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CHARACTERIZATION OF ECOSYSTEM FUNCTIONING IN ALMERIA PROVINCE, SPAIN

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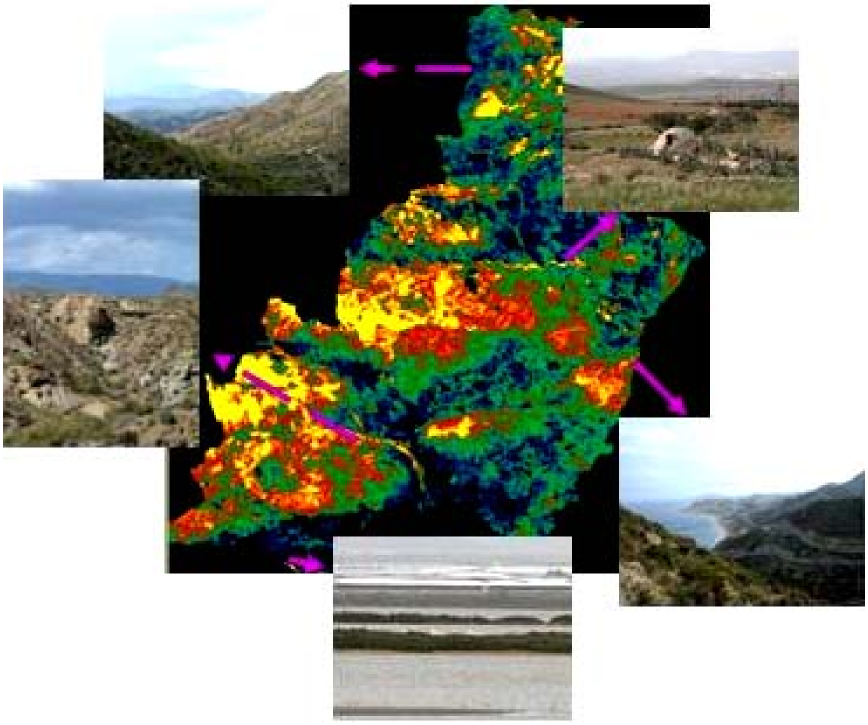

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CHARACTERIZATION OF ECOSYSTEM FUNCTIONING IN ALMERIA PROVINCE, SPAIN

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The way that bring us to search for freedom
Drive us to the knowledge
And the experience that provide us the way
Is revert in wisdom

To those who show me the way

El camino que nos lleva en busca de la libertad
Nos conduce al conocimiento
Y la experiencia que nos otorga el camino
Se convierte en sabiduría

A todos aquellos que me enseñan el camino

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ABSTRACT

Almeria province is a heterogeneous area with high biodiversity and nature value that is under severe human pressure. Land use change constitutes one of the main drivers in the dynamic economy present. The intensification of agricultural areas (intensive crops and greenhouses) together with urban development because of increase of tourism close to the coastland are the principal impacts on ecosystems.

To study the state of ecosystem functioning of the province, the spatial pattern of the fraction of Absorbed of Photosynthetically Active Radiation (fAPAR) by vegetation based on the annual dynamic of the Normalized Difference Vegetation Index (NDVI) and its derivative attributes was examined. NDVI is a spectral index related to primary productivity, as an integrative indicator of ecosystem functioning. The annual integral NDVI (NDVI-I), and the Relative Range (RREL) are indicators of seasonability of the vegetation. Maximum and Minimum NDVI (MMAX and MMIN) provide additional descriptions of vegetation phenology, indicating the intra-annual distribution of the period with maximum and minimum photosynthetic activity.

To assess the impact of land use change on the ecosystem functioning, Regression Tree analysis was applied to predict the potential NDVI (P-NDVI) and then to examine the patterns of deviation of actual NDVI (A-NDVI) in terms of land uses. It came up that urban areas, not-irrigated and mixed land uses have lower A-NDVI than P-NDVI during the time series considerate; irrigated land uses have a greater A-NDVI than P-NDVI and natural vegetation cover present slight higher value of A-NDVI than P-NDVI.

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1 INTRODUCTION

1.1 BACKGROUND

Changes in land-use have been revealed as one of the main drivers of global change. According to Sala *et al* (2000), these land use changes have and will have a major impact in the Mediterranean region. The South-Eastern part of Spain is an appropriate site to assess these impacts. Besides, this region has a dynamic economy based on the overexploitation of natural resources through intensive agriculture such as greenhouses and tourism. Both represent the main source of impact on the natural ecosystem. Besides this, ecosystems in south-eastern Spain are continuously under a critical situation of water stress, which hampers their recovery after anthropic disturbances (Latorre *et al.* 2001). The study area is located in Almeria; it is an entire Administrative entity on it-self. It is a region with high variability of environmental conditions and it bears ecosystems with high biodiversity richness and priority habitats (Cabello 2002) constituting a suitable area to carry out this study.

This thesis is based on the study of ecosystem functioning, define as: 'the interchange of material and energy between the biota and the environmental' (Nemani and Running 1996). For ecosystem characterization, remote sensing tools are used widely and they have shown their availability to carry out studies at large scale (Guerschman and Paruelo 2005). At regional scale (Pettorelli *et al.* 2005) the ecosystem functioning can be characterized by a difference state of the vegetation structure. For example, Guerschman *et al.* (2003) use the Normalized Difference Vegetation Index (NDVI), derived from remote sensing, to provide information about the spatial-temporal patterns of carbon gains by vegetation. In the Iberian Península, this index has been used use to identify ecosystem functional types (Alcaraz *et al.* 2006), and to characterize ecosystem functioning of main biomes and national parks (Alcaraz 2005). In the SE Spain, has been proposed as monitoring tool in protected areas (Paruelo *et al.* 2005).

Vegetation indices are mainly derived from reflectance data in the red and near-infrared part of the spectrum. They operate by contrasting intense chlorophyll pigment absorption in the red against the high reflectance of plant materials in the NIR (Townshend *et al.* 1991; Maselli *et al.* 1998).

Therefore, the vegetation activity can be studied in a limited range of the electro magnetic spectrum. Such is the case for the NDVI, which is derived from the ratio of the red and near infrared spectral band as follows (Rouse *et al.* 1974):

$$\text{NDVI} = \frac{Nir - Rd}{Nir + Rd}$$

Where *Nir* is Near Infrared spectral band and *Rd* is Red spectral band.

Different studies have demonstrated that the NDVI index is a linear estimator of the fraction of Photosynthetic Active Radiation (fAPAR) that is absorbed by vegetation (Sellers 1987; Fischer 1994; Paruelo *et al.* 1997; Paruelo *et al.* 2005). Hence, it is a surrogate of primary productivity, as an integrative indicator of ecosystem functioning (Myneni and Williams 1994). Pertinent measures for ecology studies can be derived from NDVI time series such as: Integral-NDVI, Annual maximum NDVI, and Relative annual Range of NDVI, dates of the beginning or end of the growing season, length of the “green” season and timing of the annual maximum NDVI (Reed *et al.* 1994; Lüdeke *et al.* 1996).

Besides, remote sensing may provide additional variables in relation to the exchange of matter and energy between the atmosphere and the land surface. The data used in the present case-study come from the MOderate Resolution imaging Spectroradiometer (MODIS) onboard the National Aeronautics and Space Administration (NASA) Earth Observing System (EOS). It is a key instrument on the Terra (EOS AM) and Aqua (EOS PM) satellites.

The MODIS sensor has a number of advantages in comparison with other satellite systems such as LANDSAT, NOAA, SPOT and so on. MODIS acquires daily images at spatial resolutions from 250m to 1 Km, offering the possibility of frequent temporal coverage at moderate resolution (Justice *et al.* 2002; Wessels *et al.* 2004).

1.2 PROBLEM DEFINITION

The Mediterranean border in general and specially our study area, is an example of the tension between economical development and environmental conservation. The singular and rich biodiversity of this region is endangered by the chaotic occupation that is taking place on the territory by sectors of big economical influence. The expansion of the greenhouse agriculture results into the conversion of large areas of natural vegetation into intensive agricultural use (Mota *et al.* 1996). The urban development close to the coast is affecting to the coastal landscape transformation which main attractiveness is its high grade of nature.

The land use change in the Almeria province is a fact. During the last thirty years, there has been a drastic change in the economy that has affected the ecosystem of the province. It is leading to agricultural intensification and increase of greenhouses, irrigation and fertilization of the land and abandonment of traditional agriculture.

Another important impact is the intensification of tourism, which has led to an increase of immigration to urban and coastland areas. The increasing tourism activity has involved the construction of more facilities like road, golf fields, and summerhouses on coastland resulting into significant landscape degradation.

Multi-temporal high to medium resolution, Remote Sensing (RS) data and Geo-Information Systems (GIS) can be used to produce ecological inventories and to monitor land use and land cover changes at local, regional and global scales (Berberoglu *et al.* 2003; Alphan and Yilmaz 2005). These geo-information tools can also be useful for the study of the relation between the land use change and the ecological influence that the ecosystem functioning has on the region (Prasad and Badarinth 2004). There is a large documentation related to the transformation of natural habitats by human activities such a logging, crop cultivation and urban expansion, posing the most important threat to biodiversity (Soule 1991; Green *et al.* 1994; Leach and Givnish 1996; Defries and Belward 2000; Sala et al. 2000).

Other studies have been done relating the land use and land cover changes to the increase of the natural vegetation fragmentation. The fragmentation is produced by the use of land for human activities that build a barrier between ecosystems. These barriers disturb the genetic flow between different communities in the area producing isolation and affecting species distribution. As a consequence, the carbon storage and biomass production are also affected (Cochrane 2001; Laurance 2004).

1. Introduction

Stohlgren *et al.* (1998) have proven that land use patterns have a critical influence on mesoscale atmospheric processes and, hence, on local climate. Land use and land cover as one of the main driving forces of global environmental changes, is a key item in the sustainable development debate. land use and land cover changes have impacts on a wide range of environmental and landscape attributes including the quality of water, land and air, ecosystem processes and functions (Alphan and Yilmaz 2005).

Therefore, quantification and identification of land use and land cover change and preserving and mitigating measures are urgently needed before irreversible losses occur. Furthermore, these data are useful for the decision maker in relation with the land use manager.

As a conclusion, the main problem is that the agriculture, tourism and infrastructures areas have developed fast without taking into account the effects on the ecosystems in the study area. So, the purpose of the thesis is to analyze how the change in land use has repercussions on the ecosystems functioning, by studying the deviation from the potential NDVI value for the natural areas. The study will focus on finding a suitable remote sensing-based tool for this application.

1.3 OBJECTIVES

The following objectives will be studied:

1. Test how can Remote sensing help to quantify the impact of land use change on ecosystem functioning.

2. Provide basal knowledge of ecosystem functioning in South-eastern Spain based on remote sensing attributes such as NDVI.

3. To assess the impact of land-use change on the ecosystem functioning, by the modelling the deviation between potential and current patterns of the NDVI values.

1.4 RESARCH QUESTIONS:

In accordance with the presented context, the main questions of this research are:

- How can we estimate ecosystem functioning by using remote sensing techniques?

- How are changes of land use affecting the ecosystem functioning?

- How are changes in the current value of NDVI being modified by land use dynamics?

- What is the response of NDVI attributes to these changes?

1.5 STRUCTURE OF THE REPORT

The first introductory chapter (1. Introduction) of this report explains the background of the case study, problem definition and objectives. In the second chapter (2. Literature review) the main concepts the thesis deals with, are defined in the scope of the research. The third chapter (3: Materials and methods) consists of the description of the study area, data collection and availability and procedures applied in the research. The fourth chapter (4: Results) gives an overview of the findings results and analysis, and in the fifth chapter (5. Discussion), the results are explain and discusser. Last but not least, the sixth chapter (6. Conclusions and recommendations) explains the final conclusions and some recommendations for future research in this field.

2 LITERATURE REVIEW

2.1 LAND USE CHANGE

Changes in landscape use and land cover take place over long periods of time as a result of changes in population distribution and economic activities (Turner Ii *et al.* 1993). Traditional land use activities such as farming has modeled the Mediterranean landscape for centuries (Alados *et al.* 2004) These include farming intensification, irrigation, pesticides, fertilizers, and so on (Mota *et al*. 1996). Others studies have been done to measure the land transformation effect on the fragmentation, habitat and biodiversity loss due to land cover change in different parts of the earth (Wilsey and Potvin 2000; Guerschman et al. 2003).

Land use is an important component of global change (Vitousek *et al.* 1997). Urbanization, desertification, and agriculture are three examples of human-driven land use change that have altered the surface of the earth. These changes affect many processes, including mesoscale atmospheric circulation, soil properties, erosion and carbon dynamics (Baron *et al.* 1998).

The land use changes have influence on the energy flows (Prasad and Badarinth 2004) because they influence the albedo and temperature surface . It causes changes in the climatic cycle at global and regional scale (Stohlgren et al. 1998; Lambin *et al.* 2000). Another trend in the studies of land use change is the effect on to water recourses (Baron *et al.* 2002; Beguería *et al.* 2003). As a conclusion, Remote Sensing and GIS provide a great source of information to develop methodologies that measure and monitoring the effects of land use change (Rogan *et al.* 2003).

2.2 ECOSYSTEM FUNCTIONING DEFINITION

The ecosystem functioning reflects the collective life activities of plants, animals, microbes and the effects these activities (such as feeding, growing, moving, excreting waste and so on) have on the physical and chemical condition of their environments. The ecology definition of ecosystem functioning is “the interchange of matter and energy between the biota and environmental” (Myneni *et al.* 1997). A functioning ecosystem is one that exhibits biological and chemical activities characteristic for its type (Ghilarov 2000). A functioning forest ecosystem, for example, exhibits a rate of plant production, carbon storage, and nutrient cycling that are characteristic of most forests. If the forest is converted to an agrosystem, its functioning changes.

The functioning of the ecosystem highly depends on the biodiversity of that ecosystem. The more biodiversity it has, the healthier, more stable and more productive the ecosystem is. Traditionally, the characterization of ecosystem states and trend are based on structural features (Milchunas and Lauenroth 1995). However, new approaches based on functional features have been done. The concept of plant functional type proposes that species can be grouped according to common responses to the environment and/or common effects on ecosystem processes. Following the rationale of this concept, several classifications of ecosystem functional types have been proposed (Paruelo *et al.* 2001; Alcaraz et al. 2006; Baeza *et al.* 2006).

2.3 DERIVATE ATTRIBUTES FROM NDVI

To quantify the impact of land use change on the ecosystem functioning, remote sensing is a tested method that can be used to describe the spatial heterogeneity of ecosystem functioning at regional and global scales. The knowledge of the temporal and spatial patterns of ecosystem functioning at the regional scale provides a proper background to assess the effects of environmental changes (Noble and Gitay 1996). Between the different possibilities that remote sensing provide, a so called 'green index' describes the patterns of the interception of radiation by vegetation. Subsequently, the NDVI-based indicators could be combined with environmental indicators for estimating ecosystem functioning by using a decision tree approach (Stoms and Hargrove 2000). For example, Lloyd (1990) proposed the use of phenology, derived from the seasonal curve of NDVI to describe ecosystem functioning, which involved a supervised binary decision tree classification. The interpretation of the various classes is limited considerably by the quality of global vegetation index imagery; the data show clearly the marked temporal asymmetry of terrestrial photosynthetic activity. On the other hand, Huete *et al.* (1999) considered the NDVI a successful index as vegetation measure in the sense that it is sufficiently stable to permit meaningful comparisons of seasonal and inter-annual changes in vegetation growth and activity.

The following variables have been derived from the seasonal NDVI curve of a year: annual integral (NDVI-I); annual relative range (RREL) (difference between maximum and minimum NDVI divided by the annual integral); month of the absolute maximum and minimum of NDVI (MMAX and MMIN). These four variables describe in a conceivable way the height and shape of the annual NDVI curve, and have biological significance (Paruelo et al. 2005). NDVI-I can be a linear estimator of fAPAR (Sellers *et al.* 1996) and thus of NPP (Tucker *et al.*, 1985; Prince, 1991; Sellers *et al.*, 1992; Paruelo *et al.*, 1997). From a functional point of view, phenology and seasonality have been reported to be of great importance to determine the strategies of carbon gains in Mediterranean environments (Floret *et al.* 1987). RREL provides a description of the intra-annual variation of photosynthetic activity, what has been used as an indicator of the seasonality of carbon fluxes (Paruelo et al. 1997). MMAX and MMIN NDVI provide an additional description of vegetation phenology, indicating the intra-annual distribution of the period with maximum and minimum photosynthetic activity (Lloyd 1990, Hoare, 2004 #22; Hoare and Frost 2004). They are summarize in the Table 1.

Paruelo *et a(2001)* did a empirical study on the impact of land use change ecosystem functioning in Eastern of Colardo. They considered three types of land use with one natural grass land. The studied concluded that the seasonal dynamics of NDVI, a surrogate for the fraction of PAR intercepted by the canopy, was significantly altered by agricultural practices. Paruelo *et al.* (2005) studied the effect of the land use change on ecosystem functioning for agriculture land use in temperate areas of North and South America based on attributes of NDVI. The NDVI has been employed from cool, moist temperate rainforests to Mediterranean forests and scrublands, and even in hot deserts (Lloyd 1990; Ricotta *et al.* 1999; Stoms and Hargrove 2000; Hoare and Frost 2004). In general, the NDVI can give us information about radiometric measures of the amount, structure and condition of vegetation (Pettorelli et al. 2005).

Table 1: Description of NDVI attributes, (Pettorelli et al. 2005)

Index	Type of measure	Definition	Biological meaning	Comments
NDVI	measures of the amount, structure and condition of vegetation	Ratio between Red- Infrared spectral bands	a linear estimator of the fraction of PAR intercepted	Index most used in ecology characterizations.
INDVI	Overall productivity and biomass (fAPAR)	Sum of positive NDVI values over a given period	Annual production of vegetation	Not relevant when resource quality is at least as important as quantity
Annual Maximum NDVI	Overall productivity and biomass	Maximum value of the NDVI over a year	Annual production of vegetation	Sensitive to false highs and noise correction
Relative annual range of the NDVI	Inter-annual variability in productivity	(Maximum NDVI-Minimum value)/NDVI	Enables inter-annual comparisons of vegetation biomass	Sensitivity of the range definition to outliers in both directions

2.4 DECISION TREE

The decision tree methodology is based on a series of binary decisions. It is a type of multistage classifier (Loh 2002) that can be applied to a stack of images. They are used to determine the potential classification of a dataset, for example land cover classification (Borak and Strahler 1999; Zhan *et al.* 2000; Sluiter 2005) or for prediction of a dependent values of one variable (Louis and Prasad 1998; Young and Morton 2003; Chen *et al.* 2004; Muñoz and Felicisimo 2004).

The decisions can be based on any available characteristic of the data set. Moreover, this methodology has been used in various studies from classifying land units into land suitability groups (Bojórquez-Tapia *et al.* 2001) until NDVI prediction (Stoms and Hargrove 2000).

There are different statistical methodologies that have included the decision tree algorithm. Classification and Regression Tree Analysis (CART) was used by Dobberting and Bibing (1998) to predict forest tree mortality, by Vayssieres *et al.* (2000), for predicting oak cover in California, Stoms and Hargrove (2000) to monitor land use stress the difference between potential and actual NDVI. They used precipitation, temperature and available soil water capacity data which capture most of the variation in NDVI in undisturbed areas by generations. Rogan *et al.* (2003) used regression tree for measure map the land use change, it were generated for three hierarchical levels of change classification with increasing detail.

Numerous studies exist comparing the advantages and disadvantages of each algorithm. For example Muñoz and Felicísimo (2004) compare the Multivariate Adaptative Regression Spliness (MARS) with CART and other statistical methods. He concluded that validation by independent data sets is needed and MARS and Regression Tree Analysis achieved the best prediction success, although the CART model was difficult to use for cartographic purposes due to the high model complexity. Loh (2005) described the advantage of GUIDE compared to CART and M5. The advantages are fast computation speed, extension to data sets with categorical variables, and direct detection of local two-variable interactions. Previous algorithms are not unbiased and are insensitive to local interactions during the split selection. Other authors compare the advantages and disadvantages with respect to other traditional statistical methods such as simple regression or Maximum likelihood (Growe 1999; Prasad *et al.* 2006). Franklin(2003) used for modelling fire disturbance, cluster and regression tree analysis. The variables used were climate, terrain variables, geology and NDVI. The regression tree method showed resulted classes that explained more variance in NDVI than classes resulting from unsupervised clustering.

The regression tree algorithms could be complementary or represent an alternative to many traditional statistical techniques, including multiple regression, analysis of variance, logistic regression, log-linear model, linear discriminate analysis and survival models. The regression tree should be simple to understand and give easily interpretable results. More generally, classification and regression tree analysis is a useful technique for identifying and estimating complex hierarchical relationships in multivariate data sets between predictors and response (Breiman and Hall. 1984; Michaelsen *et al.* 1994).

3 MATERIALS AND METHODS

3.1 INTRODUCTION

The general procedure for this study can be divided into two main parts. The first one characterizes the ecosystem functioning of the vegetation cover based on NDVI and its attributes. The second part involves the implementation of a model based on the ratio of NDVI between the current situation and the “potential” situation under natural conditions.

The first approach uses MODIS images as basis for the calculation of different attributes of NDVI. They show us the phenology, seasonality, and productivity of the vegetation during the time series.

The second approach is based on a regression tree analysis to predict values of NDVI under natural conditions. The main variables used for this analysis are the land use and the potential natural vegetation map. They describe the structural characteristic of the study area. Furthermore, other physical-climatic variables are used such as precipitation, temperature, potential solar irradiation, lithology and elevation. They were added to the analysis due to the important role that they play in the distribution of the vegetation.

This work consists therefore the following pieces:

1. Estimation of different NDVI attributes obtained from remote sensing (MODIS) in the time-series.

2. Estimation of annual integral of NDVI (NDVI-I) for the considered period of the study area that represents the actual NDVI.

3. Estimation of potential NDVI by means of a decision tree model which is built with different biophysical variables.

4. Study of the weight of the different variables in the decision tree.

5. Estimation of the current state of the ecosystems relative to the potential or ideal situation in which they could be.

3.2 STUDY AREA

The study area is located in Almeria; it is an entire administrative entity on itself inside the Andalusia region. Almeria is situated in the South-Eastern of Spain (3º9'W, 37º55'N) with an extension of 8.774 km2 (Figure 1). It is a region with high variability of environmental conditions and biodiversity richness in ecosystems (Mota et al. 1996), with priority habitats {Cabello, 2002 #139}. Inside the study region there are three Natural Parks. The Cabo de Gata-Nijar Natural Park has ecological importance due to its volcanic origin, semi-arid climate and marine-terrestrial character (Chabrillat *et al.* 2004). It was designated as Biosphere Reserve of the MAB program in 1997 by the UNESCO. The Sierra Maria-los Vélez is located in the North of the province. It is one of the few forestry areas in Almeria. The predominant vegetation cover consists of Oak trees, Conifers tree and evergreen shrubs. Finally, the Sierra Nevada Natural Park located at the mountains of west part of Almería, constitutes the buffer area of the Sierra Nevada National Park, one the main biodiversity important areas of Spain. Other locations are under different level of protection that are defined in the law of Natural protect spaces 11/94 by Junta de Andalusia.

Almeria has peculiar environmental characteristic for Mediterranean climate. It has absence of precipitation for a long summer period and a high temperature. It produces a quite high water deficit that made the region the driest area in Europe.

Figure 1: Location of the study area, in the South-Eastern Spain (Almeria).

3.3 DATASETS

The study was carried out mainly with two types of dataset: satellite images from the MOderate Resolution Imaging Spectroradiometer (MODIS) onboard the National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) and thematic maps from two sources, Junta de Andalusia and University of Almeria.

3.3.1 THEMATIC DATA

The use of thematic data is fundamental to study the natural conditions at the surface of the land. The biophysical variables have a strong influence on the distribution of the vegetation as well as on the potential locations of both agriculture and urban area. The biophysical variables used were: climatology data such as precipitation, temperature and solar radiation, and physical descriptors: Digital Elevation Model (DEM), lithology map and land use.

- Precipitation and temperature maps

The precipitation and temperature maps were obtained from the Cartography Services of the Andalusia government. The maps were built as extrapolation data on base of the data collection from the different climatic stations, which were well distributed over the whole province. There were a total of 75 stations. The temporal series used for the analysis cover from 1995 to 2005 year. The methodology followed for the data extrapolation was an Inverse distance Weighted method (IDW).

- Potential solar irradiance:

Potential solar irradiance is defined as the maximum irradiance at a location taking into account the topography and the season. It has no correction for cloudy days. The radiation in measured in Rad_unit: 10KJ/m2*day*micrometer. The potential solar radiation map has been extracted from the Digital Atlas of the Iberian Peninsula. This was done by the Barcelona University (Spain). The maps cover a period of 30 years, from 1961 to 1990 with a spatial resolution of 200 meters.

The model used considers the sun path through the day, the Sun-Earth distance, the atmospheric attenuation, the incident angles on each point and the shadow effects on each point. The model uses as a base the DEM for derivation of the main topography characteristics.

- Digital Elevation Model

DEM are digital files consisting of points of elevations, sampled systematically at equally spaced intervals. It is an important variable to incorporate the terrain attributes into the statistical decision rule to classify ecological units using remote sensing data (Moore et al. 1991). The topography influences the vegetation distribution due to slopes, shadows, moisture of the soil and hillside erosion. Moreover, the elevation may cause the development of local microclimates. The DEM used for the study was 20 meter of spatial resolution. It was derived from the digitalization of the National topographic Map with a 1:50,000 scale.

- Natural Vegetation and land use map

The Environmental minister of Junta Andalusia has been developing a project since 1987 in which the main goal is to make cartographic and statistic monitoring of the typology changes of the territory occupation. This project is based on a European Union program, CORINE-Land cover that began in 1987. Its objective is to build a dataset about the land cover. At European level the scale is 1:100,000. The map has been made from satellite image photo-interpretation. This program is actualized every four years. At this moment the new version from 2003 has not been published yet. We have this version available but we don’t know which Landsat image has been used to build up the map, but the methodology is exactly the same as the one for the 1999 map. The vegetation cover and land use map are an adaptation from CORINE methodology. The main characteristics of these maps are:

The photo interpretation elaboration has been done by combining data from Landsat-TM (30 meters of spatial resolution and 7 spectral bands) and IRS-Pan (5 meters of spatial resolution and one spectral band).

The land use legend and vegetation covers are based on CORINE with four levels of information; they are from 44 to 166 classes. With the goal to make the map interpretation easy, it has a simple legend with semi-detailed scale (1:50,000)

- Climatic vegetation cover

The climatic vegetation cover is defined as: *the vegetation structure that would become established if all the natural sequences were completed without interference by man under the present climatic and edaphic conditions* (Rivas-Martínez 1987). The climatic vegetation implies several stages; the last one is called climax. The map has been made by Rivas-Matinez for Spain at 1:400.000.

- Lithology maps

The map was created by the department of Edaphology and Agriculture Chemistry of the Granada University in 2004. The soil type map was based on the chemistry of the materials. The map has a scale of 1:100000.

Lithology of Almeria province is formed mainly for schist and quartz. There is also calcium and sandstone present. At the surface we can see crystal gypsum with Karsts formations. It has a tourists and speleological interest. It is also the main mine resource with a big influence on the regional economy that is based on marble and its different derivates. The legend was adapted to the word soil map from FAO (1997 and 1998).

3.3.2 SATELLITE DATA

The Moderate Resolution Imaging Spectrometer (MODIS) sensor on the Terra Satellite mission delivers medium resolution data. It was launched on December 1999. The products to use here are validated and data from version 4 are available and ready for scientific work. All images have been processed by the MODIS Science Team, meaning geometrically and atmospherically corrected (King 2000). MODIS has 36 bands at different spatial resolutions: bands 1-2 at 250 m, bands 3-7 at 500 m. and 8-36 at 1 km as show the Table 2. The data was obtained through the EOS Data gateway, which gives access to all satellite data from the NASA

The 250m bands were only available after release of version 3 in February 2000 in which our NDVI time-series data start. In the derivation of vegetation indices from surface reflectance, uncertainty appears at several steps (Huete *et al.* 1999): in the geo-location of the images, in the reflectance estimation at nadir influencing factors such as view solar geometry and residual/partial cloud cover or the angular effects. The MODIS validation program addresses these factors by the comparison with outputs from canopy radiative transfer models, by field-based correlative measurements, and with data from experimental aircraft and existing satellite datasets. The projection of all the MODIS images is Integrated Sinusoidal Projection, so it has to be re-projected to the same projection as our thematic maps.

The temporal profiles were built up from MODIS Vegetation Indices. In brief, a vegetation index is a mathematical function of reflection values in different spectral bands, used to estimate vegetation characteristics (RS Glossary©, Wageningen UR, 1999). They enhance the vegetation signal by combining two or more spectral bands, often at red and NIR wavelengths, and then provide robust and empirical measures for easy detection of variations in vegetation distribution and condition (phenological and biophysical interpretations). The main advantage of using these indices with respect to the use of raw reflectance data is that they minimize variations associated with external influences (atmosphere, view angles) as well as inherent influences (canopy background).

Some vegetation index images can be downloaded directly (product labeled as MODIS 13), so that the algorithms are already applied. MODIS sensor data provide three different vegetation indices, Leaf Area Index (LAI), Enhanced Vegetation Index (EVI) and NDVI at several temporal and spatial resolutions.

The images are available at several temporal and spatial resolutions. The pixel size chosen is 250 m, the finest resolution offered, and the maximum possible using the first two bands of the sensor. It has to be pointed out that nominal 250 m resolution (always varying depending on a number of factors such as latitude, position of the satellite, etc) present a spatial pixel error about 150 meters.

Table 2: MODIS band composition (MODIS gateway),

BAND	Bandwidth (µm)	Pixel size (m)	Key use
1	0.620-0.670	250	Absolute Land Cover changes, Vegetation Chlorophyll
2	0.841-0.876	250	Cloud Amount, Vegetation Land Cover Transformation
3	0.459-0.479	500	Soil/Vegetation Differences
4	0.545-0.565	500	Green Vegetation
5	0.123-0.125	500	Leaf/Canopy Differences
6	0.162-0.165	500	Snow/Cloud Differences
7	0.210-0.215	500	Cloud Properties, Land Properties
8	0.405-0.420	1000	Chlorophyll
9	0.438-0.448	1000	Chlorophyll
10	0.483-0.493	1000	Chlorophyll
11	0.526-0.536	1000	Chlorophyll

The temporal resolution is important not only in the scope of vegetation phenology to be measured, but also for avoiding atmospheric disturbances. Many algorithms and methodologies aim to obtain real land data avoiding signal atmospheric disturbances and other systematic errors (Cihlar *et al.* 1991). In the Iberian Peninsula, climatic dryness makes most of the images to have hardly any cloud cover, at least in the Mediterranean areas. However, the probability of cloud-free images decreases as the area covered increases, a circumstance that temporal composites try to overcome.

The revisiting time of this satellite allows a selection of cloud-free measurements from the available measures in the compositing period, traditionally based on the maximum value criterion. But compositing can always introduce noise as well as reduce spatial fidelity (Gao *et al.* 2003). In the case of MODIS vegetation indices, images are composited on a 16 days or monthly basis (Appendix 1). The first one will be used for its ability to better discriminate changes if they are less than one month spaced, assuming that the choice of optimal locations to obtain the temporal profiles reduces the risk of biased values. The rules for assigning one of the values for the period are determined by the compositing algorithm used. In the 16 days composite vegetation index images, the algorithms used for MODIS VI are: BRDF-C (bidirectional reflectance distribution function composite (BRDF-C), Constrained-view angle-maximum value composite (CV-MVC) and Maximum value composite (MVC). The choice is depending on data integrity and cloud flags.

The years selected were 2000, 2001, 2002, 2003, 2004 and 2005 to carry out this study. Unluckily, the last version of the VI (Vegetation Indices) algorithm from MODIS Terra Mission (version 4) starts some days after beginning of 2000, for territories out of America.

3.4 METHODOLOGY

In the next paragraphs, the structure and steps followed to carry out the study are described. The structure has been divided in two diagrams, first the preprocessing part of the images and the second is the methodology.

The first diagram starts with the acquisition of MODIS images from the MODIS gateway, for the considered period (2000-05) and the change of the projection from sinusoidal to UTM. The datum used was WGS72, 30N parallel. At the same time, it was possible to cut the images, because the area provided for MODIS was the whole south of Spain and North of Africa. The data format was changed to another standard format supporting for the software used.

The MODIS images are 16 days composites; it makes a total of 23 images per each year. One MODIS-13 image consists of 11 bands that provide different information. From this set the MODIS products NDVI and NDVI quality band were chosen. The values of the NDVI quality band were studied based on the documentation from MODIS and only the pixel that had high quality was selected. Then, this mask was applied to the NDVI band. This process was repeated for every image. The mean NDVI image per year was calculated and after that, the mean NDVI over the 6 years. Moreover, the mean NDVI over the six year per 16 days composted period was calculated. These mean NDVI images were used to obtain the attributes of the NDVI As last step in the preprocessing, the NDVI attribute was calculated, as explained in the section (3.4.2).

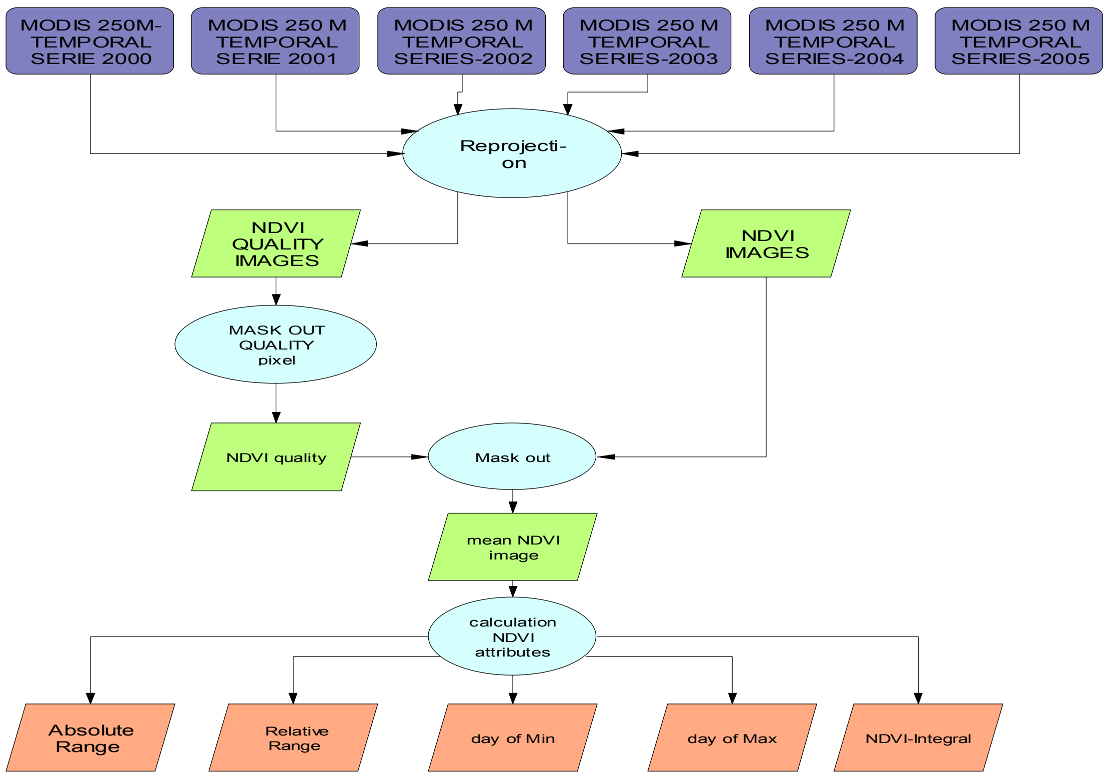


Figure 2: Pre-processing steps

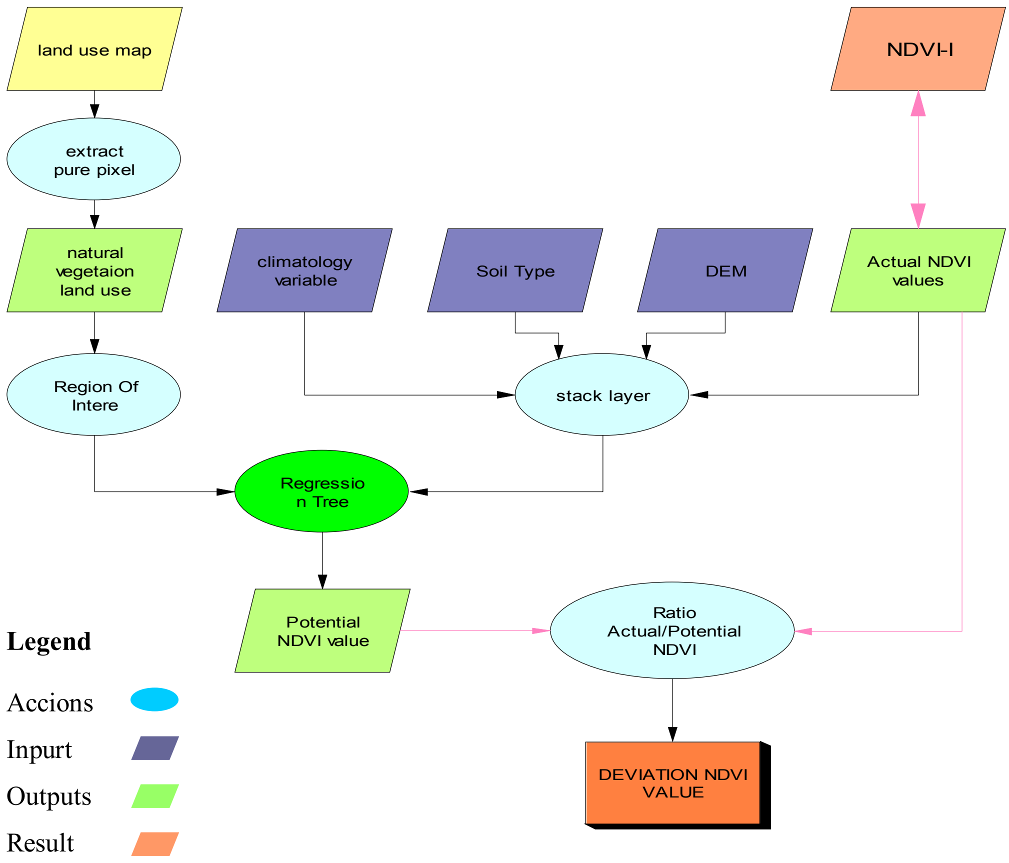


Figure 3: Methodology steps

The second diagram describes the followed methodology to carry out the regression tree analysis. Fist, the land use map was transformed into 25 meters spatial resolution and aggregated into 250 meters. With this aggregation to a major pixel size, we also know the percentage of purity of each pixel. We chose the maximum purity of them (standard pixel index SPI=1), meaning that the pixel with this value is 100% one land use. We selected from the natural vegetation land use the 'pure' pixels. Moreover, they were selected from undisturbed area assuming potential growth of the natural vegetation. These pixels were used as "Region Of Interesting" (ROI) for our regression tree. The "Regions Of Interests" are the reference data that are going to be extrapolated into the surrounding pixels. These ROI together with the biophysical variables are the inputs for the regression tree. The output of the regression tree is an image with the predicted NDVI values. This image represents the 'potential' NDVI that is used with the actual NDVI from the preprocessing for obtaining the result of the analysis.

3.4.1 DATA PREPRARATION

3.4.1.1 VECTOR MAPS PREPROCESSING

- Land use map

The land use map is a vector map at 1:50000 scale, with 110 different use-classes initially. Those classes aggregate into fewer classes for analysis. The class aggregates were several urban classes and water pools. This map was changed to raster format with 25 meters of pixel resolution. In order to support the selection of pure end-members, the database was resampled from 25 to 250-meter pixel size to match the MODIS pixel size. The aggregation method is based on using a majority filter with kernel size of 10 pixels (25m * 10=250 m) that was the resolution of the used images. Due to the very heterogeneous land use in Almeria, the proportion of every class within the kernel was also recorded during the aggregation process, such that a so called Standard Purity Index (SPI) could be calculated, using the following equation, (Zurita Milla *et al.* 2005):

$$\text{SPI}=\sqrt{\frac{\sum_{i=1}^{n}(f_i-f_{\max class})^2}{n-1}}$$

Where: f represents the fraction of each land use in the kernel, $f_{masxclass}$ is the maximum fraction and n is the number of classes. Consequently SPI=1 when only one class is present in the kernel window.

We masked out the pixels for which the SPI=1 in order to get only "pure" pixels of each land use. Afterwards, a moving window was used to check if the neighboring pixels were also the same land use classes. It helped to be sure that the pixels selected as ROI were 'pure'. This process was done for all the land use classes. Then, the natural vegetation cover classes were masked out and used for defining the ROIs that were applied in the regression tree analysis.

- Climatology images

The Junta de Andalusia provided the climatology datasets. Some of them came with a buffer around the area, with different geo-projections, coverage and pixel size. In order to work at the same geo-scale and pixel size some operations were performed on these datasets: change from 500 m to 250 m pixel size, re-project into the datum WGS72, and extract the study area from the digital map of the Andalusia region by means of clipping and masking. The processing of the data was done with ARCGIS software. The time series used are from 1995 until 2005.

- Climatic vegetation cover

The Climatic vegetation cover was subjected to re-projection into the datum WGS72 and subsetted by the shape of Almeria province. We used this map for the characterization of ecosystem functioning at land cover level.

- Digital Elevation Model

The digital elevation map was available for the whole of Spain at $20m^2$ grid size. The operation done with the DEM was to change to the same properties as above. It is related to subsurface soil moisture flow and soil texture (Franklin 2003).

- Soil type map

The soil type map had the same preprocessing as the other maps. The decision of using this dataset was conditioned by the influence that different soil types have on NDVI values of the same functional type or vegetation community (Domingo Alcaraz, personal communication)

3.4.1.2 MODIS IMAGES

MODIS images are provided in HDF-EOS format, a rich but still a complicated (Trombetti 2002) format for data handling by a number of software packages. At the same time, the MODIS science team also supplies tools to convert it into a more common one, e.g. TIFF format, easier to process in ENVI 4. The final aim of this step is to compose a stack from the downloaded layers containing the value of NDVI for each 16 days of the time series.

- Reprojection

Most of the preprocessing steps were performed with the MODIS Re-projection tool (MRT 3.0). It can also be obtained from the NASA's website together with other tools indicated for other processing levels (MODIS Swath Re-projection Tool), and browsing applications (HDF Explorer, used for viewing the quality of metadata). MRT allows re-projections, spectral and spatial sub-settings, datum conversions or resampling into different pixel sizes EOS data center (2004). The same file with different parameters for the preprocessing operations could be used for all the images. The parameters used were:

- ° Re-projection from sinusoidal projection to UTM projection and WGS 72 datum, centered in zone 30, using a bilinear interpolation in the resampling.
- ° Selecting the area of interest (spatial subset) by indicating the corner coordinates.
- ° Converting the format from HDF to Geotiff.

The output images from MRT still do not have the correct geographical extent and quality, neither the optimal format to start image processing.

Table 3: Coordinates of Almeria province

	Latitude	Longitude
Minimun	36°97'00’	-1°61'00"
Maximun	37°67'00	3°13'00

- Masks

The bands that were selected from the available metadata from the MODIS image were the NDVI and the NDVI quality bands. This quality assessment is useful for image selection and screening. A quality assessment per pixel, based on production parameters, is useful for data analysis and can be integrated in the image application.

Thus, for a more reliable detection of low quality measurements, a pixel-by-pixel approach is necessary.

The information is stored in the sixteen bits of the quality image, and it analyzes the general quality of vegetation index, the usefulness, aerosol quantity, adjacency correction, mixed clouds, water masks applied, snow and shadow occurrence, atmospheric correction methods and compositing algorithm. To account for all the factors at the same time, we can use the second factor analyzed that is composed for four bits (Appendix 3); these four bits (Useful index) provide more confidence levels of pixel quality. The quality measure is depending on the combination of this four bit. The quality is presented in five levels: Highest quality (0000), descending quality (0001-1100), not atmospheric correction (1101), lowest quality (1110) and not useful (1111). The selection of the pixel with highest quality was implemented in IDL language.

In IDL, we introducer a script in which the bit changed the DN values between 0 and 60. These values came from the change of bit to decimal. It takes into account the quality table of MODIS services. This means that the bit value 000000110000 is changed into decimal and the result is 60; its result corresponds to the lower quality. Batch processing for all the images, both NDVI and NDVI quality, was done. Some of the image results have really bad quality; they are almost without any information.

Based on this transformation, a mask was built, in which the values from 0 to 12 are selected; it means that we take the pixel values that have more that 80% of quality. Later on, a mask based on the selected values of the bits of the quality image is applied to the NDVI image of that date. In this way, only the most reliable values remain in the image. As final step, the calculation of NDVI was performed by dividing the DN by 10000, following the instructions of the MODIS manual (Appendix 2). We calculated the mean images of NDVI per year, over six year data, and over six years per 16 days composite period.

3.4.2 CALCULATION OF NDVI ATTRIBUTES

The attributes of the NDVI have biological significance and are derivates from the seasonal curves of NDVI as described in the Figure 4. The seasonal curve was obtained by means of each composite day along our time series. This mechanism was used for the 23 composite images that comprised one year. The result was one image with 23 bands that represent the mean over the years per 16 days composite period.

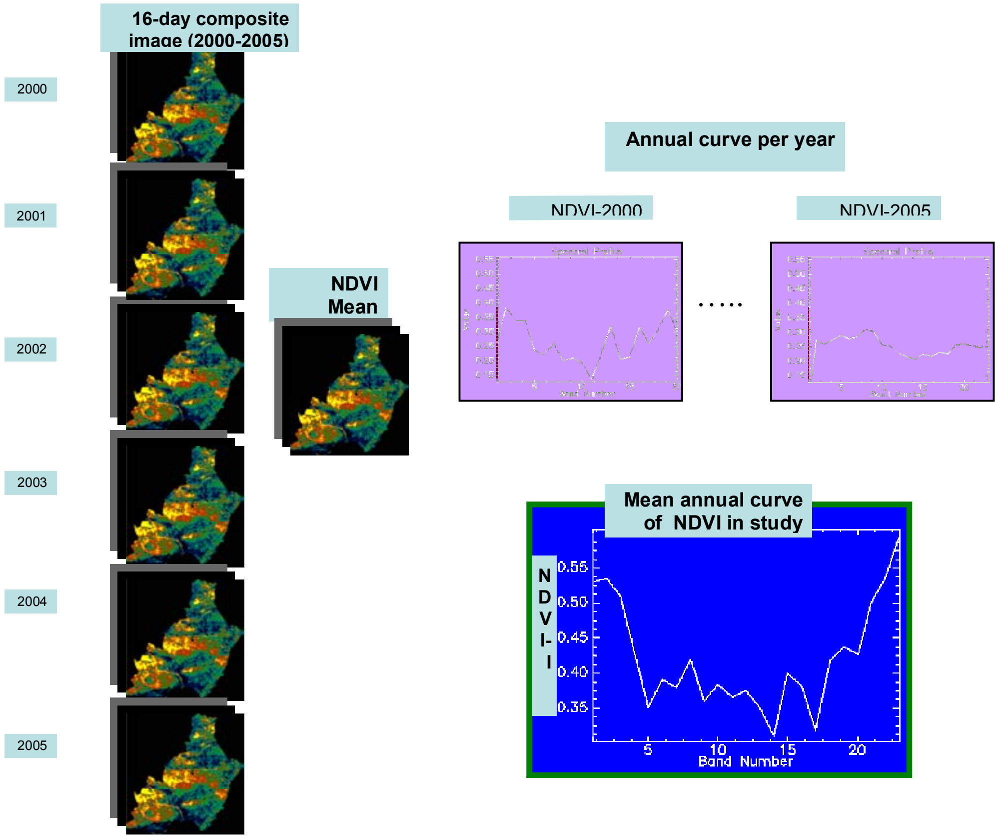


Figure 4: The calculation of the mean image of the time series.

The following variables have been derived from the seasonal NDVI curve of the averaged year, (a) the annual integral (NDVI-I) is calculated as mean NDVI over 6 year per 16 days composited period and used as an estimate of the fraction of photosynthetic active radiation absorbed by the canopy and hence of primary production (Tucker and Sellers 1986; Sellers 1987; Paruelo et al. 2001), (b) the relative annual range of NDVI (RREL), and (c) the date of maximum NDVI (MMAX) and minimum NDVI (MMIN), Three of them were used to capture the seasonality of primary production (Lloyd 1990; Potter and Brooks 1998; Paruelo *et al.* 2001; Guerschman et al. 2003; Hoare and Frost 2004)

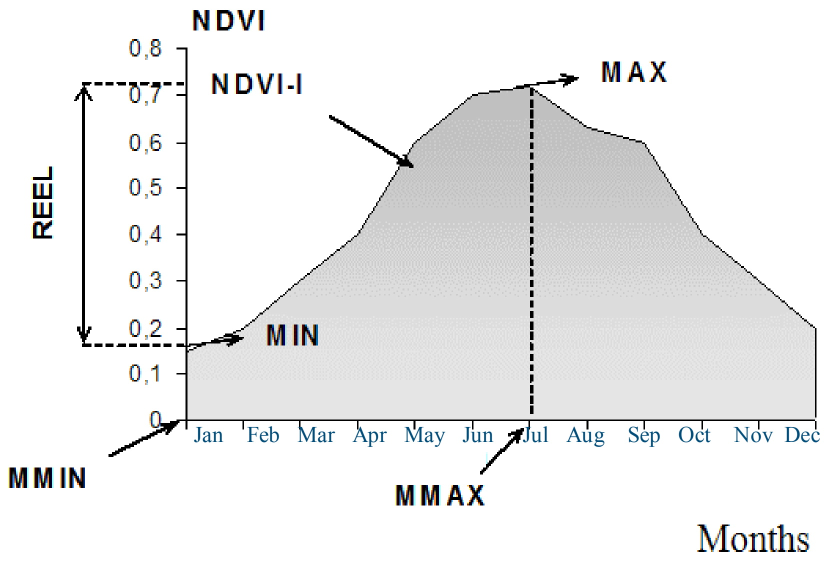


Figure 5: Example of seasonal NDVI curve and how the attributes of NDVI are calculated.

3.4.3 REGRESSION TREE PREPARATION

The regression tree procedure was carried out with ENVI software. The application inside ENVI is called RuleGen, in which different algorithms are implemented for classification and prediction of a variable. The algorithms that have been used in this study are Generalized, Unbiases, Interaction Detection and Estimation (GUIDE) (Loh 2002). It is a regression tree algorithm based on the Cart Algorithm. Classification and regression tree are ideally suited for the analysis of complex ecological data (De'Ath and Fabricius 2000). Classification and Regression Trees (Breiman and Hall. 1984; Loh 2002) are modern statistical techniques ideally suited for both exploring and modeling datasets. It is useful for classification and prediction of variables.

GUIDE is the only regression tree algorithm that can:

- Fit splits without selection bias,
- Detect pairwise interactions among predictor variables at each node; fit piecewise constant, simple linear, multiple linear and stepwise linear models,
- Fit weighted least squares, quantile, Poisson and relative risk models using categorical variables for splitting only, or for splitting and fitting.

The GUIDE algorithm was developed for least squares and quantile regression, (Loh 2002). Preliminary versions of the algorithm are described by Chaudhuri *et al.*(1994). It is inside the RuleGen application in the ENVI software, developed by Crish Jengo.

The tree explains variation of a single response variable by one or more explanatory variables. The response variable could be either categorical (classification trees) or numeric (regression trees) and the explanatory variables could be categorical and/or numeric. The tree is constructed by repeatedly splitting the data; it is defined by a simple rule based on a single explanatory variable.

The rule followed for splitting data in this case was linear regression in which the least square was taking into account to decide with which explanatory variable to begin the splitting. At each split the data is partitioned into two mutually exclusive groups, each of which is as homogeneous as possible. The splitting procedure is then applied to each group separately. The objective is to part the response into homogeneous groups, but also to keep the tree reasonably small. The size of a tree equals the number of final groups. Splitting is continued until an overlarge tree is grown, which is then pruned back to the desired size. Each group is typically characterized by either the distribution (categorical response) or mean value (numeric response) of the response variable, group size, and the values of the explanatory variables that define them.

The way that explanatory variables are used to form splits depends on their type. For a categorical explanatory variable split and fit is possible with two levels, only one split is possible, with each level defining a group. For numeric explanatory variables, a split is defined by values less than, and greater than, some chosen value. Thus, only the rank order of numeric variables determines a split. From all possible splits of all explanatory variables, it selects the one that maximizes the homogeneity of the two resulting groups. Homogeneity can be defined in many ways, with the choice depending on the type of response variable.

Trees are represented graphically, with the root node, which represents the undivided data, at the top, and the branches and leaves (each leaf represents one of the final groups) beneath. Additional information can be displayed on the tree, e.g., summary statistics of nodes, or distributional plots.

The explanatory variables used in this case were climate, terrain model, lithology, and land use and annual integral of NDVI (NDVI–I) calculated from MODIS as independent variables. The NDVI-I assign as actual NDVI (A-NDVI) The mean precipitation, mean temperature, potential solar radiation and elevation had a numerical distribution. These variables were introduced in the regression tree as numerical variables which mean that they were used for splitting and fitting the dataset. The lithology and land use were classified as categorical data, because they represent entire polygons containing the same information. The data values introduced into the regression tree were obtained by means of definition of regions of interest (ROI). The ROI were defined based on the land use with natural vegetation cover and only “pure” pixels. Several regression trees were built with different explaining variables in order to study which had more influence on the data distribution of the predictive NDVI. The outcome of the regression trees are maps with predicted NDVI (P-NDVI).

4 RESULTS

4.1 STUDY OF NDVI ATTRIBUTES: SPATIAL PATTERNS AND FUNCTONAL CHARACTERIZATIONOF NATURAL LAND USE

The study of NDVI attributes is based on the description of the patterns of the interception of radiation by vegetation. The following variables were derived from the seasonal NDVI curve of the 6 year averaged year: Annual Integral (NDVI-I) calculated as the average over 6 year 16 days composite period; Annual Relative Range (RREL) (difference between maximum and minimum NDVI divided by annual integral); Month of the absolute Maximum of NDVI (MMAX) and Month of the absolute Minimum (MMIN) as it is show in the Figure 6..

We realized the characterization of the ecosystem function by means of the NDVI. It shows the vegetation activity in a narrow part of the spectrum. The vegetation has a high reflectance in the near infrared due to scattering by leaf mesophyll cells and a low red reflectance due to absorption by chlorophyll pigments. The value of the NDVI for vegetation will hence tend to one. By contrast, clouds, water and snow have a larger red reflectance than near-infrared reflectance and these features have negative NDVI values. Rock and bares oil areas have similar reflectance in the two bands and result in vegetation indices near zero (Hurcom and Harrison 1998). These assumptions, used for the characterization of the ecosystem functioning by land cover, are due to different structure and composition of land. Moreover, our study area is a semiarid region with sparse vegetation cover.

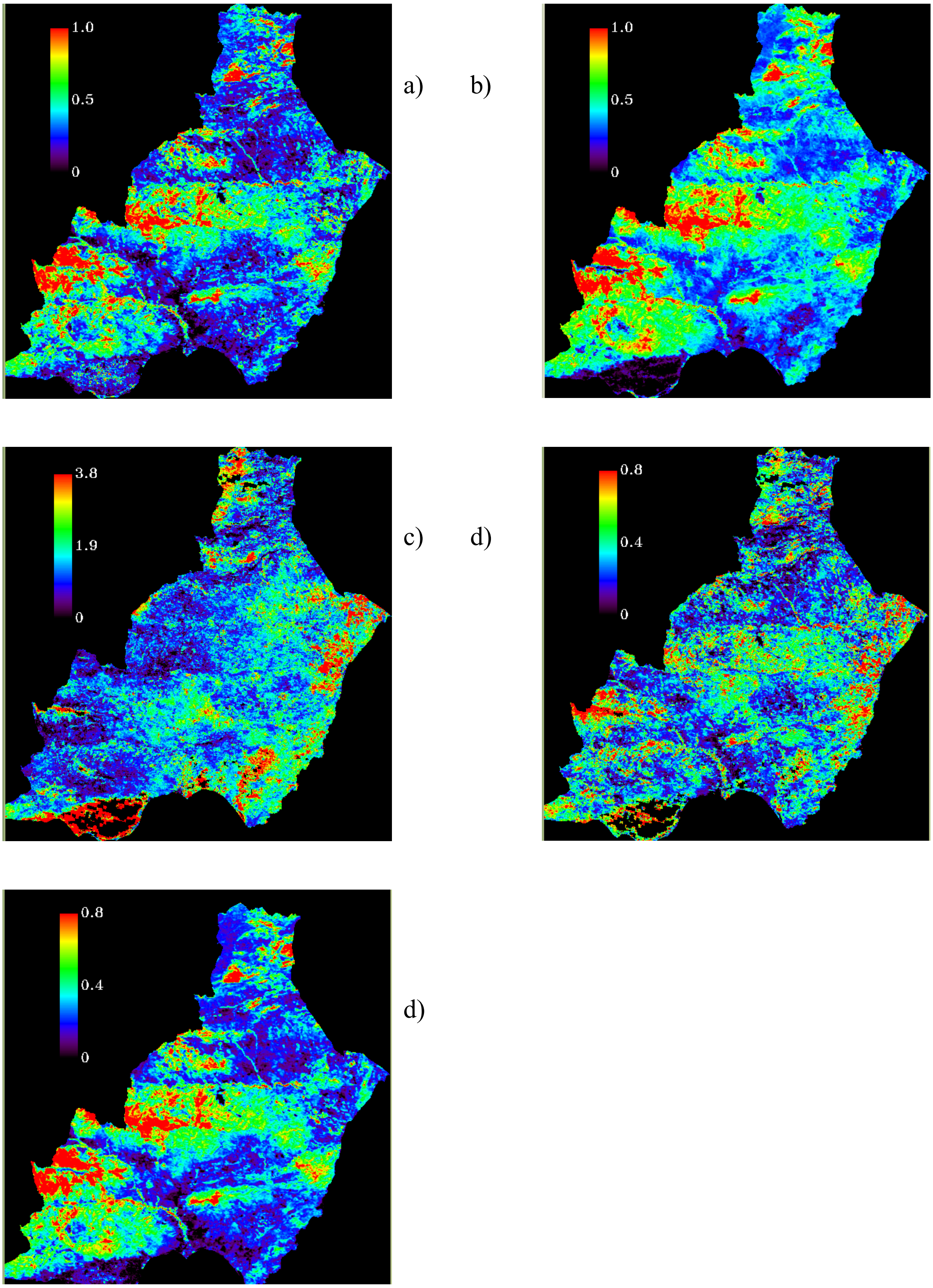


Figure 6: Images of NDVI attributes for the Almeria test site in Spain. It was calculated based a 6 yearly average NDVI profile (2000-2005) on mean year image; MINimum and MAXmum value of NDVI during the time series (a and b), Relative Range (c), Absolute Range (d) and NDVI-I (e).

To calculate the seasonal curve of NDVI for different natural vegetation covers, we based our selection on the natural covers which have a high extension within the study area. The natural vegetation covers were: 1) conifer forest, 2) dense cover of mediterranean semiarid shrublands and quercus trees, 3) dense cover of Mediterranean semiarid shrublands and conifer tree cover and 4) Scattered Mediterranean semiarid shrublands and dense cover of conifers.

The selection of the pixels for the seasonal NDVI curve of natural vegetation classes was based on the result of the Standard Purity Index (SPI=1) calculation. The selected pixels had the same pixel classification as their surrounding. The goal was to avoid selecting mixed pixels. The total pixel amount selected for each class was thirty pixels. The pixels extracted were located in different regions of the study area.

The mean of these pixels was calculated. The result is represented in the curves that show the mean of these thirty pixels for each band in the mean year image (Figure 7).

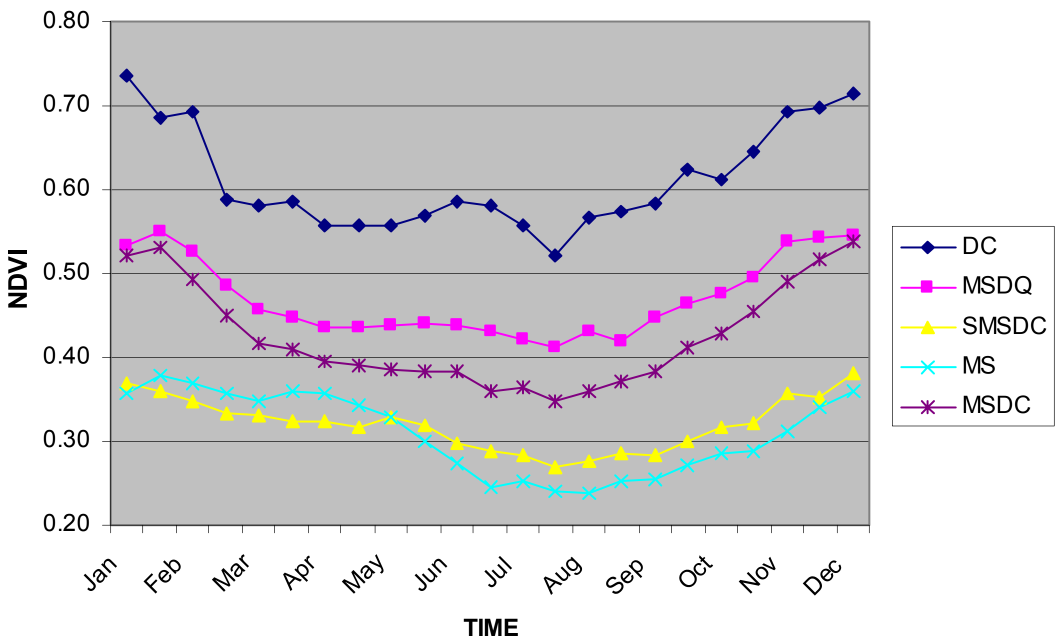
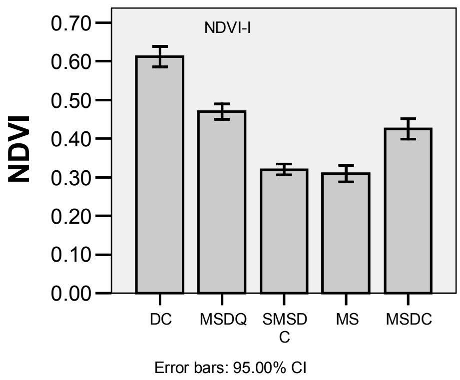


Figure 7: Seasonal curve of NDVI per mean year: (MSDC= Mediterranean Shrublands and Dense Conifer, DC= Dense Coniferous forest, MSDQ= Mediterranean Shrublands and Dense *Quercus* cover, MS= dense Mediterranean semiarid Shrublands, SMSDC= Scattered Mediterranean shrublands and Dense Conifer forest, and MSDC= Mediterranean Shrublands with Dense Conifer forest).

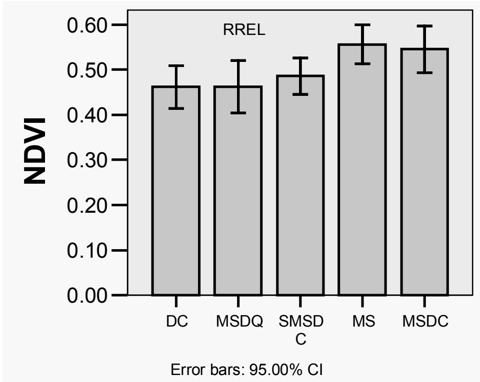
The discriminates analysis of differences in the seasonal curves of NDVI for different land covers in the Almeria province shows that the curve of NDVI has a concave shape for this region, due to the arid-dry conditions that occur during the large summer season.

The highest difference in values appears between dense coniferous forest and dense mediterranean shrubland. The dense conifers forest values show higher values than any other analyzed land cover. We see that the dense mediterranean shrublands with coniferous cover and with *quercus* describe almost the same curve of NDVI, the dense mediterranean shrublands with *quercus* show values a bit higher. The differences between mediterranean shrublands (MS) and scattered mediterranean shrubland with dense conifer forest (SMSDC) cover have similar NDVI values. However, the Scattered Mediterranean with coniferous cover shows a smaller incline of NDVI during the summer time. This is illustrate in Figure 7.

In general, the annual NDVI integral (NDVI-I) has a higher value for Dense Coniferous forest. The lowest values correspond to the mediterranean semiarid schrubs (Fig. 8a). Seasonality (RREL) was higher in mediterranean semiarid shrubs while the evergreen vegetation showed the lowest variation through the year (Fig. 8b). The maximum values of NDVI (MAX) showed a similar pattern as NDVI-I. NDVI maxima were higher in dense coniferous forest and showed the lowest values in dense mediterranean shrublands. (Fig.8c).The lowest NDVI minimum (MIN) occurred in the mediterranean shrubland with the Coniferous forest having the highest minima values (Fig. 8d). The mediterranean shrubs mixed with conifers and quecus present the maximum in summer, while the mediterranean shrubs and coniferous forest have the maximun spring (Fig. 8e). The minima occur for conifer and mediterranean shrub with *quercus* in summer and in the end of summer for the four land cover types, as we can expect in this region.



a)



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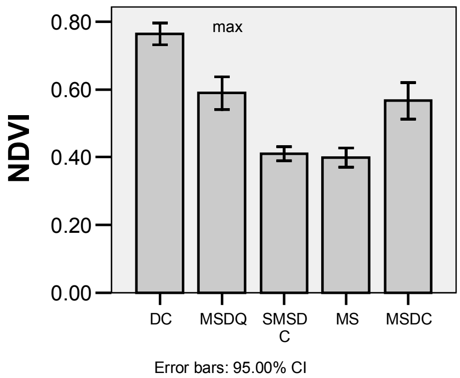
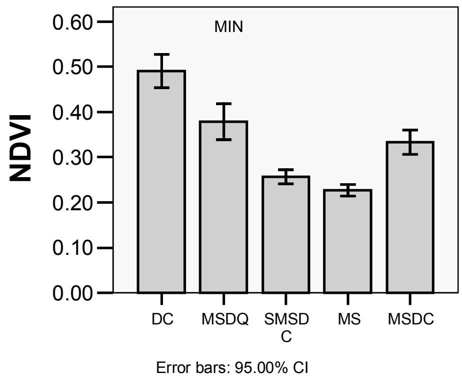
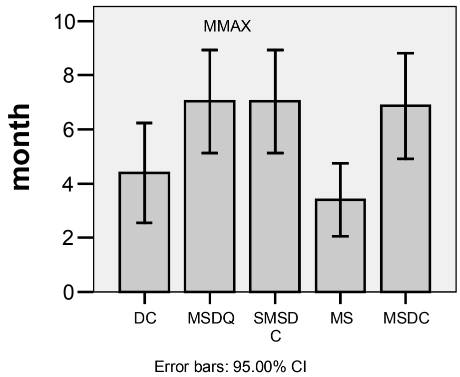


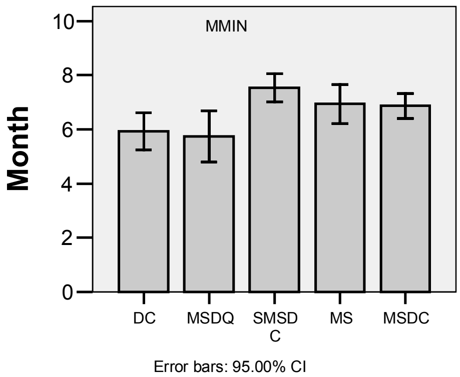
c)



d)



e)



f)

Figure 8: Functional characterization of the some land cover in Almeria province in terms of the mean values of the NDVI annual integral (a), annual relative range (b), maximum and minimum values of NDVI in the year (c and d), month of maximum and minimum (e and f). Vertical lines on top of the bars represent the spatial standard deviation of each NDVI-derived attribute. The bars correspond to the land cover characterize (DC= Dense Conifers forest, MSDQ= Mediterranean Scrublands and Dense *Quercus* cover, SMSC= Scattered Mediterranean shrublands and Dense Coniferous, MS= dense Mediterranean semiarid shrublands,MSDC= Mediterranean Scrubland and Dense Coniferous).

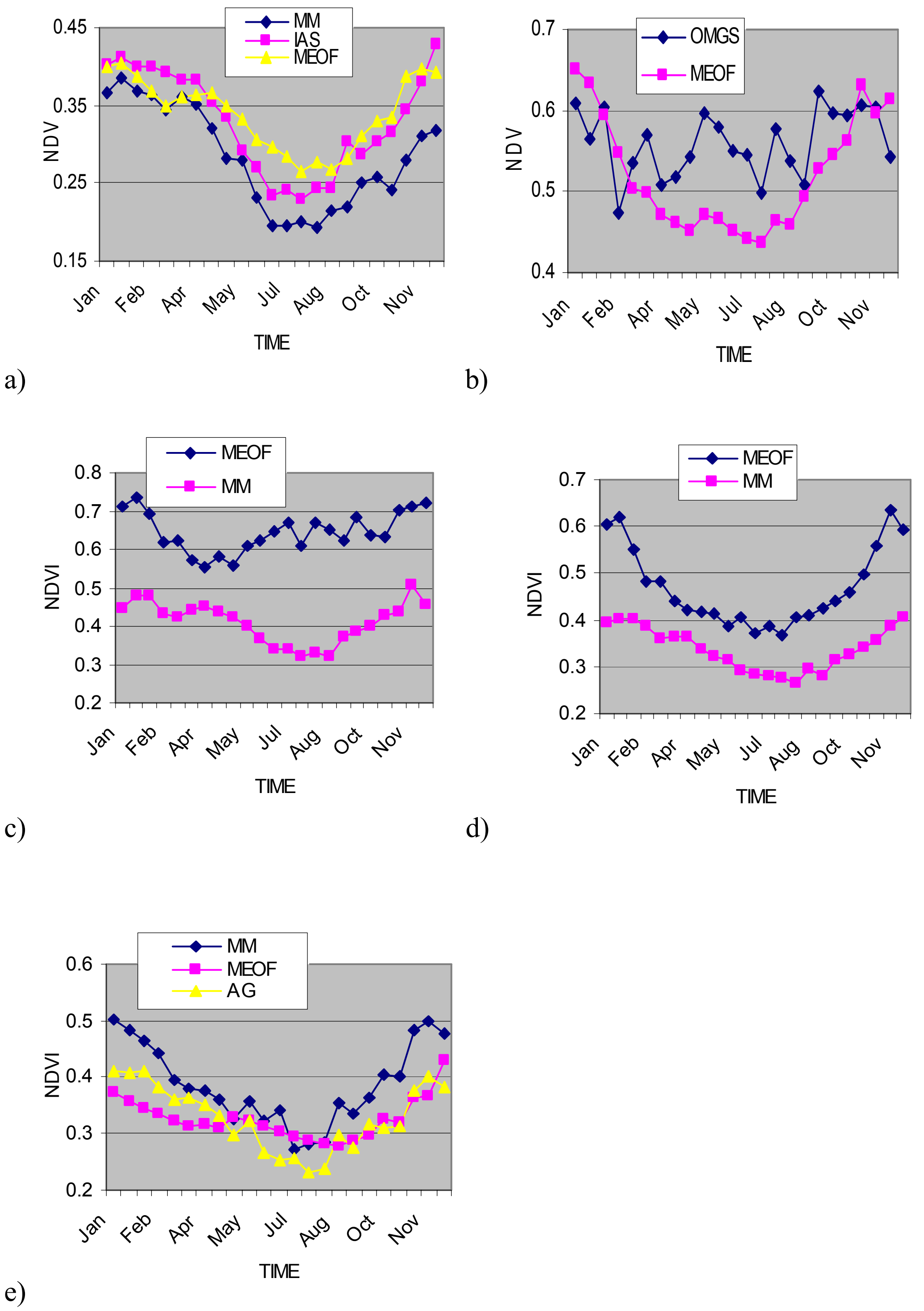


Figure 9: Characterization of natural land use by the climatic natural vegetation cover. Land cover: dense Mediterranean semiarid Shrubs, A); Dense Conifers forest B); Mediterranean Scrublands and Dense *Quercus* cover C); Mediterranean Scrubland and Dense Conifers, D); Scattered Mediterranean scrublands and Dense Conifers, E).

The climatic vegetation cover implies several stages of vegetation structure (succession). We used the last stage for the analysis. The climatic vegetation cover for the natural land use dense mediterranean semiarid shrubs in the study area is related the mediterranean maquis (MM), the iberian-african shrubs (IAS), and the mediterranean evergreen oak forest (MEOF). It is possible to observe the differences in the curve of NDVI between mediterranean maquis situated in the countryside and the two other covers close to the coastland, (Figure 9a). The mediterranean shrubland and dense *quercus* land cover is for semi-arid vegetation: mediterranean evergreen oak forest (MEOF) and oro-mediterranean grasslands and shrubs (OMGS). The OMGS describes a variable curve due to the seasonal character on the grassland and its dependence of the microclimate (Figure 9b). The mediterranean shrubland and dense conifers land cover have as climatic vegetation cover MM and MEOF. The MEOF shows higher values of NDVI, with different peaks a long the year, (Figure9, c). The land cover mediterranean shrubland and dense conifers have also a clear difference between MM and MEOF. They describe a concave curve with a high value in the areas where the climatic vegetation cover is MEOF and it presents two peaks in beginning and end of the winter time; it was located in a mountain area (Figure 9d). The last characterized land cover was the scattered mediterranean shrubland and dense coniferous forest. The climatic vegetation cover is Arid Garriges (AG), MM, and MEOF. It is possible to observe the low values of NDVI that present the AG cover; this due to the fact that they are situated in the desert area of the study area (Figure 9e).

4.2 ANALYSIS OF POTENTIAL NDVI

At this point, we present the result of the application of the Regression Tree model. The objective was to predict the potential values of NDVI (P-NDVI) for the study area which corresponds to the situation that the anthropic disturbance would not exist. To apply the model, we built a regression tree model. The regression tree consists of the input variables and through regressions with the measured P-NDVI for training pixels, values of P-NDVI are predicted and assigned. The inputs used to build the regression tree are show in table 4.

4. Results

Table 4: Variables used as inputs for the regression tree.

BAND	DESCRIPTION
B2	Potential Solar Irradiance, 1961-2005 (PSII)
B3	Mean Annual Temperature, 1995-2005 (MATT)
B4	Mean Annual Precipitation, 1995-2005 (MAPP)
B5	Lithology
B7	Elevation, 20 meters(DEM)

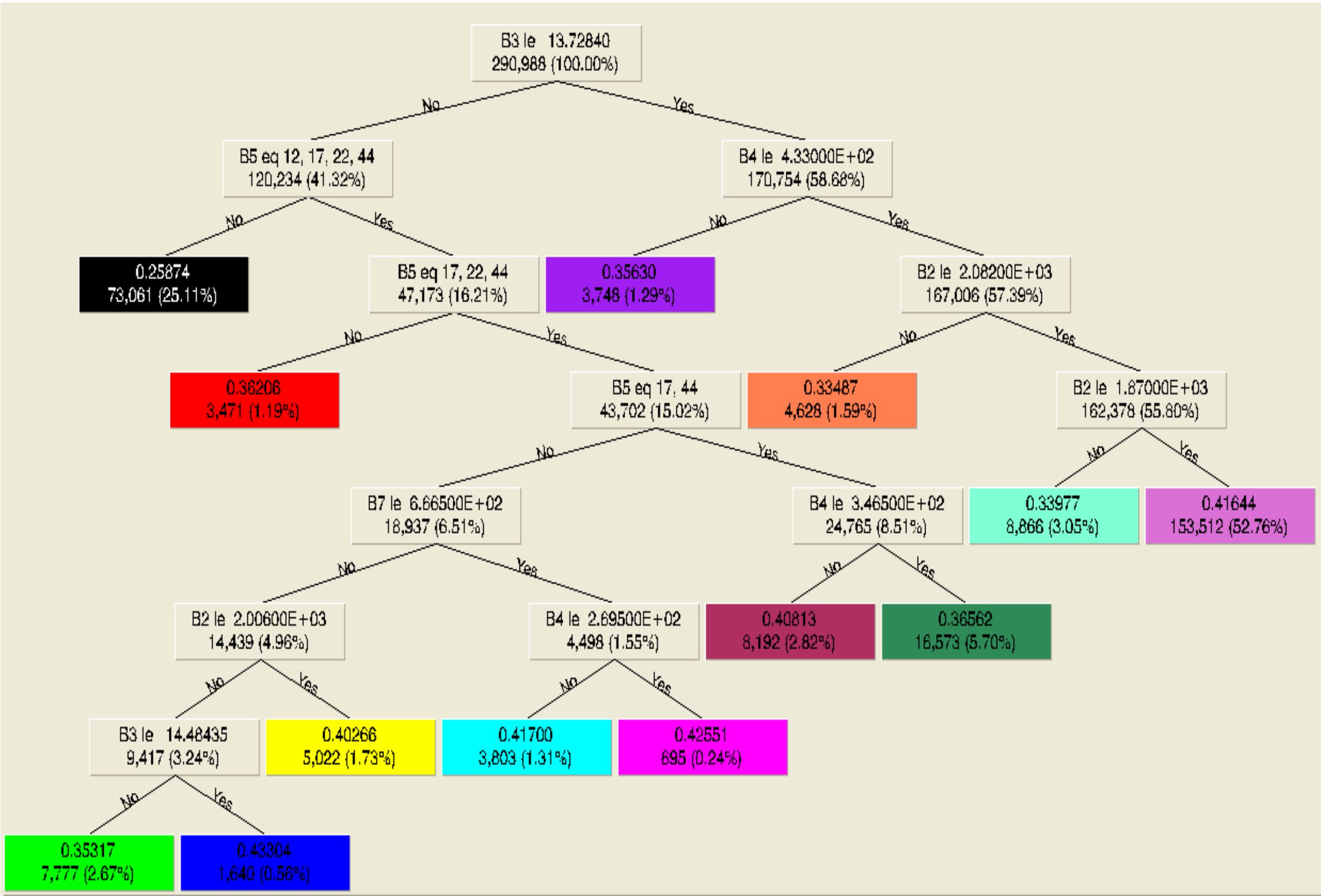


Figure 10: Regression Tree. Distribution of the splitting value with respect to the variables

Regression tree analysis of biophysical data accounted for 100% of the variance in A-NDVI for the training data (Table 4). The first division in the model was between areas of low and high mean annual temperature. The areas, which presented high mean temperature, were associated with lithology (node A) and the areas, which presented lower mean temperature, were associated with the mean annual precipitation (node B). The node A was splitting the values based on lithology. The areas in which the lithology was in majority: sandstone, quartzite, mica-schist, marble, clay, marl, or sandstones were fit as the first predictor value of P-NDVI. The next lithology classes used for fitting the NDVI value was schist. The splitting sample keeps on introducing more variables, in the left side the elevation and in the right side the mean annual precipitation as fitting values. The areas where the elevation was less than or equal to 666.5 meters were divided based on the mean annual precipitation. On the other hand, areas where the elevation was high were split based to the solar radiation and mean annual temperature. The node B was divided in terms of solar irradiance. The areas with high solar radiance got in the first split the predictor NDVI value. The rest of the areas with less solar irradiance were assigned to other predicted NDVI values. As conclusion, the regression tree was composed of 25 nodes, and the final ones were used to predict NDVI values. As a result of this regression tree, we got on output image with the distribution of the predicted-potential NDVI values distributed in the study area. This is illustrated in Figure 10. The Appendix 4 shows the statistical analysis that the regression tree carried out.

4.3 DEVIATION OF ACTUAL NDVI

We analysed the deviation of actual NDVI (A-NDVI) from P-NDVI from the various land covers. A-NDVI is divided by the P-NDVI in order to get the deviation.

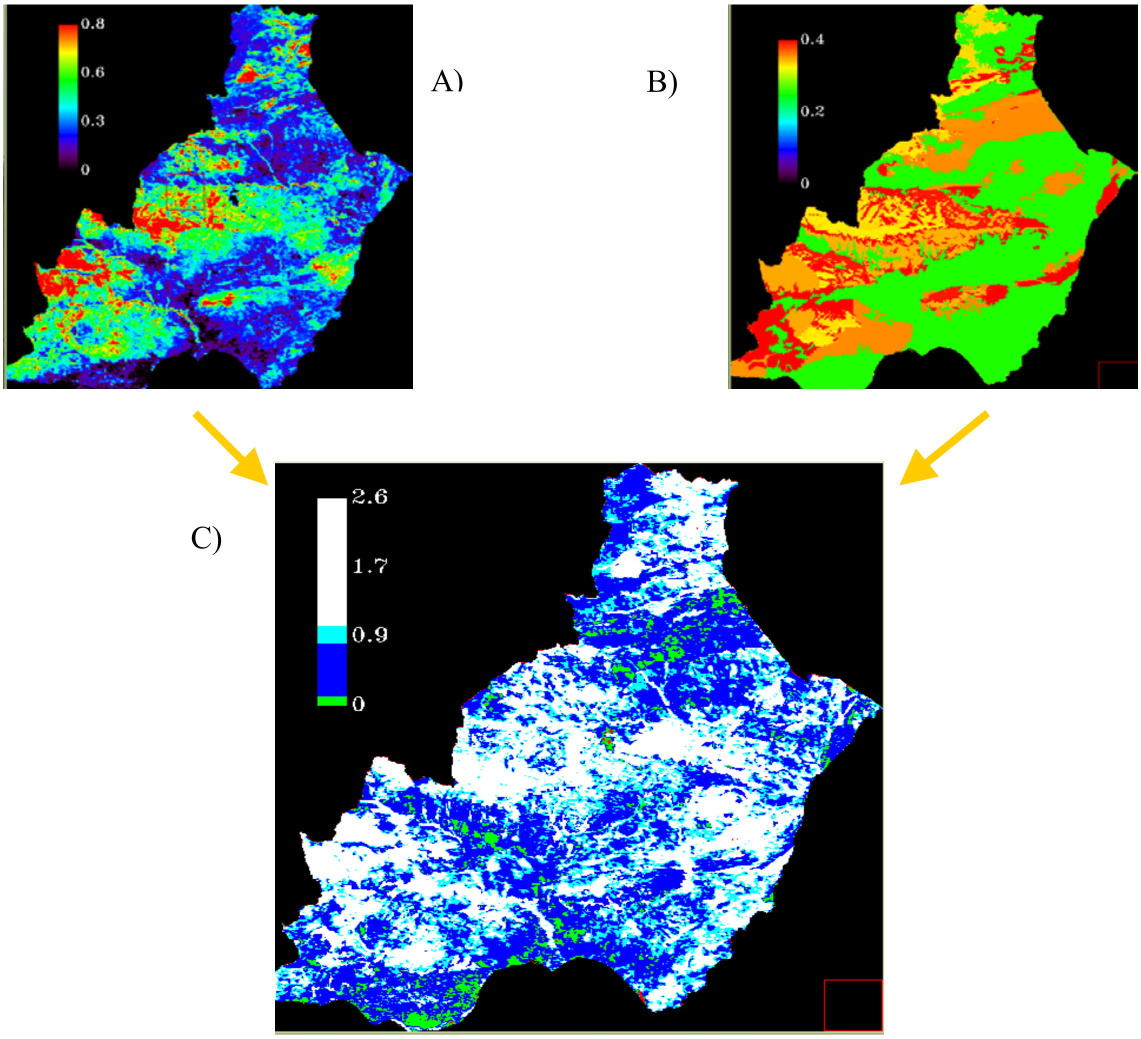


Figure 11: Ratio Image a) A-NDVI image, b) P-NDVI image, C) image representing the ratio A-NDVI/P-NDVI.

We expected that the P-NDVI would be higher than the A-NDVI value. However, the areas with a white colour in Figure 11 mean that the A-NDVI is higher than the potential one. There is a large area for which the ratio is higher than one. This deviation (greater A-NDVI than predicted P-NDVI) is present in areas with irrigated agricultural land. The expected deviations (lower A-NDVI than predicted P-NDVI) are most visible in small patches, often urban areas.

Deviations varied somewhat as expected by land use categories. The urban category tended to have a low ratio, indicating a reduction in photosynthetic activity. The different agricultural lands had the widest distribution and most obvious higher deviation. Thus, agricultural lands in the study area tend to have greater A-NDVI in the satellite imagery than would be expected from climatic and soil factors, owing to irrigation and fertilization. The agricultural land for the analysis was divided in irrigated, non-irrigated, mixed (irrigated & non-irrigated) and crops & pasture. The non-irrigated agriculture is mostly scattered olive or almond trees with grass cover in the raining season. The natural vegetation presents a slight higher A-NDVI than P-NDVI, as indicated by the position of the bar in the Figure 12. The higher A-NDVI in natural vegetation is located on the north and west of the province where the dense vegetation cover is present.

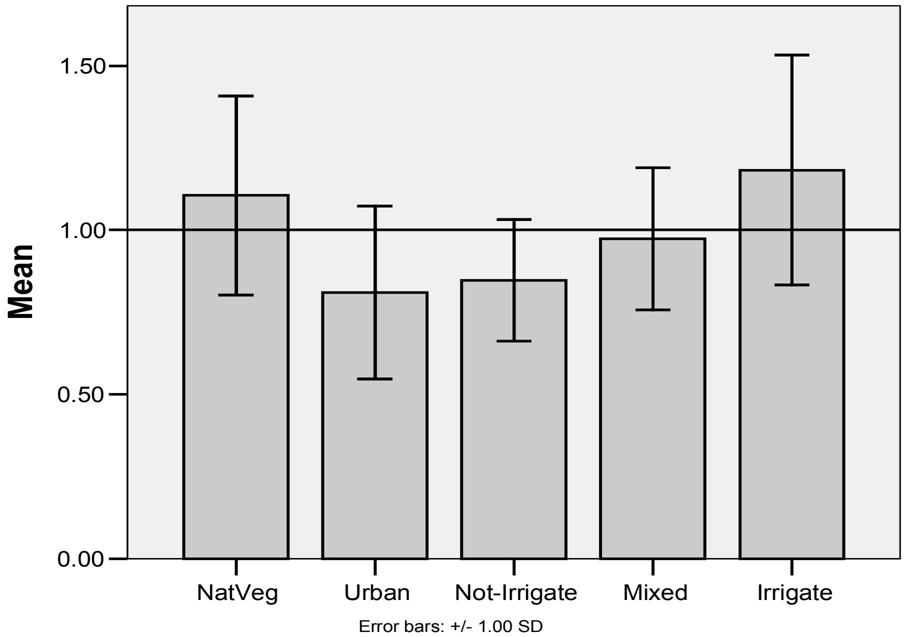


Figure 12: Ratio range of NDVI for agricultural (mixed, Irrigated, and not-irrigated), urban, and natural vegetation land uses.

5 DISCUSSION

5.1 CHARACTERIZATION OF ECOSYSTEM FUNTIONING

Periodic satellite remote sensing facilitates monitoring ecosystem functioning (Stoms and Hargrove 2000). The maps resulting from the calculation of the NDVI attributes (Figure 6) show the variation of the NDVI value along the time series considered. The areas with a high MMAX of NDVI are also the areas with high MMIN value of the NDVI. They correspond to areas with high vegetation cover. The south-west area of the image, close to the sea, is where the major concentration of greenhouses is located. We decided to remove these pixels to carry out the analysis because the reflectance of the plastic gives an erroneous interpretation.

The RREL provides a description of the intra-annual variation of the photosynthetic activity; the highest variations are located near the coastland border and in the high mountains. The high mountains are usually covered by snow for a short time in winter.

From the mean NDVI over 6 year per 16 days images was obtained the month of the MAX and MIN value of NDVI. It provides the period in which the MAX and MIN value of NDVI occurred. It is expected to have the MAX value in Winter-Spring and the MIN value in summer as we can see in the mean NDVI-I curve of five land cover types (Figure 7). These attributes, NDVI-I, MAX and MIN values present in the time series, RREL and days of the MAX and MIN provide an additional description of vegetation phenology, indicating the intra-annual distribution of the photosynthetic activity (Lloyd, 1990; Hoare & Frost, 2004).

5.1.1 CHARACTERIZATION NATURAL LAND USE BY NDVI ATTRIBUTES

The characterization of natural land use by attributes of NDVI show the trends of phenology trends and seasonality that the natural vegetation cover has. The MSDC, DC, MSDQ, MS and SMSDC present expecting results on RREL, MAX and MIN value of NDVI. The MS (mediterranean shrub) and SMSDC (scattered mediterranean shrubs and dense coniferous) have the lowest value of NDVI-I, MAX and MIN, but they show higher seasonality. This fact is expected due to the seasonal character of the mediterranean shrubs. The month of the MMAX has a high standard deviation in all the land cover. Most land cover present the MAX between winter and spring with few peaks in autumn depending on the rain occurrence. The traditional rainy season in the mediterranean areas is in autumn.

5.1.2 CHARACTERIZATION NATURAL LAND USE BY CLIMATIC NATURAL VEGETATION COVER.

The natural land use that we are analyzing has disparity in locations in the study area. It has influenced by biophysical external factors at dissimilar grade, such as irradiance, temperature, precipitation, elevation or chemical composition of the soil (lithology). Therefore, there are different climatic vegetation covers for each type of land cover. The Figure 9 provides the mean NDVI curve for each potential vegetation cover that corresponds to one land cover.

The mediterranean maquis (MM) and mediterranean evergreen oak forest (MEOF) have large spatial distribution, and they tolerate various environments. The MM is present in four of the land covers analyzed and MEOF is present in all of them. However, MM and MEOF do not describe similar curves, due to the influence of the biophysical conditions on the NDVI value (Volcani *et al.* 2005).

5.2 CONSIDERATION OF REGRESSION TREE RESULT

In this study, we have developed a model to predict potential NDVI (P-NDVI) in the absence of human land use effects to detect changes between the actual NDVI (A-NDVI) and P-NDVI. The model has as inputs temperature, irradiance, elevation and soil type, which captured most of the variation of NDVI in undisturbed areas (Franklin 2003).

The model consists of a Regression Tree analysis. The regression tree methodology followed was: assign weight to the variables based on a least square regression, detect pairwise interactions among predictor variables at each node and fit value of NDVI. In order to reduce the size of the tree, we used the prune option by cross validation. That means, a sample of the data is divided into subsamples, so the analysis is initially performed on a simple subsample. The rest of the subsample is retained and used for subsequent confirmation and validation of the initial analysis. For the estimation of the predicted values, the mean was selected using bootstrap standard error. The bootstrap estimates the sampling distribution of the standard error by resampling from the original sample. It is used to detect outliers and for cross validation, whose purpose is to make sure that the results are repeatable. This model is based on the GUIDE algorithm and implemented in ENVI software (Loh 2005). It can be an advantage *a priori* due to the automatic character of the algorithm. The regression tree does not need to be constructed for the research. However, it does not give the chance to interact with the model deciding in which order the variables enter in the regression tree and how the values are split. Furthermore, we have studied the influence of the training data (ROI) on the outputs of the RT. Obviously, this influence exists as the model is based on the mean and least square of the sample data. Then, depending on the range of the introduced values, the result will change. We were aware of select pixels for defining the ROI that had extreme NDVI-I values of the sample data.

During the RT training, we tried to use all the natural vegetation land cover as inputs, but it was not possible due to the requirement of being 'pure' class pixels of natural vegetation. As a result, the final pixels selected as ROI are not well distributed along the study area.

5.3 POTENTIAL AND ACTUAL NDVI DIFFERENCE

The actual NDVI (A-NDVI) was derived from the calculation of the mean NDVI-I over the time series and the potential was the output of the regression tree. We studied the ratio resulting from A-NDVI divided by P-NDVI.

The result shows a greater A-NDVI than P-NDVI for land covers that are transformed into intensive irrigated agricultural lands based on the land use map from 2003. Unfortunately, some patches with natural vegetation cover show also greater A-NDVI than P-NDVI. It can be due to several reasons: possible management of these areas after the realization of the land use map, although the prediction is made based on the mean NDVI over the 6 year or due to geometric error from the MODIS image, which leads to an error in the regression tree calibration, or possible error in the inputs used for the regression tree. For example, the temperature and precipitation inputs had 500 meters of spatial resolution, and the influence of the elevation, wind direction and shadow was not taken into account. We tried to compensate for this missing information with the use of the potential irradiance. Or the model underestimates NDVI value in areas with dense vegetation cover. We checked few field-data points as given in Appendix 5.

NDVI looks useful for estimating of biophysical vegetation parameters (Lüdeke et al. 1996; Maselli et al. 1998; Paruelo et al. 2001; Paruelo et al. 2001; Pettorelli et al. 2005), although we could identify limitations of the NDVI, which may impact upon its utility in global and local studies. These include: a) spatially varying atmospheric effects due to variable aerosol concentrations, water vapour, and residual clouds. The spatial error of MODIS for 250 meters of spatial resolution approximates 150 meters from the nadir (Wolfe *et al.* 2002). b) Varying sun-target-sensor geometric configurations and the resulting interactions of surface and atmospheric anisotropies on the angular dependent signal. c) saturation problems whereby NDVI values remain invariant to changes in the amount and type of dense vegetation (Zhang *et al.* 2004). d) non-linearity in biophysical coupling of NDVI with fAPAR and/ or LAI. e) Canopy background contamination in which the background reflected signal alters the NDVI value. This includes surface wetness, snow, litter, roughness, and soil type. f) Canopy structural effects associated with leaf angle distributions, clumping and non-photosynthetically-active components (woody, senescent, and dead plant materials).

Although, NDVI data sets are generally well-documented, quality-controlled data sources that have been pre-processed to reduce many of these problems, MODIS team is making great effort for reducing these problems (Zhao *et al.* 2005).

6 CONCLUSIONS AND RECOMENTATIONS

6.1 CONCLUSIONS

From this study we can conclude that periodic satellite remote sensing is a useful technique to study the impact of land use change on ecosystem functioning. However, in our case we have to take into account the spatial error of the data products from MODIS. The products used in this approach were NDVI and NDVI quality. The used of the NDVI quality band avoided complicated pre-processing of the images.

The estimation of the ecosystem functioning by using remote sensing techniques has been shown by many studies before. We investigated the possibility to used NDVI and its attributes as main variable definition for study the phenology dynamism and conditions of the vegetations. Despite the differences in vegetation structure and seasonality within the study area, the NDVI attributes provide a description of the ecosystem functioning as was also found, for example, by Garbulsky and Paruelo (2004).

The RREL provides information about the seasonality of the land cover analysed, where mediterranean shrubland presents a high variation. The highest annual production of vegetation (NDVI-I, MAX and MIN values) is present in dense conifer forests. The interpretation of the NDVI curves explains dynamics of ecosystem with respect to the biophysical factors. It shows that mediterranean evergreen oak forest that is a climatic vegetation cover present in five types of land cover. It shows a completely different curve depending on the land cover in which it is present and its location in the study area.

We conclude that the regression tree is an appropriate statistical method for predicting the value of P-NDVI. The areas converted to irrigated agricultural use and mixed use have higher values of A-NDVI than of P-NDVI, due to their management like irrigation, fertilizers, intensification of growing seasons. The not-irrigated agriculture, crops-pasture and urban areas presented lower values of A-NDVI than the P-NDVI, crops-pasture have seasonal character which reduce the mean A-NDVI. Urban areas have similar reflectance in the two bands (NIR and Red) result in vegetation indices near zero. Some patches with natural vegetation cover show also greater A-NDVI than

P-NDVI. It could be due to changes in the land use that occurred after the map was made. From the knowledge of the study area, we can conclude that intensive transformation of the land use was done in eastern areas close to the coastlands. There exist a dynamic economy which result is increasing the extensive agriculture, building new urban areas and infrastructure in the last three years. This produces a serious pressure on natural areas that can affect their ecosystem functioning and subsequently their ecosystem services. Other possible reasons for this result are the errors in the process of data acquisition or errors in the adjustment of the model that can underestimate the NDVI value of natural vegetation. To draw a conclusion about this, we need an intensive field work to map the areas in which the A-NDVI is higher than the P-NDVI.

The sample data used for definition of ROIs have influence on the predicted NDVI value. Although the requests for selecting 'pure' natural vegetation use were high, we can not be completely sure that mixed cover did not occur.

6.2 RECOMMENDATIONS FOR FUTURE STUDIES

We recommend characterizing the ecosystem functioning by means of NDVI and its attributes at a high level of ecosystem detail, for example, at plant functional types.

In relation to the regression tree analysis, we recommend using maximum and minimum values of precipitation and temperature instead of mean temporal series, because it makes easy the detection of peaks in NDVI values.

Soil moisture information could be well used as input for the analysis in dry areas, like depth of water table and available soil water capacity. In dry areas the main source of water for the vegetation comes from the consolidation of the water vapour over the leaf or from the water table.

Other useful variables to introduce into the regression tree are potential evapotranspiration, biomass, soil nitrogen, actual natural vegetation cover, land use map geologic information, soil texture and slope. The potential evapotranspiration, biomass and soil nitrogen reflect the vegetation cover and its structure; actual-natural vegetation cover or a land use map are always useful if the map are done recently. The geologic composition, soil texture and slope are recommended due to their influence on vegetation distribution and on water storage.

The sample data introduced in the regression tree have a high influence on the results. So, the sample data to be introduced in the regression tree should be increased and well distributed over the study area. The larger the number of samples introduced, the lower is the commission error inside the model. Moreover, a high correlation between inputs used in the regression tree, it should be avoided.

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APPENDICES

Appendix 1: Composite period of MODIS images

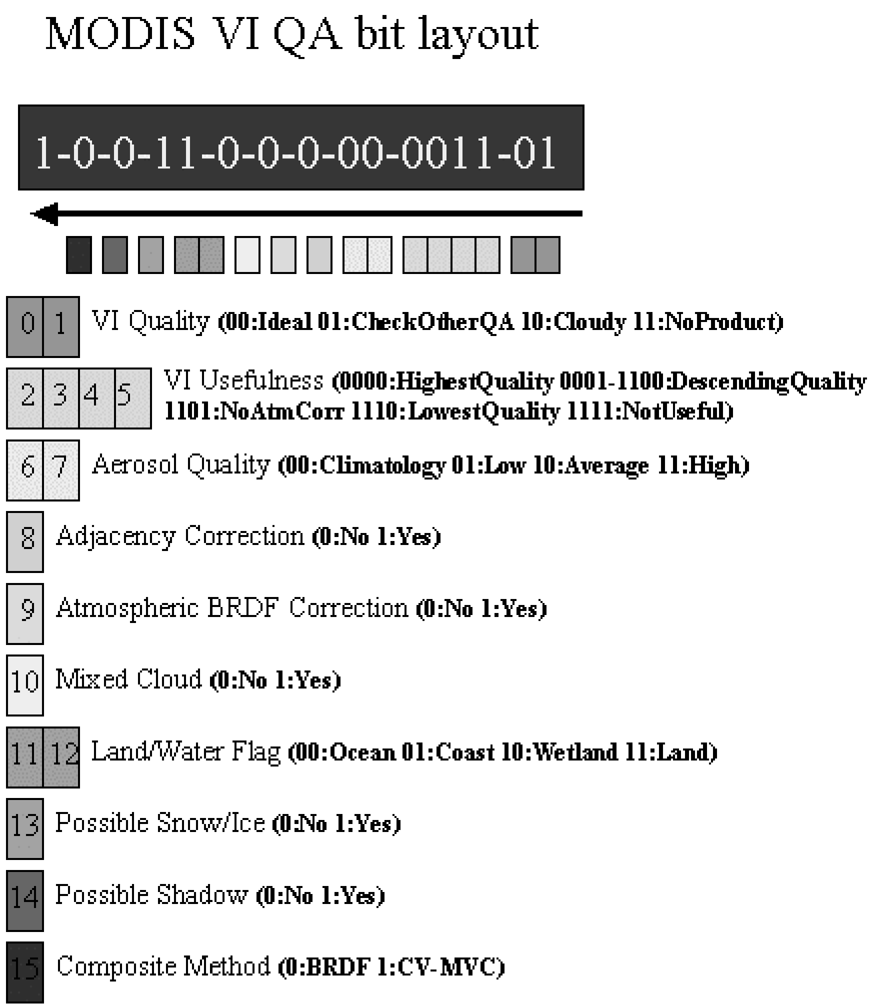
Julian day	49	65	81	97	113	129	145	161	177	193	209	225
Standard day	18/2	06/3	22/3r	07/4	23/4	09/5	25/5	09/6	26/6	12/7	28/7	12/8
Year	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Julian day	241	257	273	289	305	321	337	353	1	17	33	49
Standard day	29/8	13/9	29/9	15/10	31/10	16/11	02/11	18/12	01/01	17/01	02/02	18/02
Year	2000	2000	2000	2000	2000	2000	2000	2000	2001	2001	2001	2001..

Appendix 2: MODIS image composition.

SDS	UNITS	DATA TYPE-bit	FILL VALUE	VALID RANGE	SCALE FACTOR
250 m 16 days NDVI	NDVI	16-bit signed int	-3000	-2000-10000	10000
250 m 16 days EVI	EVI	16-bit signed int	-3000	-2000-10000	10000
250 m 16 days NDVI Quality	bit field	16-bit unsigned integer	65535	na	na
250 m 16 days EVI Quality	bit field	16-bit unsigned integer	65535	na	na
250 m 16 days Red Reflectance	relectance	16-bit signed int	-1000	0-10000	10000
250 m 16 days NIR Reflectance	relectance	16-bit signed int	-1000	0-10000	10000
250 m 16 days Blue Reflectance	relectance	16-bit signed int	-1000	0-10000	10000
250 m 16 days MIR Reflectance	relectance	16-bit signed int	-1000	0-10000	10000
250 m 16 days View Zenith Angle	degree	16-bit signed int	-10000	-9000-9000	100
250 m 16 days Solar Zenith Angle	degree	16-bit signed int	-10000	-9000-9000	100
250 m 16 days Relative Azimuth Angle	degree	16-bit signed int	-4000	-3600-3600	10

Appendix 3: Binary composition of the NDVI quality band from MODIS 250 meters spatial resolution.



Appendix 4: Statistic of Regression tree

GUIDE version 2.1
Build date: May 9, 2004
Copyright (c) 1997-2004 by Wei-Yin
Loh

This job was started on: 06/18/06 at 23:09

Least squares
regression
Data description file is: ROI34-37_1_desc.txt
Training sample file is: G:\ROI34-37_1.txt
Missing value code is: ?
Piecewise forward and backward stepwise
regression
Using as many variables as needed
F-to-enter and F-to-delete = 4.00000000000000 3.99000000000000

Variables in data file are (d=dependent, c=categorical, w=weight, x=excluded,
n=numerical var for fitting and splitting, f=fitting only,
s=numerical for splitting only):

Column number	Variable name	Variable type	Minimum value	Maximum value	Number of categories
1	B1	x			
2	B2	n	1.6230E+03	2.3500E+03	
3	B3	n	1.0659E+01	1.8713E+01	
4	B4	n	2.4000E+02	4.8200E+02	
5	B5	c		9	
6	B6	d	2.1700E-01	6.0590E-01	
7	B7	n	1.4700E+02	1.9780E+03	

Total #cases	#cases w/ miss. Y	#cases w/ miss. val	#x-var	#n-var	#f-var	#s-var	#c-var
625	0	0	1	4	0	0	1

No weight variable in data file

Split values for numer. vars based on exhaustive search
Variable selection via interaction-and-curvature tests
Minimum number of cases (MINDAT) = 6
Prune by v-fold cross-validation, with v = 625

No calibration
Number of terminal nodes in maximal tree: 79

SE-rule trees based on number of SEs = 5.0000E-
01

Tree	#Tnodes	Mean MSE	SE(Mean)	BSE(Mean) M	edian MSE B	SE(Median)
0	79	1.77E-03	1.76E-04	1.71E-04	3.73E-04	4.57E-05
1	77	1.73E-03	1.76E-04	1.68E-04	3.45E-04	3.94E-05
2	76	1.73E-03	1.76E-04	1.69E-04	3.45E-04	4.06E-05
3	74	1.73E-03	1.76E-04	1.71E-04	3.45E-04	3.68E-05
4	73	1.73E-03	1.76E-04	1.69E-04	3.45E-04	3.87E-05
5	72	1.73E-03	1.76E-04	1.70E-04	3.45E-04	3.85E-05
6	71	1.76E-03	1.79E-04	1.66E-04	3.51E-04	4.33E-05
7	68	1.76E-03	1.79E-04	1.77E-04	3.73E-04	3.92E-05
8	67	1.75E-03	1.79E-04	1.73E-04	3.59E-04	3.92E-05
9	66	1.73E-03	1.78E-04	1.88E-04	3.51E-04	4.16E-05
10	65	1.72E-03	1.78E-04	1.82E-04	3.51E-04	3.98E-05
11	64	1.73E-03	1.79E-04	1.89E-04	3.51E-04	4.06E-05
12	63	1.72E-03	1.79E-04	1.71E-04	3.45E-04	3.97E-05
13	61	1.70E-03	1.79E-04	1.85E-04	3.40E-04	3.56E-05
14	59	1.67E-03	1.73E-04	1.74E-04	3.44E-04	4.06E-05
15	58	1.68E-03	1.73E-04	1.67E-04	3.51E-04	3.81E-05
16	56	1.70E-03	1.73E-04	1.69E-04	3.71E-04	3.66E-05
17	55	1.58E-03	1.50E-04	1.49E-04	3.44E-04	4.13E-05
18	52	1.58E-03	1.52E-04	1.52E-04	3.42E-04	4.60E-05
19	51	1.57E-03	1.52E-04	1.55E-04	3.40E-04	4.30E-05
20	50	1.57E-03	1.51E-04	1.60E-04	3.40E-04	4.37E-05
21+	49	1.57E-03	1.51E-04	1.55E-04	3.40E-04	4.46E-05
22	47	1.58E-03	1.51E-04	1.47E-04	3.42E-04	4.52E-05
23	46	1.58E-03	1.51E-04	1.58E-04	3.46E-04	4.78E-05
24	44	1.60E-03	1.53E-04	1.50E-04	3.45E-04	4.73E-05
25	43	1.55E-03	1.45E-04	1.39E-04	3.45E-04	4.47E-05
26+	42	1.54E-03	1.45E-04	1.46E-04	3.46E-04	4.40E-05
27	41	1.56E-03	1.45E-04	1.38E-04	3.75E-04	4.45E-05
28	39	1.56E-03	1.45E-04	1.46E-04	4.01E-04	4.50E-05
29	38	1.58E-03	1.45E-04	1.48E-04	4.12E-04	4.57E-05
30	37	1.58E-03	1.45E-04	1.39E-04	4.12E-04	4.90E-05
31	35	1.57E-03	1.45E-04	1.46E-04	4.12E-04	4.76E-05
32	34	1.56E-03	1.45E-04	1.47E-04	3.85E-04	4.73E-05
33	33	1.55E-03	1.46E-04	1.47E-04	3.73E-04	4.70E-05
34	32	1.56E-03	1.46E-04	1.52E-04	3.85E-04	5.00E-05
35	31	1.56E-03	1.46E-04	1.52E-04	3.69E-04	4.35E-05
36	30	1.57E-03	1.47E-04	1.52E-04	3.73E-04	4.61E-05
37	27	1.62E-03	1.59E-04	1.65E-04	3.81E-04	4.20E-05
38	26	1.56E-03	1.57E-04	1.59E-04	3.81E-04	4.20E-05
39	25	1.56E-03	1.55E-04	1.50E-04	3.86E-04	4.34E-05
40	23	1.52E-03	1.45E-04	1.44E-04	4.12E-04	4.27E-05
41	22	1.52E-03	1.42E-04	1.50E-04	4.60E-04	4.69E-05
42	21	1.57E-03	1.42E-04	1.43E-04	4.91E-04	4.64E-05
43	20	1.58E-03	1.41E-04	1.45E-04	5.17E-04	5.11E-05
44	19	1.59E-03	1.42E-04	1.44E-04	5.22E-04	5.26E-05
45	17	1.55E-03	1.40E-04	1.42E-04	5.28E-04	5.02E-05
46	16	1.48E-03	1.31E-04	1.27E-04	5.28E-04	5.00E-05
47	15	1.48E-03	1.31E-04	1.31E-04	5.22E-04	5.18E-05
48*	14	1.43E-03	1.15E-04	1.12E-04	5.16E-04	4.68E-05
49*	* 13	1.45E-03	1.17E-04	1.24E-04	5.16E-04	4.82E-05

50	12	1.50E-03	1.21E-04	1.20E-04	5.17E-04	5.00E-05
51	11	1.72E-03	1.65E-04	1.65E-04	5.30E-04	5.39E-05
52	10	1.81E-03	1.64E-04	1.59E-04	5.75E-04	5.20E-05
53	9	2.10E-03	1.75E-04	1.79E-04	6.74E-04	5.37E-05
54	4	2.68E-03	1.94E-04	1.94E-04	1.02E-03	1.16E-04
55	3	3.02E-03	1.97E-04	1.92E-04	1.41E-03	1.08E-04
56	2	3.34E-03	2.03E-04	2.12E-04	1.64E-03	1.45E-04
57	1	5.08E-03	2.99E-04	3.06E-04	2.43E-03	2.23E-04

0-SE tree based on mean is marked with *
Selected-SE tree based on mean using naive SE is marked with
**
Selected-SE tree based on mean using bootstrap SE is marked with --
0-SE tree based on median with finite bootstrap SE is marked with +
Selected-SE tree based on median and bootstrap SE is marked with ++
** tree same as -- tree

Following tree is based on median with bootstrap SE estimate.

Structure of final tree. Each terminal node is marked with a T.
Only cases with positive weights and non-missing
numerical covariate values are used to fit nodes

Y-mean is mean of nonmissing Y values
Fitted cases are those non-missing in selected variables
MSE and R^2 are based on complete cases

Node label	No. case	Cases s fit	Mat. rank	Node Y-mean	Node MSE	Node S R^2	plit variable	Interact. variable
1	625	625	4	3.69E-01	5.05E-03	0.0769	B3	B3
2	241	241	4	3.49E-01	2.31E-03	0.6419	B4	B4
4	176	176	4	3.47E-01	1.67E-03	0.7911	B2	B4
8	88	88	5	3.59E-01	1.14E-03	0.9013	B2	B2
16T	22	22	4	4.16E-01	5.57E-04	0.9655	B3	B2
17	66	66	5	3.40E-01	7.31E-04	0.9215	B7	B3
34	24	24	3	4.26E-01	1.07E-03	0.8655	B7	B2
68T	8	8	1	5.04E-01	8.29E-04	0		
69	16	16	3	3.87E-01	8.93E-04	0.867	B3	B2
138T	9	9	3	3.50E-01	1.54E-04	0.8945		
139T	7	7	3	4.33E-01	5.17E-04	0.9599		
35	42	42	4	2.91E-01	3.96E-04	0.8779	B3	B2
70T	14	14	3	2.72E-01	4.95E-05	0.814	B2	B3
71T	28	28	5	3.00E-01	3.37E-04	0.9314	B5	B4
9	88	88	3	3.35E-01	1.63E-03	0.6492	B4	B4
18	20	20	3	3.37E-01	8.09E-04	0.7184	B4	B3
36T	8	8	3	2.87E-01	6.16E-05	0.8445		
37T	12	12	2	3.71E-01	5.26E-04	0.5946	B2	B4

19	68	68	3	3.34E-01	1.62E-03	0.6951	B3	B4
38	44	44	3	3.14E-01	1.42E-03	0.6922	B3	B2
76	36	36	2	2.90E-01	9.24E-04	0.4719	B3	B7
152	15	15	1	2.60E-01	6.37E-04	0	B2	B7
304T	7	7	2	2.71E-01	2.30E-04	0.4991		
305T	8	8	4	2.51E-01	5.34E-05	0.9579		
153T	21	21	3	3.12E-01	4.99E-04	0.6695	B4	B3
77T	8	8	1	4.21E-01	2.34E-03	0		
39	24	24	4	3.71E-01	1.33E-03	0.7521	B7	B7
78	16	16	2	3.98E-01	1.10E-03	0.6158	B2	B3
156T	6	6	1	3.83E-01	5.83E-04	0		
157T	10	10	3	4.07E-01	6.61E-04	0.8673		
79T	8	8	5	3.18E-01	8.48E-05	0.9922		
5	65	65	3	3.56E-01	1.51E-03	0.3796	B3	B2
10T	12	12	4	3.13E-01	3.05E-04	0.8463		
11	53	53	3	3.66E-01	1.35E-03	0.374	B7	B7
22T	29	29	3	3.67E-01	8.81E-04	0.3168	B2	B2
23T	24	24	4	3.66E-01	1.29E-03	0.6501	B2	B2
3	384	384	4	3.81E-01	3.89E-03	0.1369	B5	B7
6	359	359	5	3.90E-01	3.29E-03	0.102	B5	B7
12	352	352	3	3.90E-01	3.50E-03	0.0513	B5	B3
24	113	113	3	3.83E-01	1.81E-03	0.5707	B4	B4
48	66	66	4	3.66E-01	9.28E-04	0.8074	B2	B2
96T	10	10	2	4.06E-01	1.32E-03	0.6849		
97	56	56	3	3.58E-01	4.43E-04	0.9044	B4	B4
194T	33	33	3	3.11E-01	3.38E-04	0.7867	B2	B2
195T	23	23	3	4.26E-01	2.54E-04	0.7153	B3	B3
49	47	47	3	4.08E-01	7.38E-04	0.7212	B3	B3
98	40	40	2	4.17E-01	5.99E-04	0.6798	B2	B7
196T	8	8	2	4.69E-01	9.07E-04	0.4329		
197T	32	32	3	4.04E-01	3.83E-04	0.6787	B7	B4
99T	7	7	2	3.59E-01	8.20E-04	0.839		
25	239	239	4	3.94E-01	3.20E-03	0.0785	B7	B7
50	74	74	2	4.23E-01	1.78E-03	0.1516	B4	B4
100	50	50	3	4.26E-01	6.96E-04	0.5079	B4	B4
200T	8	8	3	3.95E-01	1.37E-03	0.7683		
201T	42	42	3	4.31E-01	4.06E-04	0.4354	B2	B2
101	24	24	4	4.17E-01	1.18E-03	0.7174	B3	B3
202T	16	16	4	4.44E-01	3.37E-04	0.8747	B4	B4
203T	8	8	5	3.63E-01	8.80E-05	0.984		
51	165	165	3	3.81E-01	2.94E-03	0.1703	B2	B2
102	39	39	2	4.03E-01	1.45E-03	0.41	B4	B3
204T	24	24	2	4.20E-01	1.14E-03	0.5853	B7	B2
205T	15	15	2	3.74E-01	3.97E-04	0.5283	B3	B3
103	126	126	3	3.74E-01	2.83E-03	0.2412	B3	B3
206	33	33	5	4.33E-01	2.42E-03	0.6399	B4	B3
412	25	25	4	4.26E-01	1.54E-03	0.7262	B2	B2
824T	12	12	3	4.21E-01	4.95E-04	0.9504	B2	B7
825T	13	13	2	4.31E-01	1.04E-03	0.5858	B7	B4
413T	8	8	4	4.54E-01	2.85E-04	0.9826		

207	93	93	3	3.53E-01	1.02E-03	0.201	B4	B7
414	60	60	3	3.49E-01	9.59E-04	0.4218	B2	B2
828	34	34	2	3.55E-01	9.77E-04	0.2842	B4	B7
1656T	13	13	1	3.49E-01	6.35E-04	0	B2	B4
1657T	21	21	3	3.59E-01	7.21E-04	0.6318	B3	B3
829	26	26	3	3.41E-01	8.28E-04	0.6021	B4	B4
1658T	19	19	3	3.50E-01	4.26E-04	0.8196	B3	B3
1659T	7	7	4	3.15E-01	1.26E-05	0.9902		
415	33	33	1	3.61E-01	5.54E-04	0	B3	B3
830T	20	20	2	3.54E-01	2.70E-04	0.4762	B4	B7
831T	13	13	1	3.71E-01	5.10E-04	0	B2	B4
13T	7	7	3	3.62E-01	4.01E-05	0.8925		
7	25	25	2	2.59E-01	4.16E-04	0.4122	B5	B3
14T	10	10	1	2.84E-01	3.01E-04	0		
15T	15	15	3	2.42E-01	1.06E-04	0.6115	B4	B4

Appendix 5: Natural vegetation coordinates. Field data

Id	Coord_X	Coord_Y	NDVI ratio
1	569506	4185028	0.93300
2	569800	4175201	0.87346
3	512694	4085573	0.79344
4	517758	4083766	0.95024
5	566179	4167385	0.76958
6	551733	4122194	1.19000
7	545758	4123804	0.80789
8	533085	4118533	1.11090
9	507104	4101922	1.25000
10	614800	4139947	0.78000
11	609051	4124442	0.58418
12	593607	4137157	0.81450
13	593556	4093648	0.98842
14	589215	4103410	0.92298
15	588930	4077994	0.59189
16	577429	4082852	1.16650
17	575848	4065928	0.86062
18	537000	4088457	0.96024
19	521508	4062304	0.54510
20	567072	4081754	0.98814
21	538937	4107646	0.91038
22	595309	4126561	0.83302
23	602518	4118583	0.81099

24	594911	4151732	1.04932
25	504634	4089258	0.83338
26	536758	408954	0.78438
27	595258	4126554	0.83321
28	542758	4120804	1.64068
29	498508	4107054	0.91634
30	595758	4095304	1.03939
31	609008	4124554	0.58418
32	589356	4090628	1.16992
33	593258	4087554	0.86041