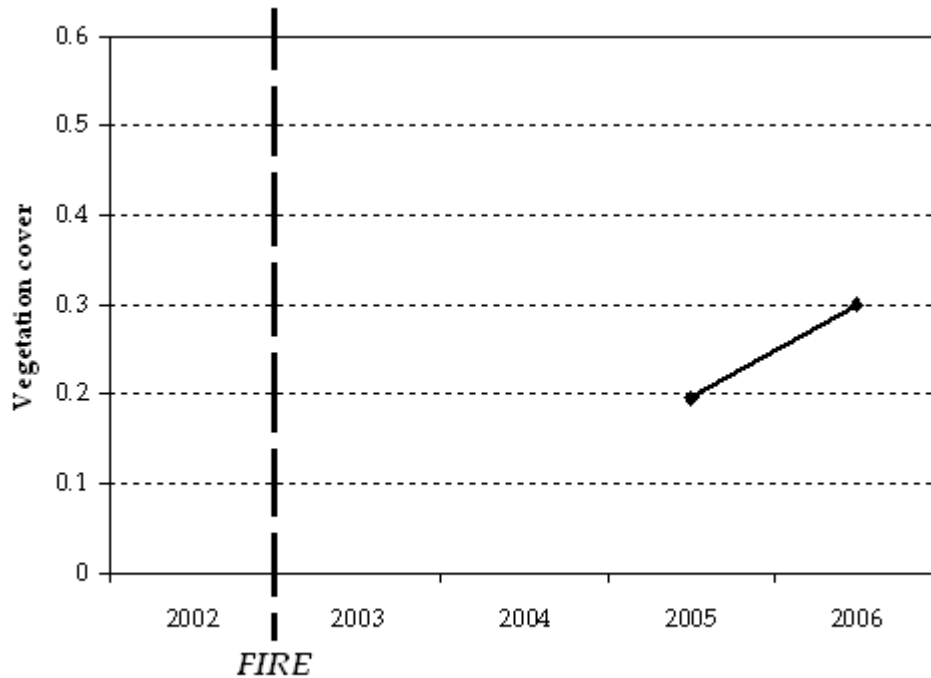


Figure 60. Vegetation regeneration trend (Mação-CHRIS-Proba)

In this study area, the study of the trend of vegetation outside the burned area was not possible, as the whole area around the study area burned during the same fire in 2003.

The GV recovery of the site between 2005 and 2006 can be observed in Figure 61. This figure shows how the whole area is recovering from the fire, with a mean recovery rate of 10%. However, certain areas show a vegetation cover decrease (blue pixels). Looking at the f-NDVI immediate post-fire images (Figure 54) not a clear reason for this was found. In the other study sites it was evident that these areas were the ones where vegetation survived after the fire, but in this study area it is not possible to say the same, as no pre-fire and immediate post-fire images were available. In order to identify the reasons for this phenomenon, pre-fire and immediate post-fire images should be studied. However, even if this experimental sensor was launched on 2001, it did not start to acquire images of the study area until 2004. Unfortunately, the study area in 2004 image was entirely

covered by clouds, yielding this image useless for the study. Therefore, only the acquisition and analysis of other sensor images of pre-fire and immediate post-fire images could provide the information necessary to explain the regeneration trend of this study area.

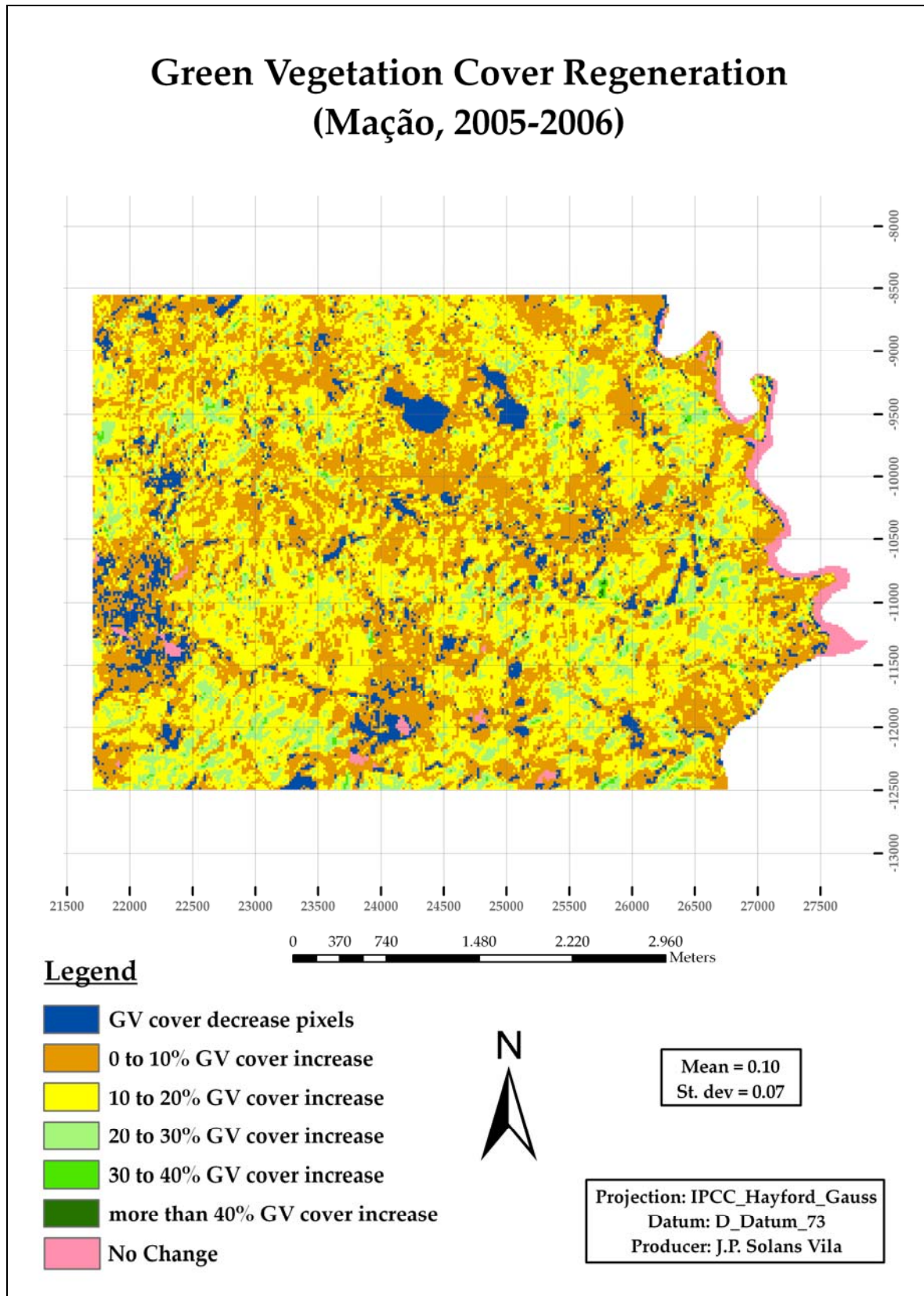


Figure 61. GV cover regeneration map for Mação site (CHRIS-Proba) between 2005 and 2006

6. DISCUSSION OF RESULTS

As explained in the introduction of this work, Mediterranean forests are suffering from an increase of burned area during the last years. And this is occurring in spite of the efforts that the administrations are doing in order to control and reduce the fire events. Neither the legal instruments implemented nor the increment of fire-extinction means have produced the desired reduction of burned area. It is the opinion of the author that until the real problem of the Mediterranean forests will not be faced, this situation would not find a solution: Mediterranean forests are not economically profitable. Many products can be extracted from our forests, as wood, mushrooms, truffles, medicinal plants, honey, cork, paper, ... These are just some of the quantifiable products that the Mediterranean forest offers. But these products are not enough to transform forests into an economically profitable product, and in most cases they can be extracted from the forest by anyone, leaving nothing to the forest owner. Other services that nowadays is still not possible to economically count are even more important: protection from erosion, aquifer renewal and conservation, oxygen production, landscape beauty, ... These products are called externalities in the economical language. And they are the key factor in order to transform Mediterranean forests into an economically profitable business.

Mediterranean forests are mainly private forests. To be the owner of a forest nowadays is more a problem than a benefit, as regulations and laws limit the use and management of the forest by the owner, and the economical revenue that the owner can get from the forest is almost negative. Therefore, the forest owner has no interest at all in properly manage his forest, abandoning it to its own. This could be a positive thing in other parts of the world, but not in the Mediterranean environment. The latter is a highly anthropic environment, and the auto-regulation is a process that is not happening from a long time ago. As a consequence of this non management of Mediterranean forests, fuel loads are increasing. Even if fire is an important ecological factor of this type of forests, the amount of area burnt is far from being ecologically positive for the environment. The increment of fuel in these forests is becoming a problem, as fire has its path free from barriers, both horizontally and vertically.

The problem of the non management or bad management of Mediterranean forests would only be solved by awaking the interest of forest owners for their forests. Unfortunately, altruistic and ecological reasons are not enough for these owners, as the management of a forest has an cost in economical terms. The transformation of the externalities mentioned above into economically valuable products may solve almost completely this problem. This is easy to say but is not easy at all to implement. How can the beauty of the landscape be measured in economical terms? How much would pay a person for 1 litre of oxygen produced by a forest? Which is the economic value of 1 square meter of soil protected from erosion? All this questions must be answered if a definitive solution to the problem of private forest management must be found.

The administration could then implement an ecological tax which would cover the subsidies used to pay forest owners for the services and products that their forests are producing for the benefit of us all. If forest owners receive economic resources from the management of their forests, several problems that nowadays are very difficult to manage would be easily solved. One of these problems would be the amount of area burned by forest fires, as owners would be the most interested ones in avoiding that their forest could burn.

Nowadays, most efforts are focused in implementing technologies, methods and instruments that are able to detect promptly forest fires, and to extinguish them. But despite these efforts, burned area is still increasing. Therefore, attention needs to be paid to the burned areas, not only to map their perimeter and to calculate some statistics at the end of the fire season, but also to decide and implement which management has to be applied to these areas. Should the entire area be reforested? Is the area recovering by itself, or a desertification process is starting? Which areas need urgently to be reforested in order to avoid erosion processes? Managers need instruments in order to answer these questions. The present work pretends to be a starting point in order to define a methodology that allows the evaluation of the regeneration processes in burned areas. The conclusions extracted from this evaluation would help strongly the decision process, and the management of economic resources when implementing solutions to the burned

areas. If a more precise use of the technical and human resources would be implemented, economical resources would as well better applied.

The principal aim of this research is to provide information for the decision making process and management of fire-affected forest ecosystems, by implementing an accurate and simple method for retrieving quantitative estimates of vegetation regeneration on fire-affected ecosystems, from remotely sensed data.

In order to achieve this, an accurate pre-processing of the images has been carried out. The most significant result obtained from this process was the developing of an automated Pseudo-Invariant Features extraction by means of the multi-Temporal n-Dimensional Principal Component Analysis (mT-nD-PCA). This technique was only applied to the Landsat images (Lythrodontas and Deiva Marina study sites). The temporal principal component analysis performed demonstrated that the first temporal principal component contains the no change areas, allowing the application of the PIF extraction technique. PIF errors obtained showed that the latter proved to be a valid technique for extracting image PIFs for the atmospheric normalization of an image time series, avoiding the subjectivity of a visual PIF selection. A further advantage of mT-nD-PCA is that it can be applied to any type of sensor with no limit to the number of images in the time series. The only necessary condition is the presence in the images of a large enough amount of areas without drastic changes for the whole time series. However, also the visual PIF extraction showed to be accurate if spatial resolution of remote sensing and ancillary data is high enough, as demonstrated in the Parra study site.

The first objective of this thesis was to compare different spectral analysis techniques for monitoring burned area changes in order to select the best among them. This comparison was performed in all four study areas, concluding for all study areas that the best performing technique was the f-NDVI. This seems to be not coherent with previous studies which demonstrated that the SMA approach was superior to the NDVI one. However, all these studies focused their interest in the qualitative analysis capabilities of these techniques, and not in the quantitative aspect. In this thesis, the quantitative aspect was the aim of the study. In order to retrieve quantitative estimates from the vegetation

indices, a scaling approach was adopted. This scaling approach was never compared against SMA technique (to the author's knowledge). Therefore, even if previous studies demonstrated the superiority of SMA, the conclusions of this study could be considered out of the frame of comparison that other studies adopted. The main problem reported by the other studies when using NDVI with a qualitative approach in low vegetated areas is the soil background effect. This soil background effect is avoided when using the SMA technique. However, as explained before, in this project NDVI was scaled between dense vegetation NDVI value and soil NDVI value. This scaling could have eliminated the soil background effect and thus, improved the resulting quantitative analysis, yielding f-NDVI superior to SMA. However, further studies should be carried out in order to prove this assumption.

The comparison of methodologies yielded also some other interesting results. When analysing shade normalized SMA results in all study areas (except Mação) it became evident how the increase of GV cover respect to the SMA results was closely related to the vegetation cover present in the area. In order to check this relation, GV cover increase values between SMA and shade normalized SMA were computed and regressed against the mean GV cover values obtained from the f-NDVI method. This was performed for Lythrodontas, Deiva Marina and Parra study area. Mação study area was not considered as no pre-fire and immediate post-fire images were available. The resulting correlation coefficients demonstrated that the increase in GV cover values resulting from the shade normalization of SMA GV cover results was correlated with the vegetation cover present in the area. This can be explained by the canopy shadowing effect, which decreases when vegetation cover is low and increases when vegetation cover increases. Therefore, it can be said that the shade normalization results depend highly on the canopy shadowing effect of the vegetation present in the area.

The second objective of this thesis was to analyse the performance of different satellite sensors when sensing changes in vegetation regrowth after forest fires. The accuracy assessment made with the gathered field data showed how all sensors used in this project performed well when producing vegetation fraction images. The standard deviation

values of GV cover results from each methodology further prove the good performance of Landsat and SPOT sensors (Lythrodontas, Deiva Marina, and Parra study areas). However, standard deviation values for Mação study area (CHRIS-Proba sensor) show how the performance of this sensor is inferior to the other sensors. This high value of standard deviation may be due to high landscape variability but it is most probably due to a high level of noise of the sensor since one of the characteristic effects of fire in landscape is the homogenization of the areas burned. This is in agreement with a number of studies that reported a high noise level for CHRIS-Proba. However it must be said that for an accurate comparison between sensors, images of different sensors should be acquired over the same study area. Comparing the performance of different sensors in different study areas leaves a big amount of uncertainty when analysing results obtained, as the reasons for a better or a worse performance may not be due only to the sensor, but to the inherent properties of each study area. Unfortunately, images of different sensors acquired over the same study area were not available for this project, and this must be taken into account when analysing the results.

The third objective of this thesis was to study the dynamics of post-fire vegetation regeneration in the European Mediterranean basin in order to model it and extract post-fire vegetation regeneration paths from field and satellite data. Figures presenting the GV cover regeneration trend for three study areas (excluding Mação study area, as no pre-fire and immediate post-fire data was available) show how vegetation cover for the first two years after the fire increases very slowly or even decreases during the first two years after the fire. The immediate post-fire GV images show the decrease in vegetation that the fire directly caused. For the second year after the fire, two different behaviours have been identified in the study areas. The first one is a slight increase of vegetation cover, which corresponds to an initial recovery of the area. The second behaviour is a further decrease in vegetation cover. The latter is caused either by natural causes (vegetation that survived to the fire event dies due to the stress that the fire caused), or by anthropic causes (vegetation remaining in the burned area is removed in order to facilitate re-vegetation programs). The behaviour during the third year after the fire is common to all three study areas where data allows this analysis. During this third year, the increase of vegetation is

the maximum registered of the time series. After this high increase during the third year, the vegetation cover increase is lower, adopting an asymptotic behaviour which tends to an horizontal maximum which does not equal the pre-fire vegetation cover level. However, in order to further prove this behaviour, a longer analysis period would be necessary.

GV cover regeneration maps were analyzed in order to study the spatial pattern of the regeneration process. Mainly slope degree, aspect, pre-fire vegetation and road and river networks were compared with the GV cover regeneration in the study areas. Other variables that could affect the recovery of the areas were not assessed as they were not available (e.g. soil type, geology, fire intensity/severity maps).

In relation to slope degree and aspect, it was possible to observe how North and West aspects had a slightly bigger level of vegetation cover recovery. This may be due to the fact that these aspects are the less directly exposed to the sun radiation. However the differences between GV cover increase in N and W aspects, and S and E aspects is too low to consider it as a determinant factor. In relation to slope degree, no significant correlation was found with GV cover increase.

Pre-fire vegetation has been considered by several authors a determinant factor in the recovery rate of burned areas (see the introduction chapter of this thesis). As explained in the introduction chapter, several regeneration strategies are possible depending on the vegetation present in the area previously to the fire. In the study areas of this project, the fact that in each of them there was one and only one dominant specie, has not allow to derive conclusions from this variable. Only in the Portuguese sites (Parra and Mação), a slightly bigger increase of vegetation was detected in areas where eucalyptus (very vigorous resprouting specie after a fire) plantations were present (Mação study area), and where strawberry tree (*Arbutus unedo*) was present (Parra study area).

The relation between GV cover regeneration and road and river networks was the most evident. Along road networks, GV cover regeneration was almost null. This could be easily explained by the fact that these roads have not been abandoned after the fire. They have been used for extraction of the burned trees, so vegetation has not been able to

regrowth along these roads. Possibly when nearby trees will be tall and wide enough in order to cover the roads, this evident difference between road pixels and their neighbouring pixels will disappear.

The relation between river networks and GV cover regeneration was evident. The rate of increase was bigger along rivers as the presence of water helped strongly the recovery of the vegetation cover within these areas.

The GV cover regeneration figures produced for each study area for the whole period considered show how the large majority of the surface affected by the fire events is recovering. However, some small areas show a vegetation decrease (blue areas in the figures). Looking at the f-NDVI fraction images of each study area, is clear that these areas of vegetation decrease correspond to the areas where certain amounts of vegetation have survived after the fire. This survived vegetation slowly disappears due to the long-term fire effects, compromising the regeneration of these small areas. However, another explanation exist for almost two of the study areas (Parra and Lythrodontas). In both study areas, extensive works of fire prevention structures have been carried out by the local administration. Big firebreaks have been implemented all around the study areas, and therefore, all vegetation present has been eliminated. This could be considered as an anthropic boundary effect and may explain the loose of vegetation cover in this particular areas.

7. CONCLUSIONS

The main conclusions of this thesis can be summarised in the following sentences:

- The f-NDVI methodology is the best performing vegetation cover extraction technique from remotely sensed data among the methodologies compared in this thesis for all study areas.
- Landsat and SPOT sensors performed well when sensing changes in vegetation regrowth after forest fires. Oppositely, results obtained from CHRIS-Proba data have a considerably high standard deviation due to sensor noise.
- The third year after the fire is the most important regarding the regeneration of GV cover. The first two years after the fire can represent a slight recovery or even a further decrease in vegetation.
- The recovery trend of GV cover following the third year after the fire adopts an asymptotic behaviour tending to an horizontal maximum which does not reach pre-fire GV cover conditions.
- Areas that survived the fire event seem to suffer long-time fire effects which cause a vegetation cover decrease in these areas.

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9. APPENDICES

Common landforms code (from Lutes, D. –FIREMON Lead-, 2004).

Common Landforms	
Code	Landform
GMF	Glaciated mountains-foothills
UMF	Unglaciated mountains-foothills
BRK	Breaklands-river breaks-badlands
PLA	Plains-rolling planes-plains w/breaks
VAL	Valleys-swales-draws
HIL	Hill-low ridges-benches
X	Did not assess

Erosion type types code (from Lutes, D. –FIREMON Lead-, 2004).

Erosion Type Types	
Code	Erosion type
S	Stable, no erosion evident
R	Water erosion, rill
H	Water erosion, sheet
G	Water erosion, gully
T	Water erosion, tunnel
W	Wind erosion
O	Other type of erosion
X	Did not assess

Erosion severity code (from Lutes, D. –FIREMON Lead-, 2004).

Erosion Severity Codes

Code	Erosion severity
0	Stable, no erosion is evident.
1	Low erosion severity; small amounts of material are lost from the plot. On average less than 25 percent of the upper 8 in. (20 cm) of soil surface have been lost across the macroplot. Throughout most of the area the thickness of the soil surface layer is within the normal range of variability of the uneroded soil.
2	Moderate erosion severity; moderate amounts of material are lost from the plot. On average between 25 and 75 percent of the upper 8 in. (20 cm) of soil surface have been lost across the macroplot. Erosion patterns may range from small, uneroded areas to small areas of severely eroded sites.
3	High erosion severity; Large amounts of material are lost from the plot. On average 75 percent or more of the upper 8 in. (20 cm) of soil surface have been lost across the macroplot. Material from deeper horizons in the soil profile is visible.
4	Very high erosion severity; Very large amounts of material are lost from the plot. All of the upper 8 in. (20 cm) of soil surface have been lost across the macroplot. Erosion has removed material from deeper horizons of the soil profile throughout most of the area.
-1	Unable to assess

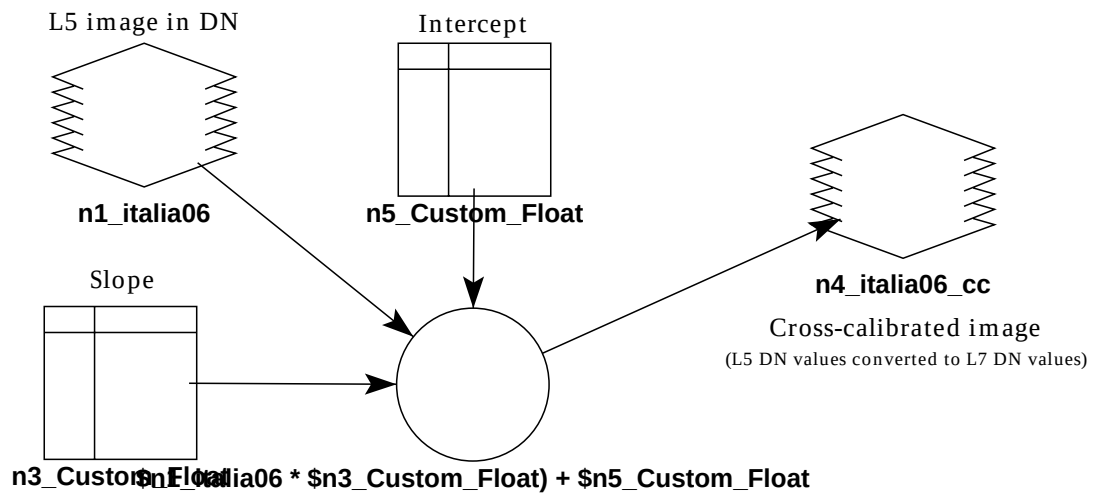
Fire severity code (from Lutes, D. –FIREMON Lead-, 2004).

Plot Level Fire Severity Codes

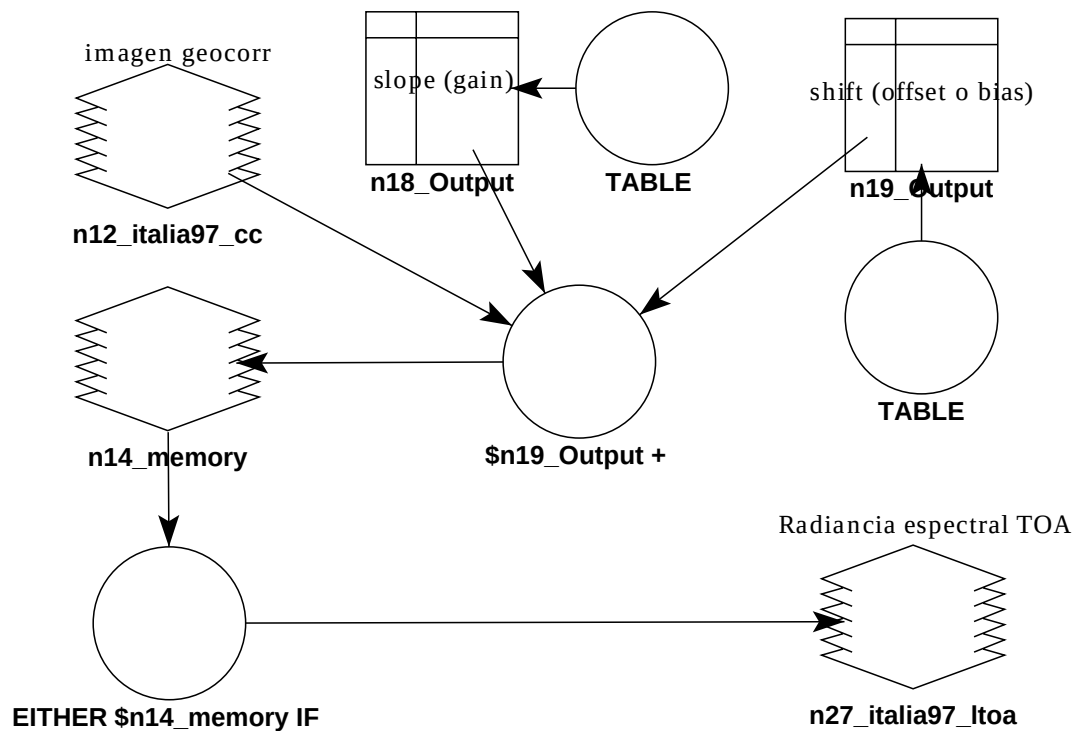
FIRE SEVERITY CODE	Substrate	Forest Vegetation	Shrubland Vegetation	Grassland Vegetation
Unburned (5)	Not burned	Not burned	Not burned	Not burned
Scorched (4)	Litter partially blackened; duff nearly unchanged; wood/leaf structures unchanged	Foliage scorched and attached to supporting twigs.	Foliage scorched and attached to supporting twigs.	Foliage scorched
Lightly Burned (3)	Litter charred to partially consumed; upper duff layer may be charred but the duff is not altered over the entire depth; surface appears black; where litter is sparse charring may extend slightly into soil surface but soil is not visibly altered; woody debris partially burned; logs are scorched or blackened but not charred; rotten wood is scorched to partially burned.	Foliage and smaller twigs partially to completely consumed; branched mostly intact.	Foliage and smaller twigs partially to completely consumed; branched mostly intact; typically, less than 60 percent of the shrub canopy is consumed.	Grasses with approximately two inches of stubble; foliage and smaller twigs of associated species partially to completely consumed; some plant parts may still be standing; bases of plants are not deeply burned and are still recognizable.
Moderately Burned (2)	Litter mostly to entirely consumed, leaving coarse, light colored ash (ash soon disappears, leaving mineral soil); duff deeply charred, but not visibly altered; woody debris is mostly consumed; logs are deeply charred, burned out stump holes are evident.	Foliage twigs and small stems consumed; some branches still present.	Foliage twigs and small stems consumed; some branches smaller branches (0.25-0.50 in.) still present; typically, 40 to 80 percent of the shrub canopy is consumed.	Unburned grass stubble usually less than two inches tall, and mostly confined to an outer ring; for other species, foliage completely consumed, plant bases are burned to ground level and obscured in ash immediately after burning.
Heavily burned (1)	Litter and duff completely consumed, leaving fine white ash (ash disappears leaving mineral soil); mineral soil charred and/or visibly altered, often reddish; sound logs are deeply charred, and rotten logs are completely consumed.	All plant part consumed, leaving some or no major stems or trunks; any left are deeply charred.	All plant parts consumed leaving only stubs greater than 0.5 in. in diameter.	No unburned grasses above the root crown; for other species, all plant parts consumed.
Not Applicable (0)	Only inorganic material on site before burn.	None present at time of burn.	None present at time of burn.	None present at time of burn

APPENDIX B: ERDAS MODELS

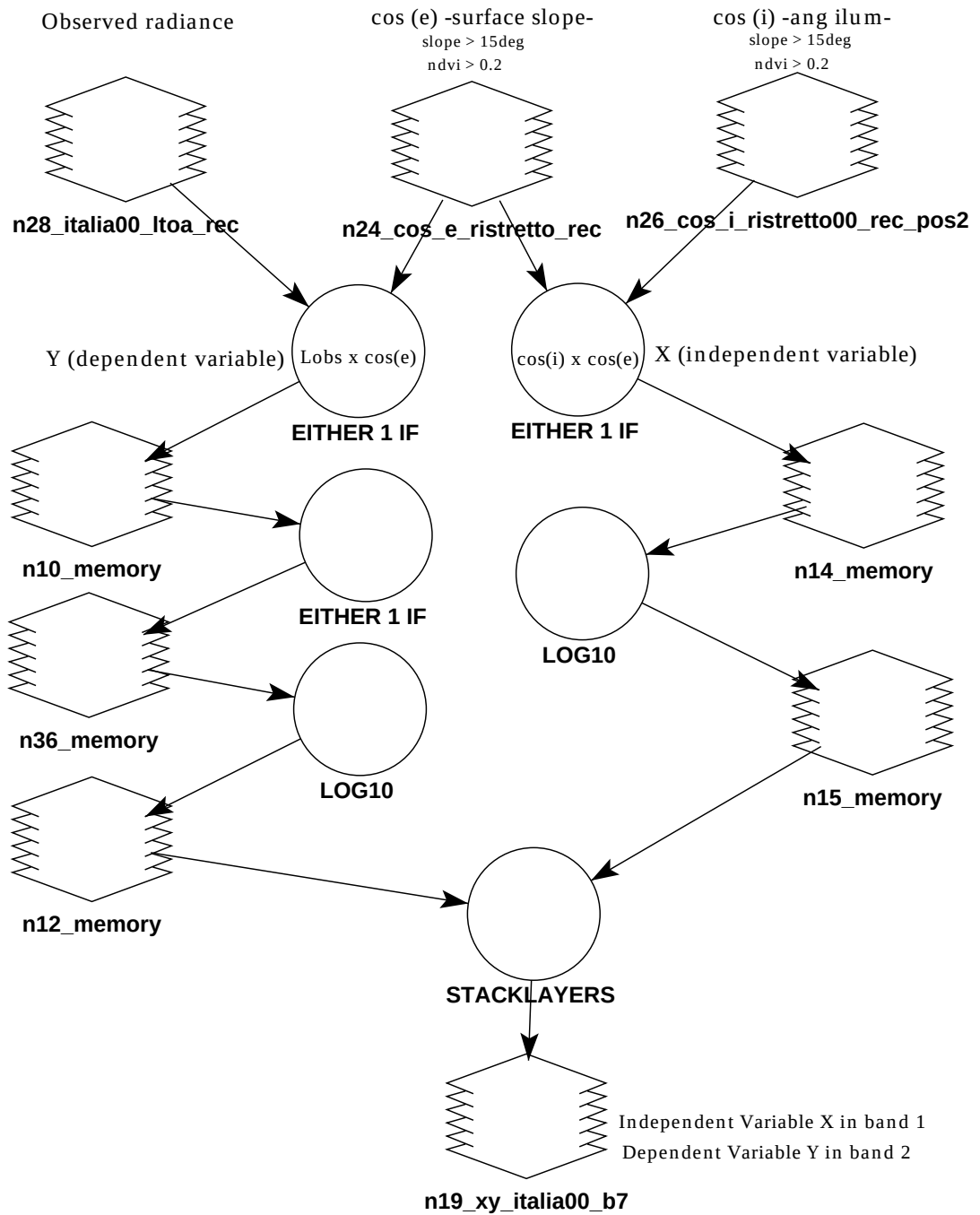
L5 - L7 CROSS-CALIBRATION



ND to TOA radiance values of Landsat ETM+



k Minnaert regression parameters definition



Minnaert k constant estimation by regression

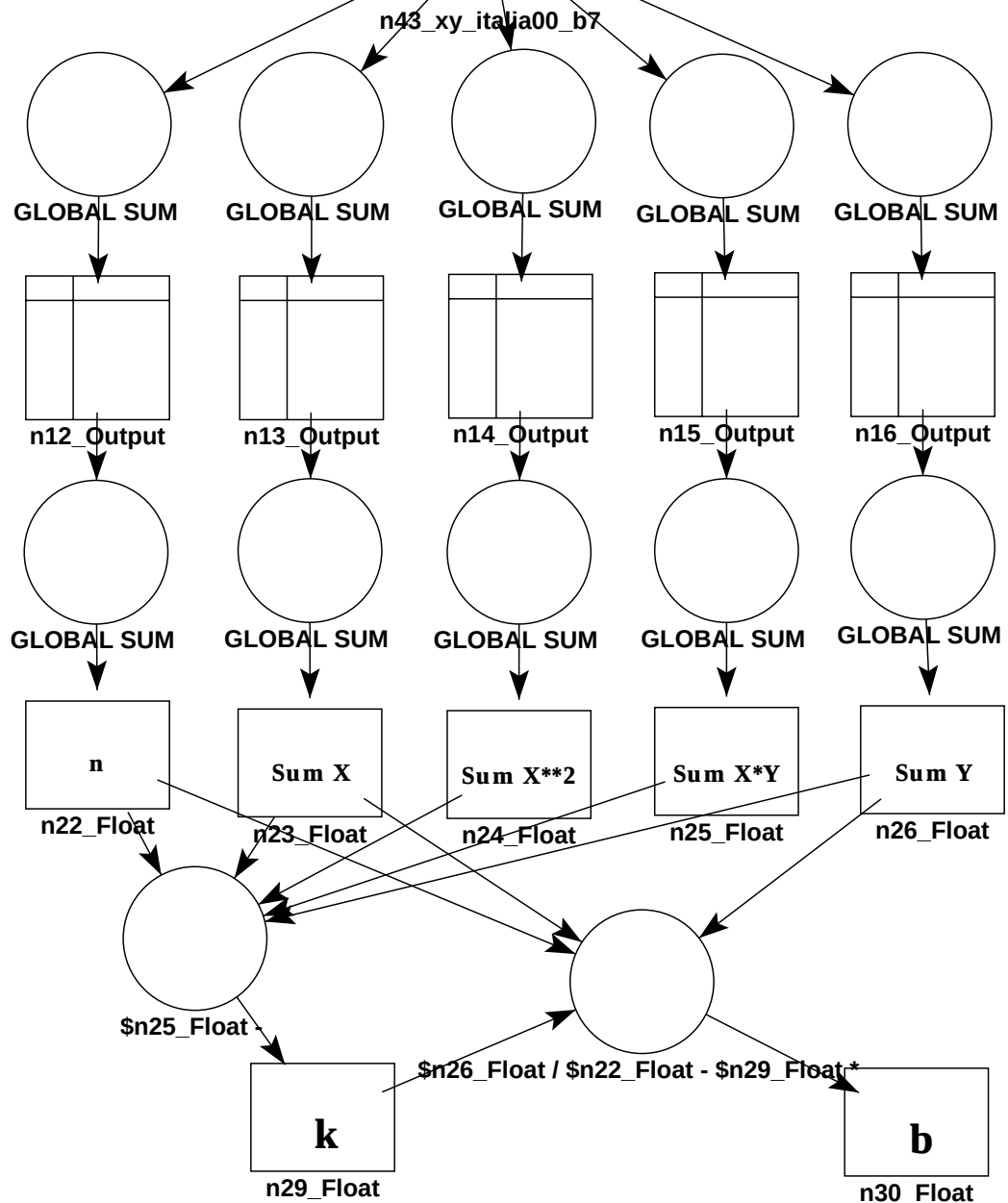
$$y = aX + b$$

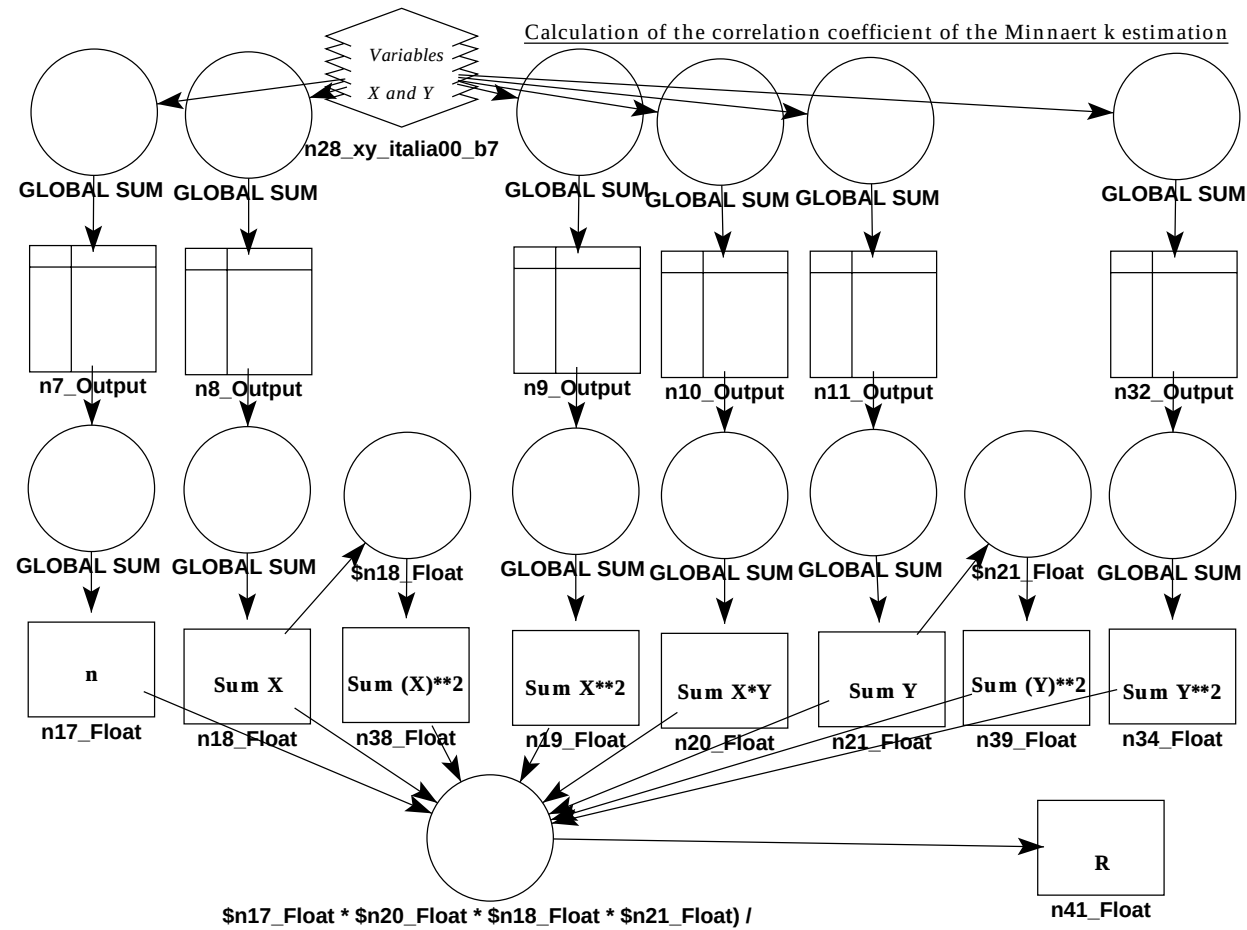
Variables
X and Y

X = band 1 = $\log_{10}(\cos i * \cos e)$

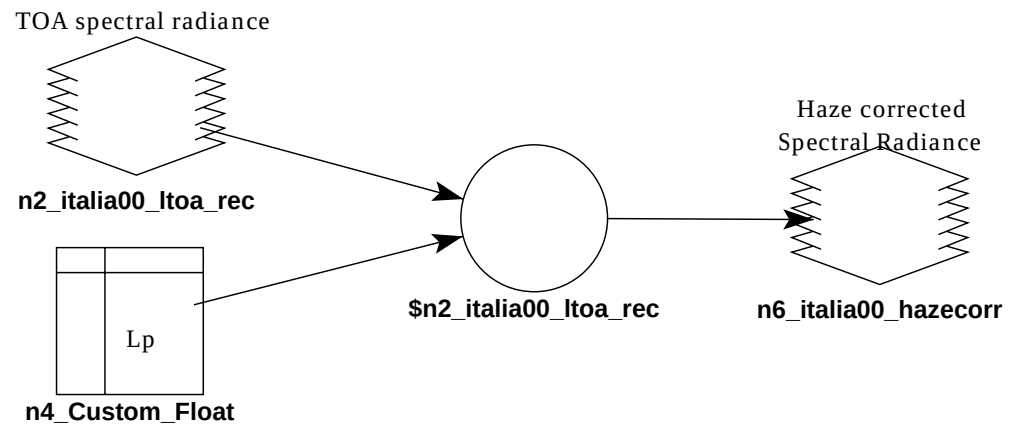
Y = band 2 = $\log_{10}(\text{Lobs} * \cos e)$

a = k ; b = $\log_{10} \text{Lnorm}$

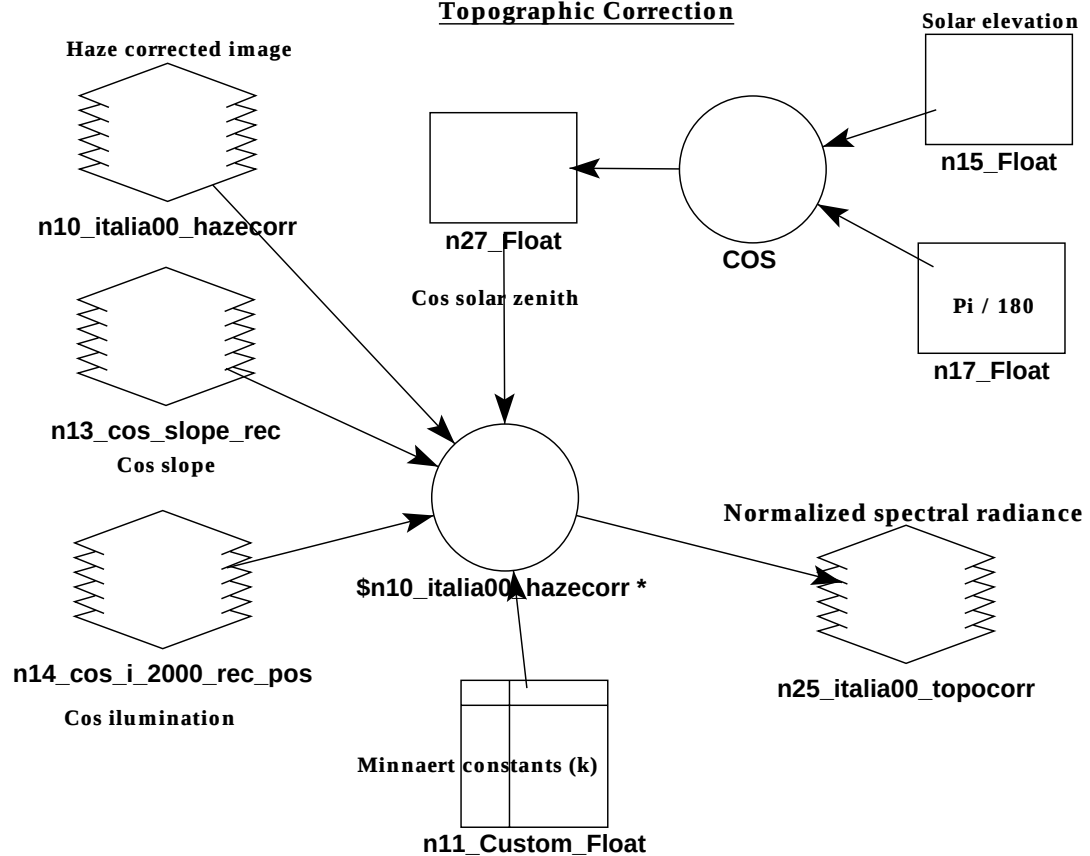




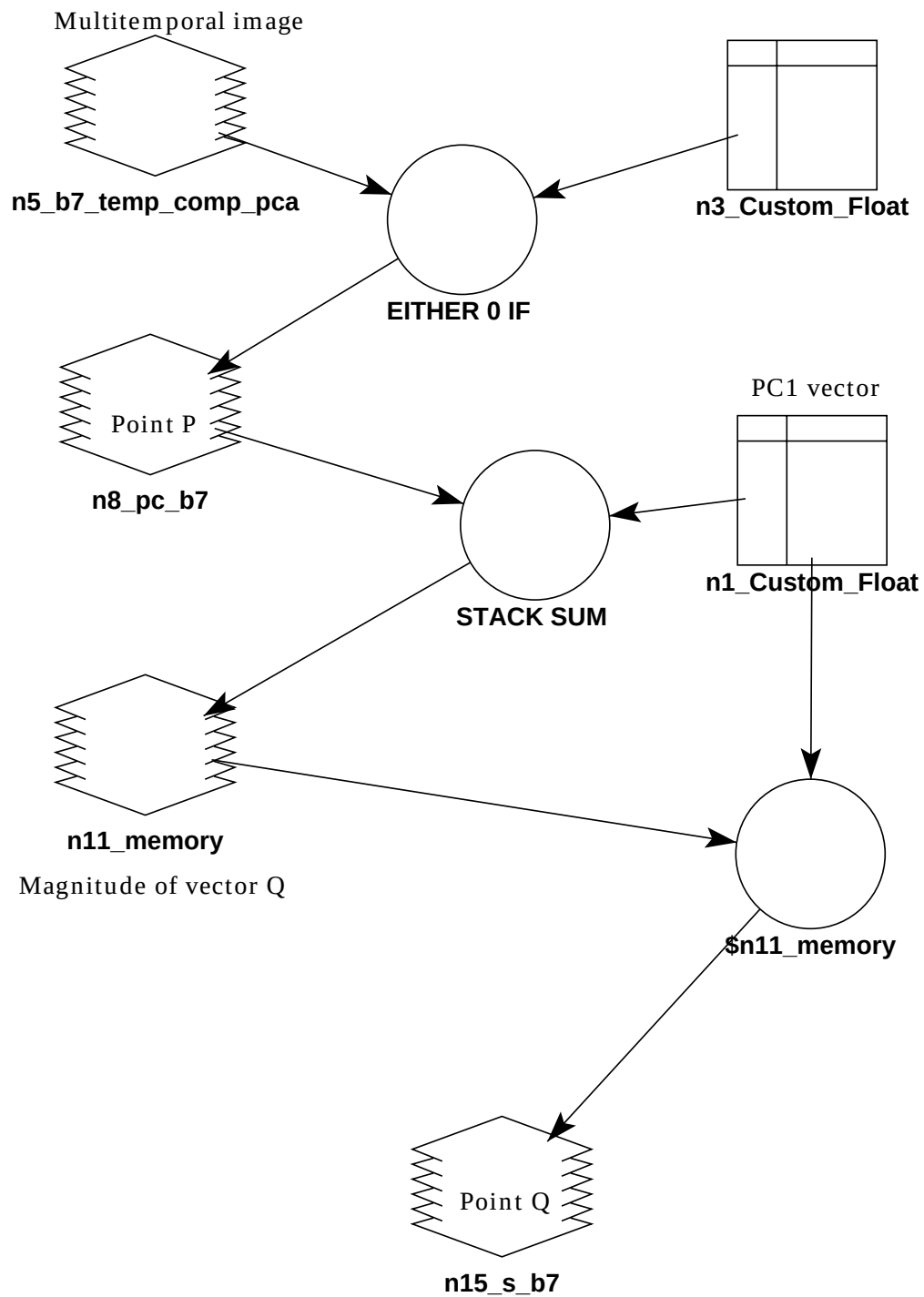
Haze Correction (DOS) Italia -Landsat-



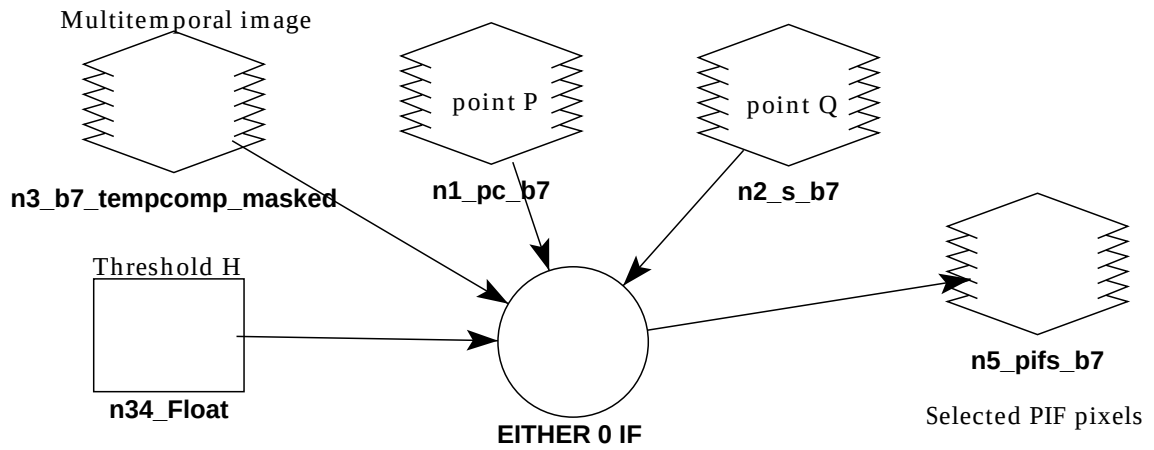
Topographic Correction



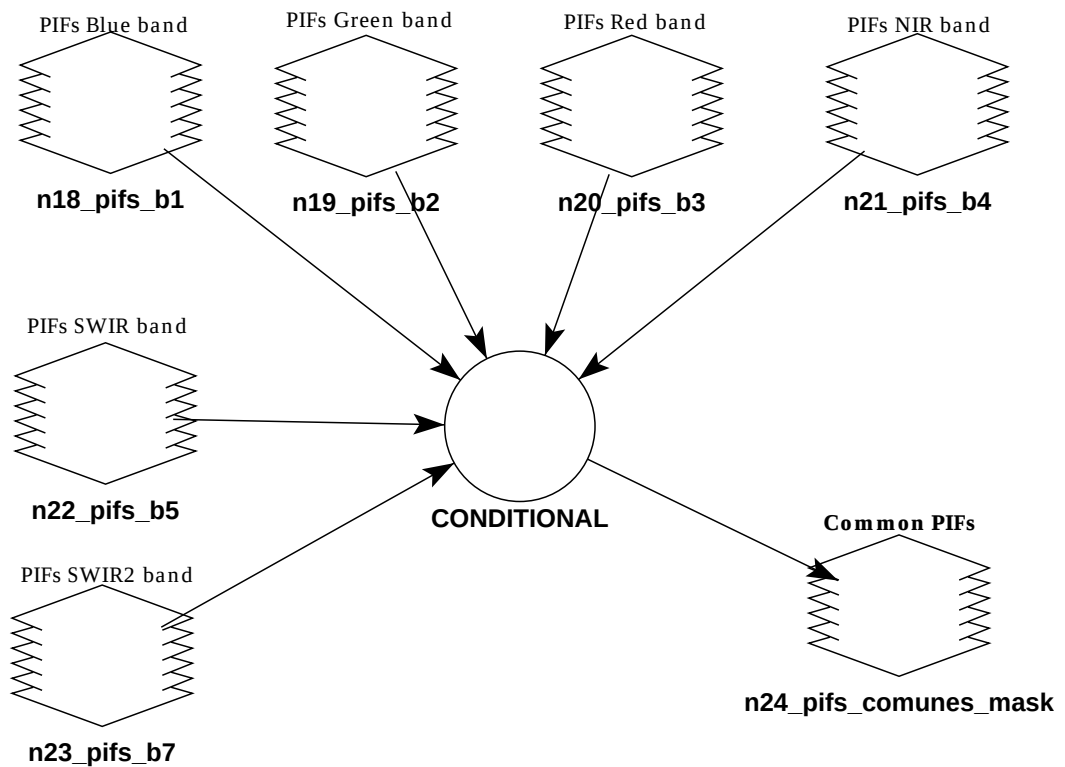
Computation of needed points for distance d computation



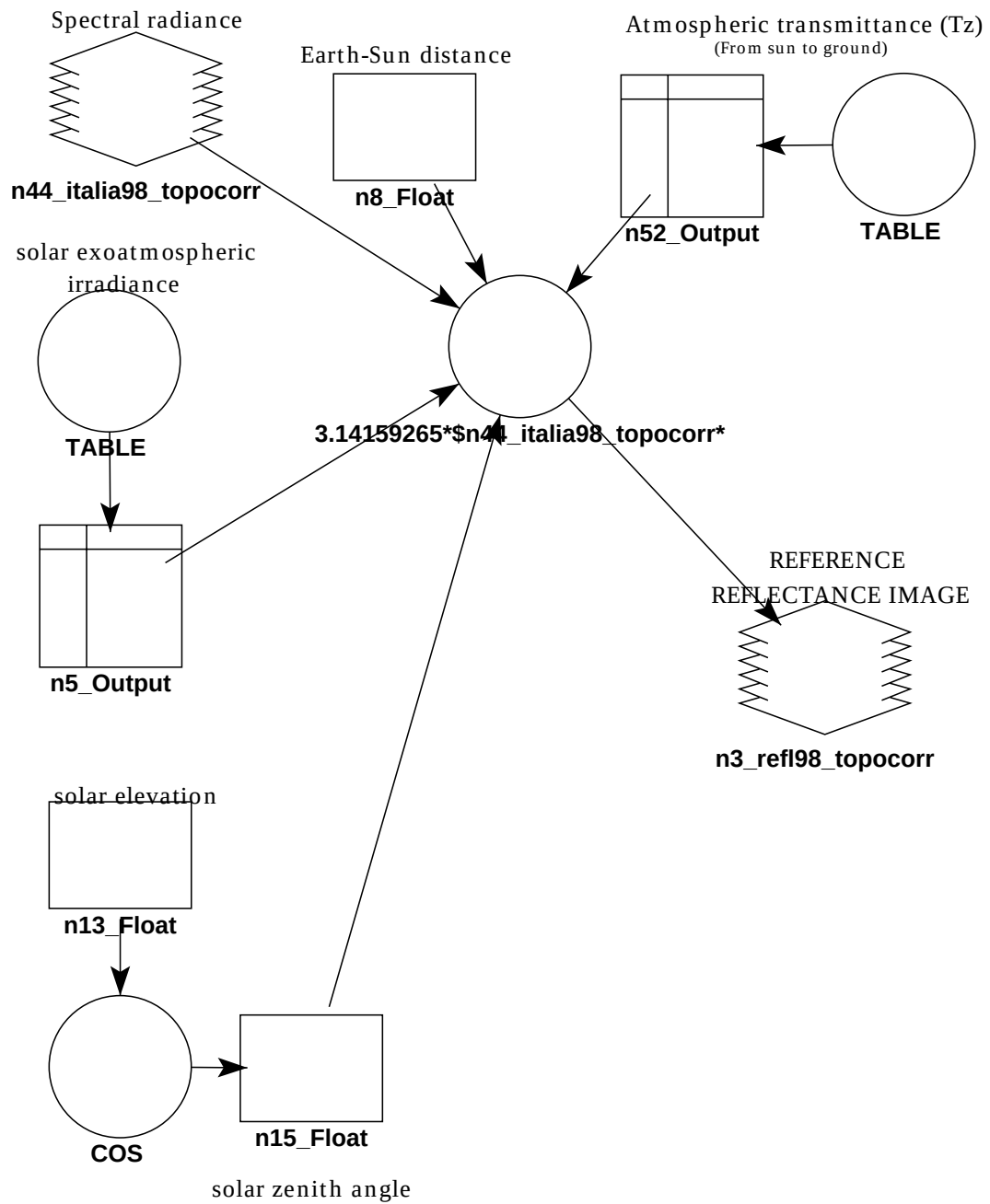
PIF selection by means of mT-nD-PCA



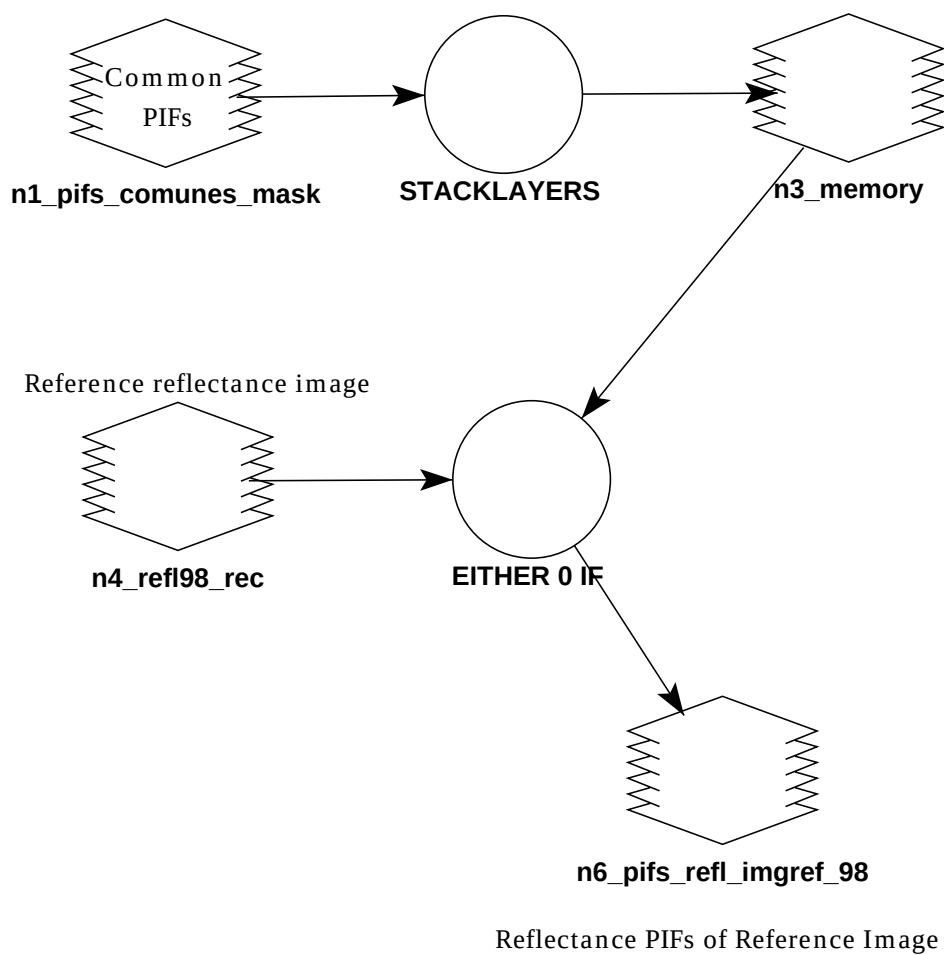
Selection of PIFs common to all images



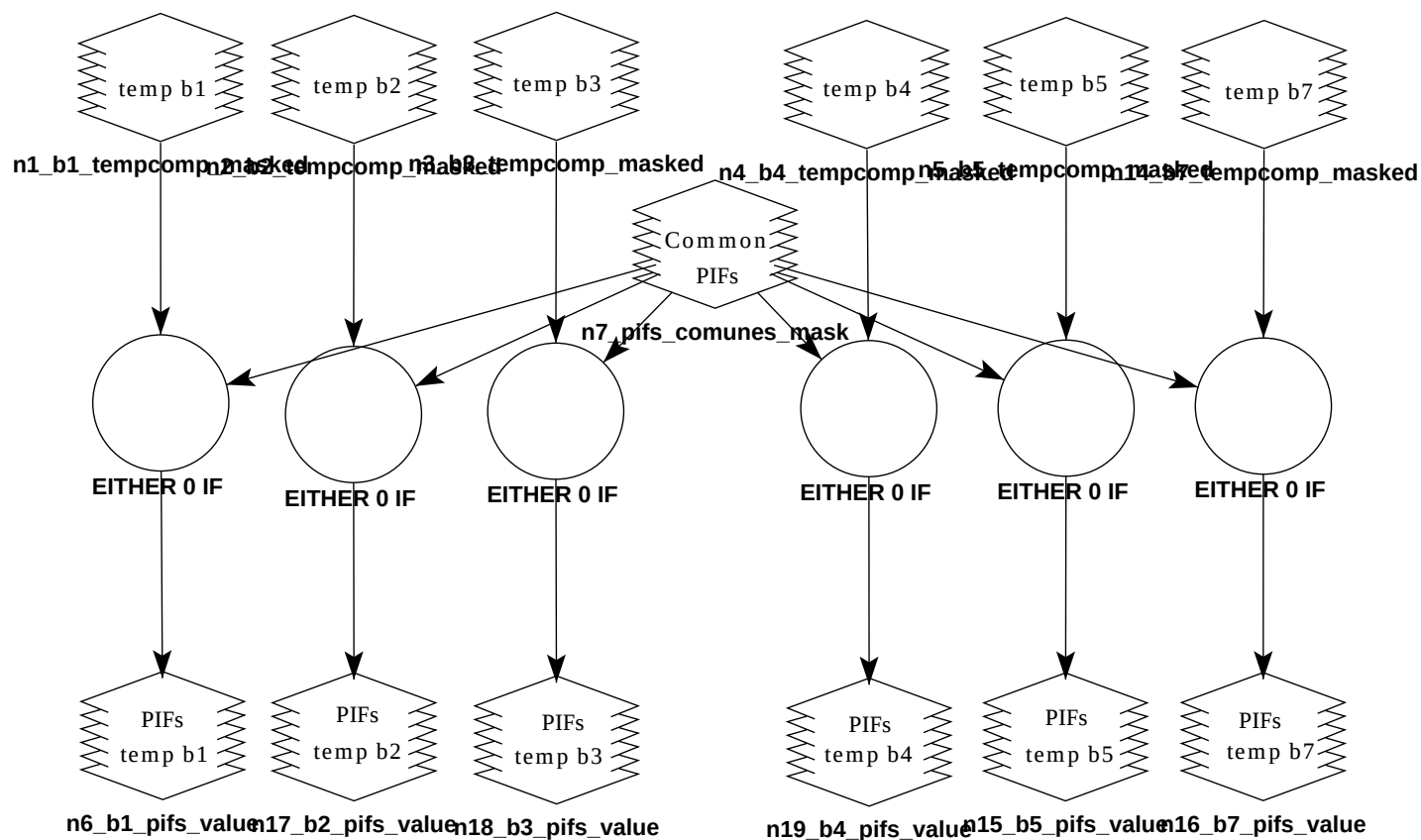
Reference Image COST correction

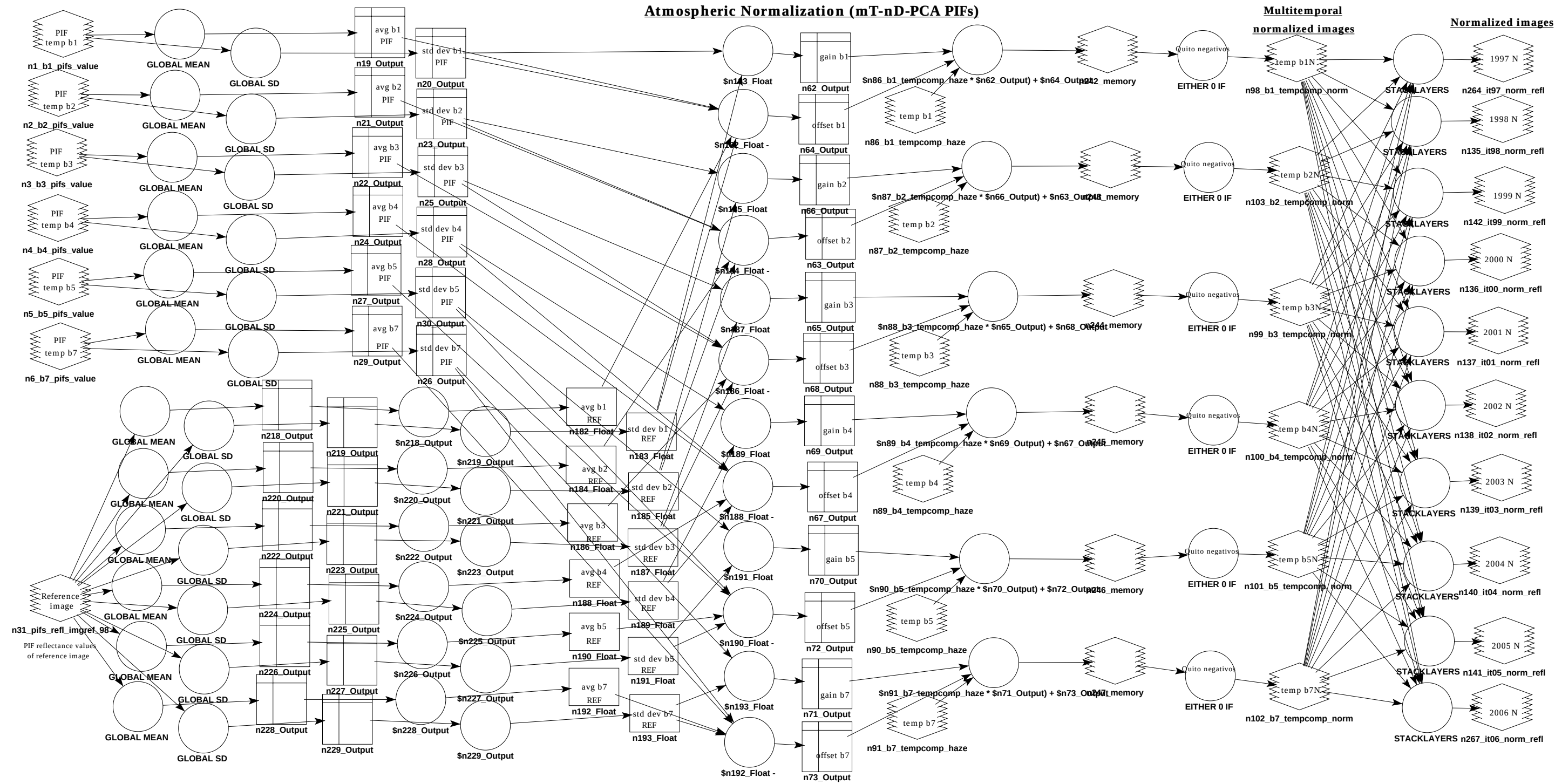


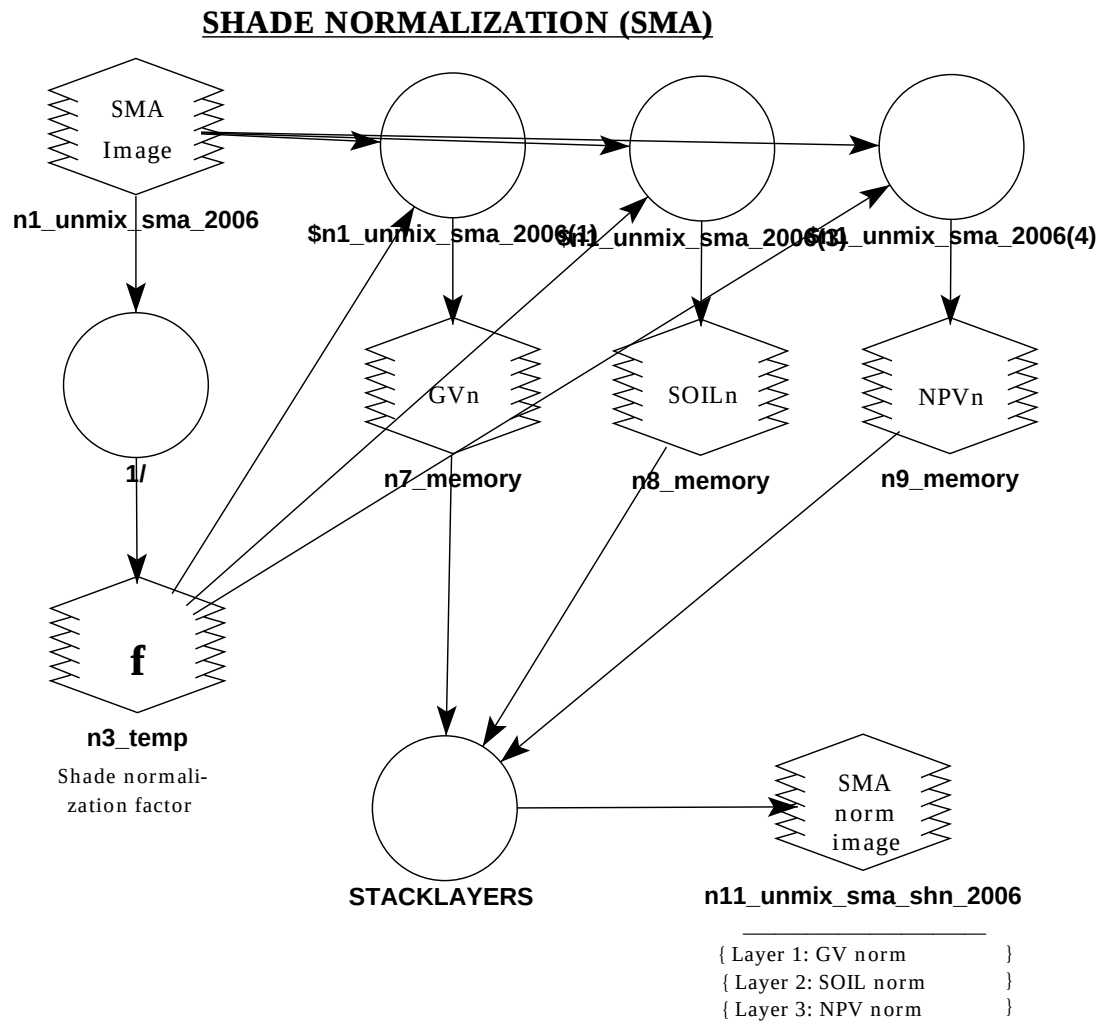
Extraction of reflectance values
for PIFs in reference image

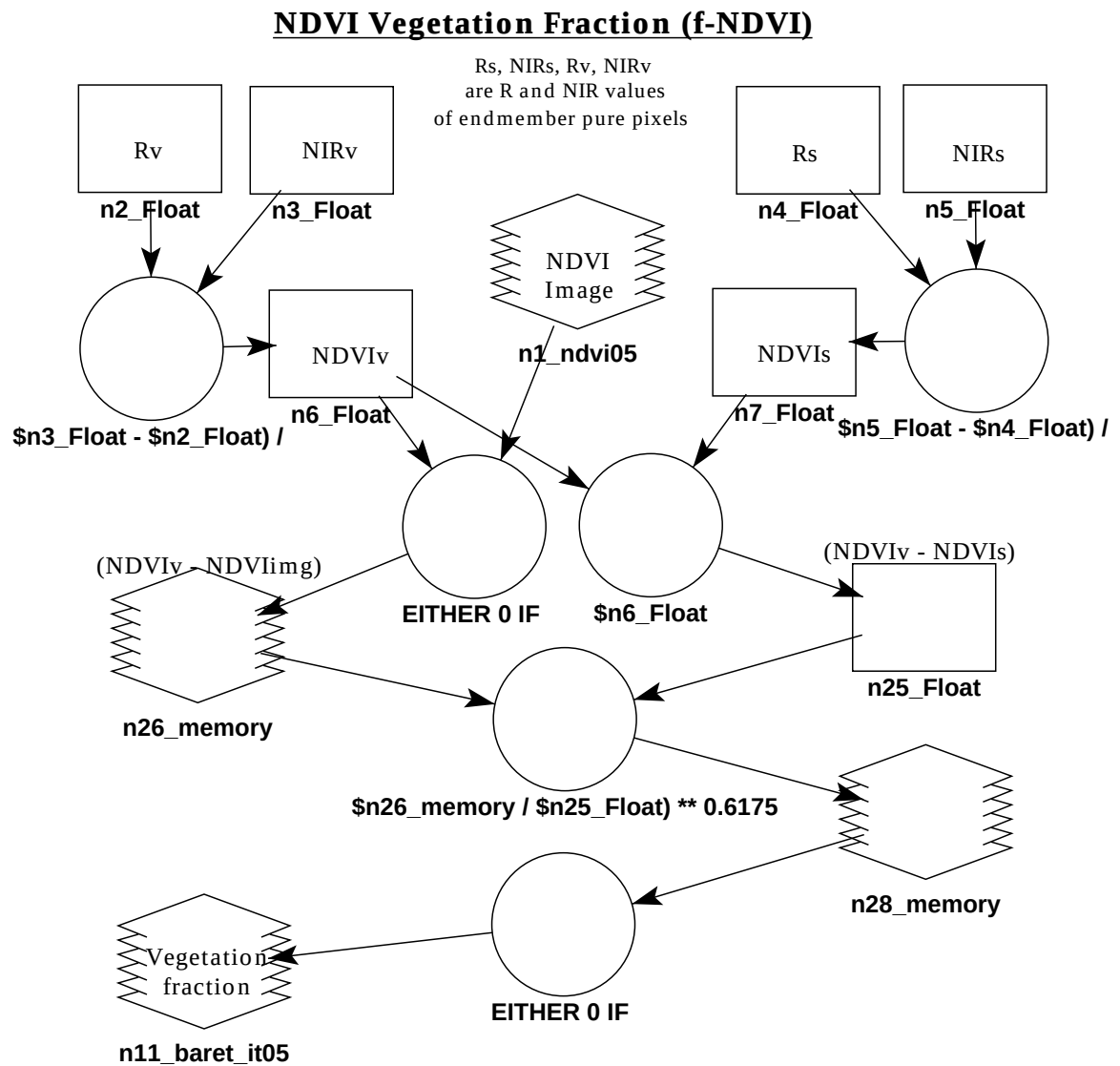


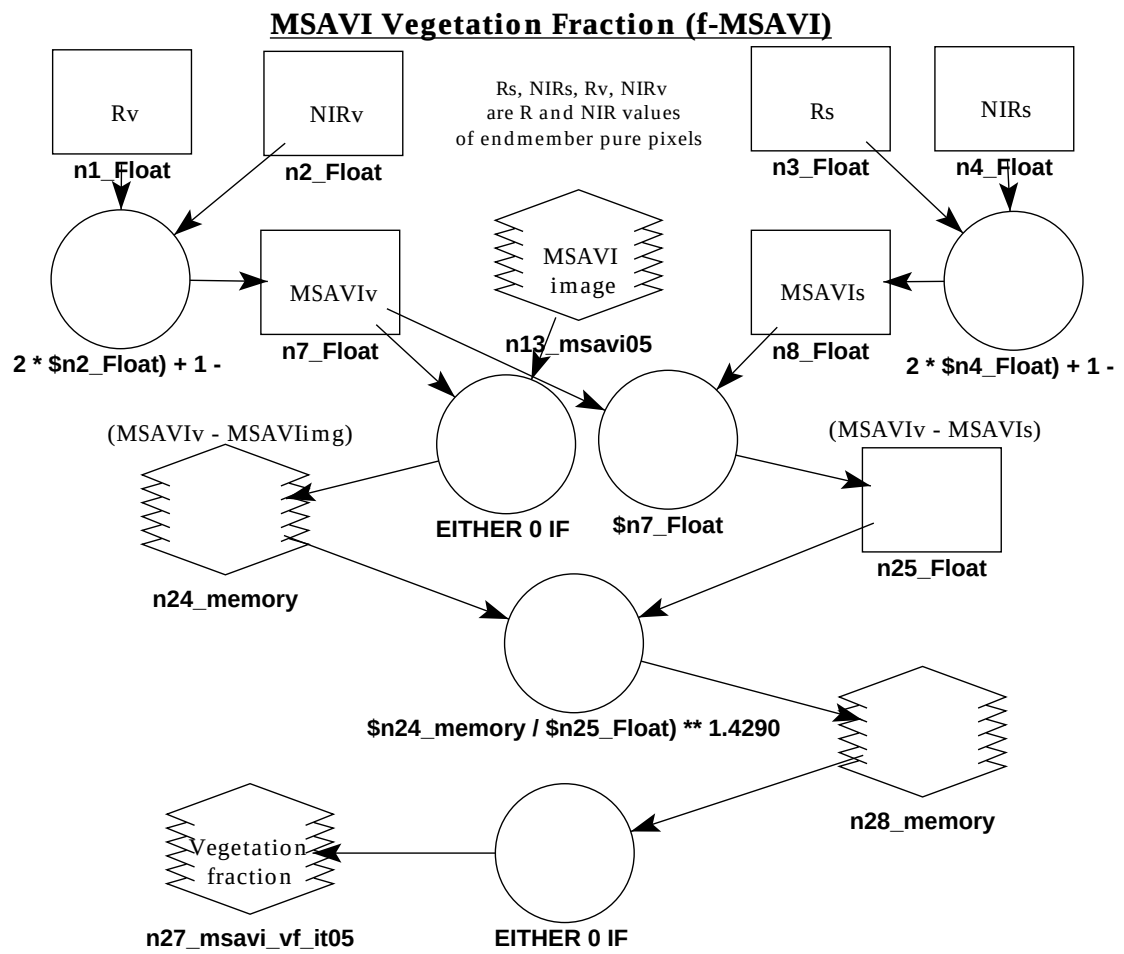
PIFs radiance value extraction from multitemporal images



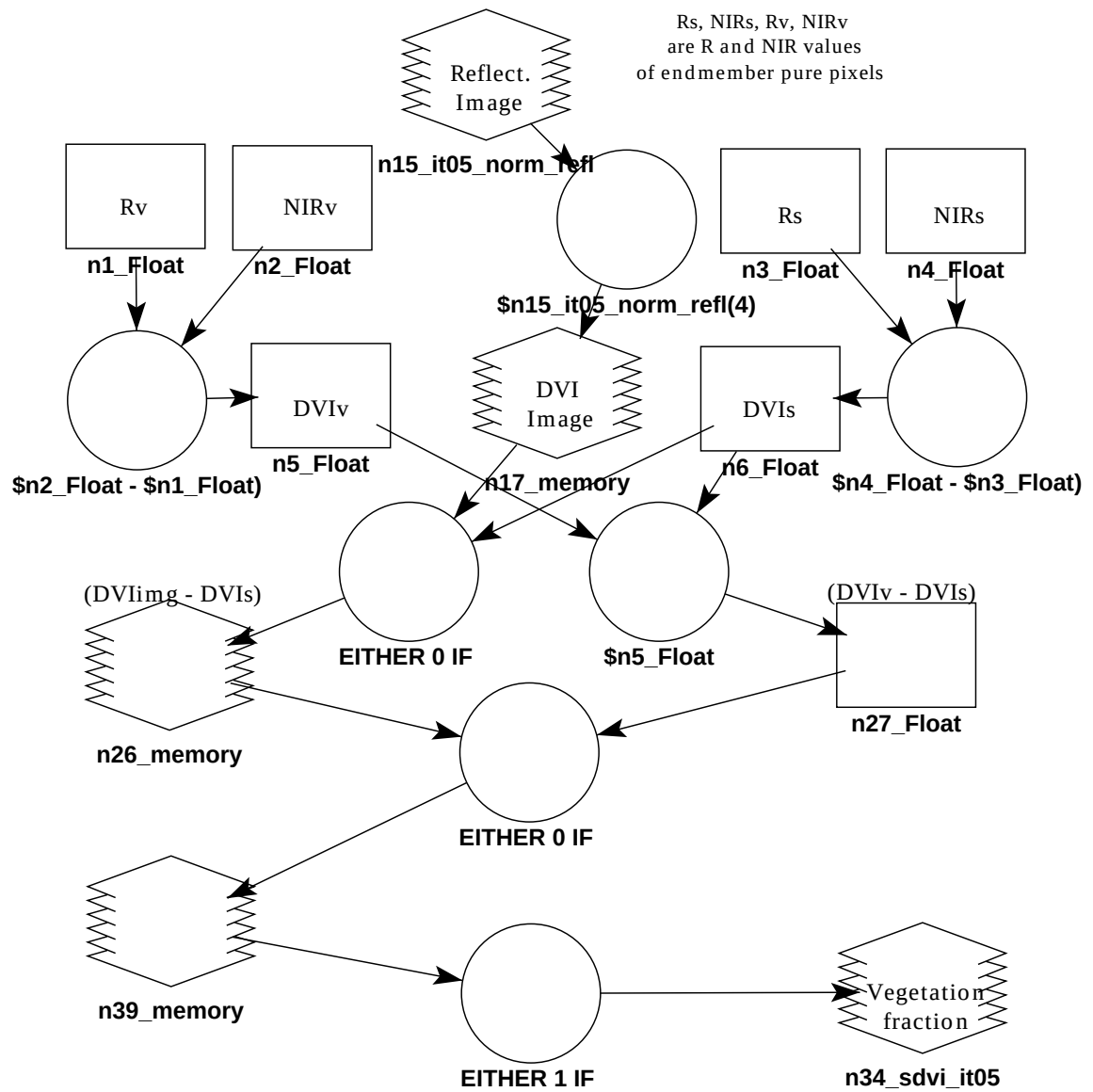








SDVI Vegetation Fraction (f-SDVI)



APPENDIX C: RESULTING FIELD DATA

Lythrodontas field data

Point	Coordinates (UTM36N)		Altitude (m asl)	Aspect (°)	Slope (%)	2005 veg cover (%)	2006 veg cover (%)
	N	E					
1	3866408	523651	588	SW225	37	23.41	39.41
2	3866473	523941	590	N350	50	39.16	44.05
3	3866560	522939	648	N10	58	35.46	38.14
4	3867023	523067	661	S185	31	33.45	34.77
5	3867157	523955	597	SE130	45	16.26	32.64
6	3866933	524160	521	SE130	25	27.60	50.94
7	3865057	523406	512	S160	42	39.33	50.11
8	3864518	523526	511	NE40	22	50.21	69.01
9	3864812	523068	543	N5	10	39.24	48.15
10	3865512	524378	656	E75	42	33.60	34.20
11	3865661	523450	638	SW220	46	22.21	28.66
12	3865751	523817	620	NW320	55	38.45	53.47
13	3865751	523117	613	E70	50	37.43	45.85
14	3865652	522700	650	N15	32	83.90	80.90
15	3865351	523259	603	E90-W245	38	24.18	42.54
16	3865356	522297	649	SE150	17	35.14	42.91
17	3864700	522288	642	N25	35	73.19	85.66
18	3865616	521894	779	SE155	39	38.33	49.03

Deiva Marina field data

Point	Coordinates (UTM32N)		Altitude (m asl)	Aspect (°)	Slope (%)	2006 veg cover (%)
	N	E				
1	4898113	546177	217	W270	25	57.39
2	4898738	546469	544	E90	5	56.78
3	4899304	546151	613	SW240	30	71.14
4	4900059	544911	608	N15	65	31.95
5	4900157	544307	611	S200	50	75.55
6	4899227	543826	422	SW220	40	80.25
7	4897891	544005	254	E115	50	70.74
8	4899038	545508	389	S165	20	67.88
9	4898903	545951	440	W280	40	56.43
10	4898466	545608	321	NW300	70	47.59
11	4898437	545045	223	S180	40	61.24
12	4898440	544981	200	NW300	45	50.25
13	4898348	544370	236	NW240	60	60.68
14	4897435	543525	112	S160	30	52.91
15	4898091	544235	194	SE140	40	85.67
16	4898365	543354	240	S200	25	62.58
17	4898280	543783	310	W255	25	65.92
18	4899260	544178	487	SW230	40	41.97
19	4899300	545175	558	NW310-E110	80	47.66

Parra field data

Point	Coordinates (UTM29N)		Altitude (m asl)	Aspect (°)	Slope (%)	2005 veg cover (%)	2006 veg cover (%)
	N	W					
1	4128122	550284	304	W305	30	35.97	58.77
2	4128146	550864	250	N35	45	24.98	49.47
3	4128391	550910	218	S210	45	23.76	35.83
4	4128893	550609	230	W280	40	46.51	51.47
5	4128873	550832	253	E55	35	18.50	32.33
6	4129082	549286	161	N35	40	32.95	46.06
7	4128782	551462	194	N355	50	28.18	51.88
8	4129105	551592	223	N350	40	38.10	53.03
9	4129434	552121	192	NW325	25	44.10	51.60
10	4128828	552699	233	N350	25	34.61	45.63
11	4128760	553137	243	W295	45	43.81	51.13
12	4129721	551417	166	S180	35	19.55	26.51
13	4130349	551126	168	W280	40	20.29	35.00
14	4130390	551466	157	W285	40	35.00	47.05
15	4130350	551747	120	N230	50	48.20	63.11
16	4130576	551000	156	E90	35	11.77	30.04
17	4130998	550785	182	S160	35	25.00	32.75
18	4129156	553292	221	S195	45	14.97	28.31
19	4129546	552953	181	W240	45	23.07	44.75
20	4130296	552742	246	NE55	45	36.76	37.30
21	4130449	552163	212	S170	40	11.62	34.73
22	4129838	550171	187	N25	20	15.50	30.91
23	4130017	550190	200	NE55	40	20.31	36.57

Mação field data

Point	Coordinates (UTM29N)		Altitude (m asl)	Aspect (°)	Slope (%)	2005 veg cover (%)	2006 veg cover (%)
	N	W					
1	4381837	597613	313	SW220	20	39.40	58.92
2	4381388	598227	290	NE30	28	31.05	43.78
3	4381331	600646	250	S160	50	82.41	80.74
4	4380909	600369	258	NW315	25	50.47	46.26
5	4380890	599734	270	NE30	45	49.86	44.56
6	4382612	588616	224	SW240	40	29.53	32.66
7	4382394	600599	215	N0	35	53.40	64.87
8	4382078	601112	148	NE50	75	39.41	57.85
9	4381993	599274	325	N17	35	59.65	71.23
10	4381435	599278	266	S185	55	16.55	31.62
11	4380276	599436	256	SW245	25	16.29	29.01
12	4380348	599806	329	SW217	40	22.38	35.15
13	4380600	599629	358	W255	52	59.42	65.65
14	4380761	599300	320	SE164	42	41.37	52.24
15	4380799	598670	335	S200	45	15.01	25.44
16	4379928	599973	206	SW202	30	17.06	26.52
17	4379961	600381	210	S170	35	20.98	43.81
18	4380606	601453	218	NW344	40	11.58	32.35
19	4380304	600869	293	E98	53	50.21	48.78
20	4380453	600610	338	NW310	30	66.82	62.55
21	4381616	598923	265	W255	80	62.78	65.82
22	4382605	598027	334	SW230	30	56.32	67.64