Remote sensing and geographical modelling to assess *montado* change patterns: causes, impacts and biogeophysical process

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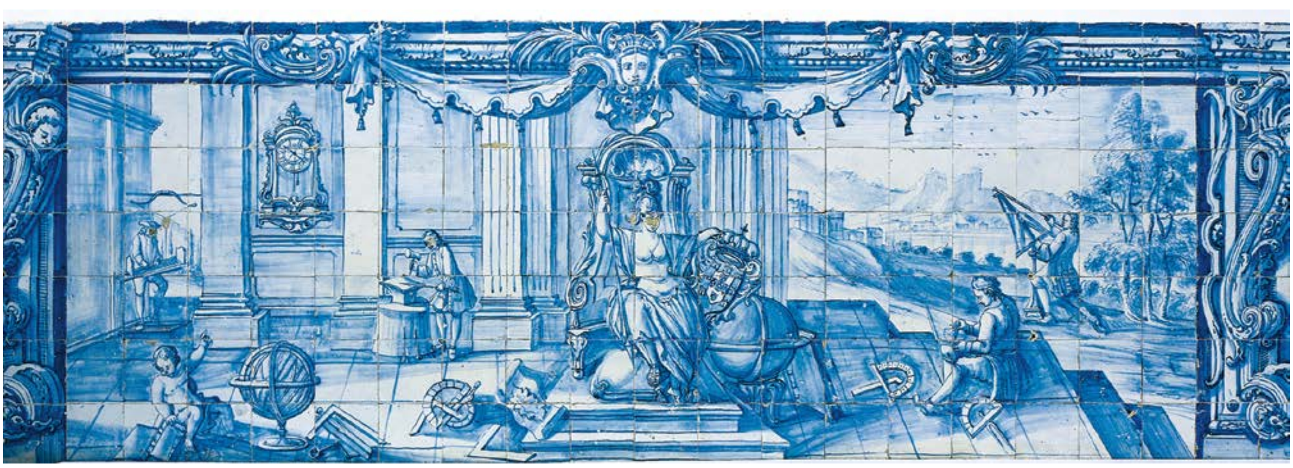

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Index

Abstract

The magnitude of *montado* change patterns over times, as well as their causes and effects on natural process, remains poorly understood. A comprehensive analysis of these spatio-temporal processes using an integrated and multidisciplinary approach was implemented in this doctoral thesis to better understand the main causes and impacts of *montado* landscape changes. The main goal of this doctoral thesis was to analyse the *montado* landscape dynamics by using cartographic information and remote sensing-derived data for assessing change patterns, its causes and impacts on biogeophysical processes. The central topic of this thesis was to study the usefulness and effectiveness of Earth Observation Satellites (EOS) in providing accurate and comparable *montado* land cover information to support detailed long-term landscape change analysis. To achieve such goal four specific research objectives were addressed: (i) determine the recent spatio-temporal patterns of *montado* changes in southern Portugal; and identifying the effects of selected environmental, land management, and spatial factors in these changes; (ii) explore the capability of EOS and advanced image classification techniques for producing accurate *montado* land cover maps; (iii) assess the effectiveness of existing remote sensing-based approaches for estimating the percentage of *montado* tree canopy cover at the pixel level; and (iv) develop an effective remote sensing-based methodological approach to understand the effects of *montado* canopy cover decrease in local land surface biogeophysical process dynamics. From the investigations conducted, a decline trend of *montado* ecosystem was clearly identified through the estimated *montado* area and tree canopy cover regression. Furthermore, the demonstrated usefulness and effectiveness of EOS was one of the most important outputs of this thesis towards a broader long-term *montad*o change analysis which may also include the assessment of its effects on local biogeophysical processes.

Keywords: *montado/dehesa; remote sensing; landscape change; landscape drivers; biogeophysical processes*

Detecção Remota e modelação geográfica para avaliar os padrões de alteração do montado: causas, impactes e processos biogeofisicos

Resumo

A magnitude dos padrões de alteração do *montado* ao longo do tempo, bem como as suas causas e efeitos nos processos naturais, continua pouco estudada. Uma análise compreensiva destes processos espacio-temporais usando uma abordagem integradora e multidisciplinar foi implementada nesta tese de doutoramento para melhor conhecer as grandes causas e impactes das alterações da paisagem de *montado*. O grande objectivo desta tese de doutoramento foi analisar as dinâmicas do *montado* através da utilização de informação cartográfica e dados derivados de detecção remota para avaliar os padrões de alteração, as suas causas e impactes nos processos biogeofisicos. O tópico central desta tese foi estudar a utilidade e a eficácia dos Satélites de Observação da Terra (SOT) em providenciarem informação comparável e precisa da cobertura espacial do *montado* que permitam análises mais detalhadas sobre as alterações deste sistema numa prespectiva de longo termo. Para atingir este propósito quatro objectivos específicos de investigação foram tidos em conta: (i) determinar os padrões de alteração espacio-temporais recentes da paisagem de *montado* no sul de Portugal; (ii) explorar as capacidades dos SOT e de técnicas avançadas de classificação de imagem para produzir mapas de ocupação do *montado* com elevada exactidão. (iii) analisar a eficácia de abordagens de detecção remota existentes para estimar a percentagem de cobertura das copas das árvores do *montado* à escala do pixel; e (iv) desenvolver uma abordagem metodológica com recurso a técnicas de detecção remota para compreender os efeitos da perda de cobertura das copas do *montado* na dinâmica dos processos biogeofísicos à escala local. Com base na investigação levada a cabo, identificou-se a tendência clara de declínio do ecossistema *montado* através das estimativas da regressão na área ocupada por *montado* bem como da redução da percentagem de cobertura por copas. Para além disso, a demonstração da utilidade e eficácia dos SOT para apoiar uma análise mais abrangente das alterações do *montado*, bem como os seus efeitos nos processos biogeofísicos locais, foi um dos resultados mais importantes desta tese.

Palavras-chave: *montado/dehesa; detecção remota; alterações da paisagem; drivers da paisagem; processos biogeofisicos*

Chapter

1

General Introduction

1.1. Thesis Focus and main goals

Changes in Earth´s ecological systems have been considered as one of the main global environmental problem and consequently as an alert to the long-term human life sustainability (Hooke, 2012). Key ecological, biogeochemical and biogeophysical processes have been altered mainly as a result of land use and land cover changes, which in turn may have important effects on the local and regional climate (MEA, 2005; Claussen et al., 2001; Lawrence et al., 2012). The magnitude and increasing rate of these changes mean that ecosystems are, and will continue to be, affected. Altering ecosystems functioning leads to huge modifications in several and crucial ecosystems services such as water recycling, food production, biodiversity conservation, and climate regulation, therefore affecting the sustainability worldwide (Foley et al., 2005; Pielke, 2005).

Many of the most rich ecosystems around the world have resulted from changes induced by human action. At a higher scale, ecosystems are organized in landscapes. Landscapes have been changed or transformed significantly all over the world by anthropic activities in order to meet the needs of human societies (Emanuelsson 2009; Plieninger and Bieling, 2012). The rates and types of human-induced landscape changes throughout the ages depend on several economic, social and cultural activities that vary in their scale, intensity and impact (e.g. Vitousek et al. 1997; Bürgi et al. 2004). Human population increase and the resulting demand for more resources, such as soil and water for food production, are pointed out as the main causes of land use and cover changes

(Hooke, 2012). In fact, this same author argued that more than 50% of the Earth´s surface has been modified by human activities.

As a reflection of the ancient history of human occupation and intervention, the Mediterranean region is one where the human-nature interaction has been longest and most diverse, and has been interpreted as a 10,000 year story of human-nature interaction (Blondel 2006; Blondel et al. 2010). As a result, one of the most evident human-induced impacts on the Mediterranean landscapes was a huge and progressive deforestation process over the past millennium (Blondel and Aronson, 1999). Historical records reveal that forest areas dominated in the past almost everywhere in the Mediterranean Basin (Grove and Rackham, 2003). Indeed, as stated by Blondel and Aronson (1999) "*during the sixteenth century the armies of Charles-Quint travelled across Spain and France without ever leaving the shadow of tree canopy"*, thus revealing the dominance of dense forests in the western part of the Mediterranean region in the past. Currently, Mediterranean forests are reduced to 9-10% of the region's total land area (Matteucci et al., 2013). From this long-term human-induced forest clearings, large oak woodland areas in some Mediterranean native ecosystems were transformed into a savannah-like landscape (or oak parkland) that is predominant in the western Iberian Peninsula, the so-called "*montado*" in Portugal and "*dehesa*" in Spain (Blondel and Aronson 1999; Joffre et al. 1999; Vicente and Alés 2006; Surová and Pinto-Correia 2008; Acácio and Holmgren 2012).

Montado/*dehesa* is one of the most characteristic and important ecosystems existing in the Mediterranean basin, occupying an area of about 3.5-4.0 million hectares (Olea and San Miguel-Ayanz, 2006). It constitutes complex agroforestry system with high tree spatial variability (*Quercus suber* and/or *Q.* [*ilex*] *rotundifolia*) and an understory mosaic of annual crops, grasslands and shrublands (Joffre et al., 1999). These land uses are exploited as a multifunctional system to produce cork, firewood, charcoal, acorns and pastures for livestock feeding and grazing. Wild game, cultural and recreational services such as ecotourism are also considered as relevant and profitable goods and services of this agroforestry system (Joffre et al., 1999; Bugalho et al., 2009; Coelho and Campos, 2009; Pinto-Correia et al., 2011). Furthermore, the *montado* ecosystem is considered as one of the highest biodiversity-rich ecosystems of the western Mediterranean Basin (Branco et al., 2010; Díaz-Villa et al., 2003) , and also of Europe, being often presented as a biodiversity hotspot and a paradigmatic example of a High Nature Value farming system (HNV) (Oppermann et al., 2012).

Despite the socio-economic and environmental importance of *montado* ecosystem, a decline trend has been reported throughout its distribution area, and is driven by a combination of several factors over time (Brasier, 1996; Cano et al., 2006; Carvalho, 1870; Ferreira, 2001; Gallego et al., 1999; Linaldeddu et al., 2013). Understanding when, where and how the *montado* landscape has changed is important to develop new insights into the spatio-temporal dynamics and long-term resilience of this agroforestry system. The development of detailed studies focused on *montado* land cover changes, its causes and impacts on biogeophysical mechanisms is crucial to understand the overall process and to support policy makers in their decision process. However, the main outputs of these studies, which need to be precise, consistent, and effective, are mostly dependent on the availability, comparability and accuracy of *montado*-related spatial information for a medium/long time period (e.g. ~30 years). In Portugal, such required detailed approaches are restricted to the temporal coverage of the available national land use/land cover cartographic information (e.g. COS 1990, 2007, forestry inventories), which is insufficient to understand in depth the patterns and trends of *montado* ecosystem changes at a large temporal scale. Long-term *montado* landscape change analysis has been performed in Portugal at local scale by using available aerial photographs since the 1950s (e.g. Acácio et al., 2009; Costa et al., 2009). Aerial photo interpretation can be used for *montado* cover mapping, however this task is often time consuming, too expensive, and limited in providing spatially continuous information over large territories. Therefore, it is critical to develop effective spatial information systems, namely with remote sensing-based methodologies to monitor and systematically assess *montado* ecosystem condition at a comprehensive spatio-temporal scales, as well as to assess and co-relate the effects of environmental, socio-economic and other geographical factors that may act as driving forces in *montado* landscape changes.

An important variable to support a comprehensive *montado* landscape change analysis is the information on the spatio-temporal dynamics of *montado* trees. Changes in *montado* landscape are primarily manifested through the variability of tree cover density over time (Plieninger and Schaar, 2008). Tree canopy cover plays a fundamental role in *montado* ecosystem processes, such as water recycling, surface cooling and shelter to a high number of species (e.g. Bugalho et al., 2011; Díaz et al., 2003; Godinho and Rabaça, 2011; Plieninger and Schars, 2008). In addition, *montado* tree cover constitutes an important parameter for a more accurate identification of *montado* areas as High Natural Value farmlands (HNV) (Almeida et al., 2013). Changing *montado* tree canopy cover can disrupt the functioning of the ecosystem and services they provide, and can particularly modify key biogeophysical processes such as Land Surface Albedo (LSA) and Land Surface Temperature (LST), and hence alter the micrometeorological conditions (Bonan, 2008). Although changes in *montado* tree canopy cover show dominant biogeophysical impacts at local scale (being consequently more relevant for land planning and management policies), research progresses on this issue are hindered by certain limitations of existing data and methods (e.g. Li et al., 2015). Thereby, regular and accurate *montado* land cover information at high spatial resolution is essential to undertake these types of analysis. Earth Observation Satellites (EOS) permit repeated and consistent assessment and monitoring of the local effects of landscape changes, improving therefore our understanding of these issues and also allowing a better support for decision-making process (planning and management). Using remote sensing technology, land cover mapping can be gathered by deploying a reduced amount of field data, therefore making it more cost-effective (Bhandari et al., 2012; Franklin et al., 2000; Rogan and Chen, 2004).

Hence, this thesis focuses on the study of *montado* landscape dynamics by using cartographic information and remote sensing-derived data for assessing change patterns, its causes and impacts on biogeophysical processes. Remote sensing techniques and advanced image classification methodological approaches are the one of the main foundations of this thesis, as this dissertation is focused on the study and assessment of the usefulness and effectiveness of EOS for producing accurate and up-to-date *montado* land cover information as a key data source to understand the local effects of *montado* landscape change.

Accordingly, this thesis has four specific research goals:

i. Determine with the most possible accuracy the recent spatio-temporal patterns of *montado* changes in southern Portugal; and identifying the effects of selected environmental, land management, and spatial factors in these changes;

ii. Exploring the capability of EOS and advanced image classification techniques for producing accurate *montado* land cover maps;

iii. Assessing the effectiveness of existing remote sensing-based approaches for estimating the percentage of *montado* tree canopy cover at the pixel level;

iv. Developing an effective remote sensing-based methodological approach to understand the effects of *montado* canopy cover decrease in local land surface biogeophysical process dynamics.

1.2. Outline of the thesis

This thesis consists of six main chapters. The organization and connection among them were established in order to increase the knowledge on the *montado* landscape change process; on improving the accuracy of *montado* land cover information estimation by using remote sensing tools; and also on inferring change effects in biogeophysical processes at a local scale. The main chapters include an introduction; four scientific papers, published (Chapters 2 and 4) or submitted for publication (Chapters 3 and 5) in international peer reviewed journals; and a section of general conclusions. All six chapters are organized as follows:

- Chapter 1 (this one) provides the general introduction which includes the thesis focus, its main objectives, the thesis structure, and also a brief background for the most important topics addressed in this research.
- Chapter 2 presents the changes detected in the *montado* distribution pattern for southern Portugal from 1990 and 2006. It also evaluates the relative effects of selected environmental, land management, and spatial factors on *montado* land cover change. To achieve this, a geoprocessing approach was developed to extract *montado* areas using CORINE land cover maps (1990

and 2006) as the main data source, as well as the national land cover maps (COS 1990 and 2007) and the forest inventories as auxiliary information. A three-stage statistical analysis involving exploratory analysis, model building using generalized additive models (GAM), and variance partitioning were used to assess the relative effects of the abovementioned factors on recent *montado* change patterns.

- Chapter 3 introduces the effectiveness of EOS for producing accurate *montado* land cover information. In fact, Chapter 2 only reports results on *montado* land cover changes from a short time period due to the lack of accurate and comparable multi-temporal *montado* land cover maps. To contribute for a broader long-term *montado* change analysis, Chapter 3 presents a thorough and effective methodological approach for *montado* ecosystem mapping by using a classification scheme which integrates remote sensing multispectral data, vegetation indices, and an advanced machine learning algorithm, which can be applied using current (Landsat 8 OLI) and past mission Landsat data (TM and ETM+ sensors).
- Chapter 4 investigates the applicability and effectiveness of Forest Canopy Density model (FCD), which is a remote sensing-based approach developed for tropical forest, for estimating *montado* canopy density at the pixel level. Chapter 4 discusses the potential usefulness of tree canopy density information to promote a more accurate identification and assessment of *montado* areas as HNV farmlands.
- Chapter 5 focuses on the effects of long-term (1987-2011) *montado* tree canopy cover decrease on local biogeophysical processes, namely Land Surface Albedo (LSA) and Land Surface Temperature (LST). In fact, Chapter 4 showed some limitations of the FCD model for estimating accurately the percentage of *montado* canopy cover, mainly in very sparse *montado* areas (11% – 40% tree cover class). Thus, the first part of Chapter 5 is dedicated to the development of a remote sensing-based approach for accurately estimating the percentage of *montado* tree canopy cover for 1987 and 2011 at pixel level. This same chapter shows how *montado* canopy cover decrease over a 24-years period may have modified local land surface

biogeophysical properties, discussing at the same time their implications to local/regional climate changes.

- Chapter 6 summarizes and integrates in a broader discussion perspective, the main achievements obtained in the previous four chapters, as well as their main conclusions and implications to the overall understanding of *montado* landscape dynamics, its causes and effects. At the end, this chapter provides some suggestions for future work, emphasizing topics for which further research is needed in the field of applied remote sensing and *montado* dynamics effects on local/regional climate changes.

1.3. Background

1.3.1. Historical perspective of *montado* landscape changes

Different trends of *montado* gain and loss, as well as different driving forces acting in the *montado* landscape change process have been occurring over time. A long-term analysis carried out by Ferreira (2001) indicates that *montado* land cover in southern Portugal has experienced profound changes in the last 100 years (Figure 1). These changes were clearly related to particular socioeconomic, political, technological, natural and cultural driving forces that vary across and within particular periods and regions.

Figure 1 – Example of montado landscape conversion to crop/pasture lands in southern Portugal (Cabeção Village)

Around the year 1880, practically all Europe underwent a serious crisis in the agricultural sector due to the invasion of cheaper agricultural products (mainly cereals) from the U.S.A., Canada, Argentina and Russia (Reis, 1979; O'Rourke, 1997; Swinnen, 2009). In Portugal, due to this crisis and the high price of fertilisers (superphosphate), the agricultural sector was not economically viable for landowners. In order to reverse the agricultural crisis, the first supportive regulations for wheat production were published, which included a review of wheat prices to higher values as well as the implementation of import barriers in order to protect national producers ("Elvino de Brito Cereal Law"; Reis, 1979). The interaction between the wheat policies protection, the significant decrease in superphosphate prices and the abundant human workforce availability, caused the rapid expansion of cultivated areas with arable crops (mainly wheat). This crop increase was inversely proportional to the *charneca* area dimension (a *maquis* type land cover, where bushes and shrubs dominate the *Quercus spp.* trees), since *charneca* clearing for dense bush and shrub removal provided open extensive areas for cultivation and/or for restoring the grassland natural pasture (Carvalho, 1870; Crespo, 2006). During these cleaning operations, scattered holm and cork oak trees were maintained due to the manual operations operated by human workforce and by using traditional narrow pulled by animals (Bugalho et al., 2009). During this process, the area of arable crops increased and the *montado* area also benefited as a sub-product of *charneca* clearance driven by cereal cultivation. This *montado* formation stage, which mainly occurred between 1880 and 1920, reflects the reduction in *charneca* area and a strong increase in *montado* area (Ferreira, 2001). Indeed, it was estimated that *montado* ecosystem covered an area of about 370,000 ha in 1867 and 868,850 ha in 1902 (Vieira, 1991).

With the establishment of the dictatorial regime of government in Portugal (1926–1974) the cereal agriculture was the object of a new reform, with the so-called "Wheat Campaign" implemented in 1929, in order to increase its national production (Saraiva, 2010). The increase in *montado* area in the first quarter of the 20th century was gradually replaced by a large degradation stage (Ferreira, 2001) due to the first wave of agricultural mechanisation started in the middle of 1930s (Leeds, 1983). This degradation stage was markedly higher from 1950 until the early years of the 1960s, where the use of fertilisers and machinery received intensive financial support. With an increase in agricultural mechanisation, traditional *montado* management was progressively replaced by less labour demanding practices. As the labour demand decreased, the rural depopulation trends started, and progressively, when needed, the required day-wage labor was more difficult to arrange. The synergy among the "Wheat Campaign" goals, and the progressive mechanisation constituted a significant driver in agricultural land expansion, as thousands of hectares of land in southern Portugal were cleaned and intensively cultivated with wheat, even in the poorest soils (Natividade, 1950). The intensive cereal cultivation between 1930–1960 (Figure 2) has led to soil depletion; destruction of the natural regeneration process of cork and holm oak; and partial or total elimination of trees towards open fields for cereal cultivation, with more negative impacts on marginal soils (Ferreira, 2001; Pinto-Correia and Vos, 2004; Mendes, 2007). The gradual development of farm mechanisation led to the general use of wide plows, disc harrows and scarifiers (Bugalho et al., 2009). According to the same author, this heavy machinery unselectively destroys young trees and damage the roots, therefore weakening established trees. Another relevant problem for *montado* conservation arrived with the propagation of African swine fever in the 1960s. Pig ranging, with the Iberian balck pig, was so far one of the most spread livestock use of the *montado*, as pigs profit in the best way from the acorns feed value. This disease prophylaxis implied the prohibition of grazing pigs, accelerating therefore the destruction of significant areas of holm oak *montado* to promote more open grazing areas for cattle, or even other land use types with better economic returns (Crespo, 2006).

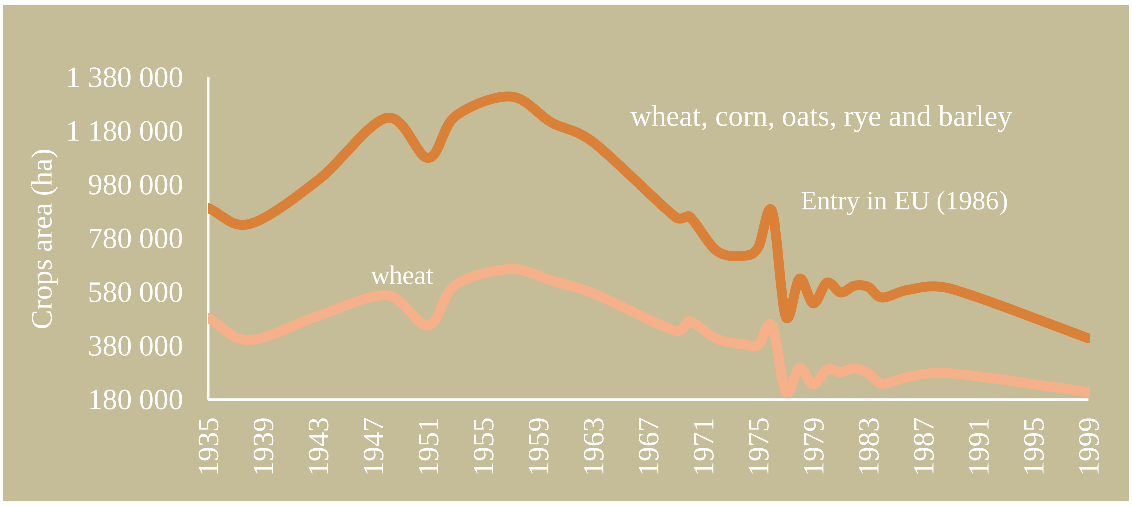

Figure 2 – Evolution of cereal crops area (ha) in southern Portugal since 1935 until 1999. Data used to perform the graph was obtained from official agriculture statistics available in https://www.ine.pt.

After the establishment of democracy in 1974, an agrarian reform was implemented (1975–1979) and intensive cereal production returned, mainly in the abandoned *montado* areas. This new intensification phase was short-lasting but very aggressive due to the intensive use of heavy machinery, as many trees were uprooted (Ferreira, 2001). Therefore, the trends of *montado* decrease observed in this period reflect, in particular, the holm oak *montado* decline caused by the propagation of swine fever, use of heavy machinery and intensive cereal cultivation.

From 1980 to 2000, changes in the economic context of farming mainly induced by several financial support programs of pre and post-adhesion to the European Economic Community (EEC) in 1986 and consequently to the Common Agricultural Policy (CAP), led to an increase in difficulties for maintaining the traditional agricultural system. Under such EEC policies, in particular those with more focus on southern Portugal, *montado* land use and its respective options of management strategies were mostly determined by CAP subsidies, instead of by management strategies based on *montado* singularities and needs (Pinto-Correia and Mascarenhas, 1999). During the first decade of Portugal in the EEC (1986–1996), livestock, together with sunflowers and tomatoes, were the most profitable activities for the private agroforestry economy (Jones et al., 2011). The economic attractiveness of the CAP incentives for livestock production (where cattle gets by far the highest payment), supported by payments to farmers based on a per-head basis, the so-called coupled payments (Bugalho et al., 2011), led many landowners to intensively explore this financial support. As a consequence large *montado* areas were intensively grazed with severe negative impacts for the balance of the system. On another side, since 1990, European Union (EU) policies have stimulated the implementation of large areas of new cork oak plantations, in particular in set-aside agricultural lands. These new plantations have mainly been established as forestry, due to the EU goals, and thus in this particular case, aiming for cork production purposes. Consequently they presented higher stand densities than traditional agroforestry systems (Coelho et al., 2012). It is known that between 1990 and 2000, 84,000 ha of cork oak were planted in Portugal (Pereira et al., 2010). Nevertheless, these new plantations of cork oak may not be interpreted as a compensatory measure for the huge mature *montado* loss that occurred over the last 100 years. In fact, the loss of mature *montado* areas during this period may constitute a strong influence on environmental processes, including potential regional climate changes, loss of biodiversity, reduction in water quality and ecological functions (e.g. Ferreira, 2001; Lee et al., 2009; Polasky et al., 2011; Wimberly and Ohman, 2004).

Relevant studies on *montado/dehesa* landscape dynamics and their respective driving forces have been conducted in Spain and Portugal, mostly by relating the spatial and temporal changes of this landscape with several drivers (Acácio et al., 2009, 2010; Brasier, 1996; Camilo-Alves et al., 2013; Catry et al., 2012; Costa et al,. 2008, 2010; Cubera and Moreno, 2007; David et al., 1992; Díaz-Delgado et al., 2002; Guiomar et al., 2015; Linaldeddu et al., 2013; Moreira et al., 2006; Pelegrín et al., 2008; Pérez-Sierra et al., 2013; Pinto-Correia, 1993; Pinto-Correia and Vos, 2004; Plieninger, 2006, 2007; Sheffer, 2012; Vicente and Alés, 2006). Despite the existence and recognition of this huge amount of studies dedicated to the *montado*/*dehesa* landscape change analysis and respective drivers, some issues are still remaining and need to be studied (e.g. what are the relative effects of environmental and land management factors in *montado* loss process at a broader scale?). In addition, there is still plenty of room for improving the understanding of *montado* landscape change process as a whole. This may be done through the use of spatial data which production and application are supported by the development of robust and cost-effective remote sensing-based methodological approaches for assessing the spatio-temporal patterns of *montado* changes.

1.3.2. Earth Observation Satellites and *montado* monitoring

Satellite-based Earth observation is the process of studying the Earth and its environment through the so-called remote sensing technique. Remote sensing can be described as the science of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with this same object, area, or phenomenon under investigation (Lillesand and Kiefer, 2000). The electromagnetic energy sensors existing in Earth-orbiting satellites acquire data while earth surface features emit and reflect electromagnetic radiation, being these data posteriorly analysed in order to provide information about the surfaces under investigation.

Earth Observation Satellites (EOS) are artificial satellites intentionally placed into orbit to monitor the Earth from space, acquiring global observations of the land surface, biosphere, solid Earth, atmosphere and oceans (NASA´s Earth Observing Systems, Project Science Office, 2015). Earth orbiting-satellites constitute the most relevant way for providing information on Earth physical, chemical and biological systems at both small and global scales. EOS provide advanced space technology able to map, measure and monitor how, when and where Earth surface and resources are changing across the globe for long periods of time, in an effective, synoptic, systematic and consistent way (Townshend et al., 2008). The era of EOS started around 60 years ago with the launch of the first artificial satellite, Sputnik 1, by the Soviet Union (NASA History Program Office, 2015). Since the launch of Sputnik 1, satellite instrumentation and missions performance have become more and more sophisticated due to the technological development in spaceflights and remote Earth observations systems. The paradigm of Earth observations from space literally changed at the beginning of the 1970s with the emergence of the NASA´s Landsat Program (NASA History Program Office, 2015). The Landsat program provides the largest temporal records of space-based Earth observations, having been acquiring images of Earth's surface for more than 40 years (Roy et al., 2014). In 1972 Landsat 1 was launched, and between 1975 and 2013 six more Landsat missions were successfully launched to the space: Landsat 2 (1975), Landsat 3 (1978), Landsat 4 (1982), Landsat 5 (1984), Landsat 7 (1999) and Landsat 8 (2013).

Since 1972, and including Landsat platforms, 197 individual satellites with a global land cover observing capacity have been successfully launched, of which 98 were still operating at the end of 2013 (Belward and Skøien, 2015). One of the most recent and ambitious Earth observation project is the Copernicus Program from the European Commission (EC) in partnership with the European Space Agency (ESA). In general, this program aims providing accurate, up-to-date and easily accessible satellite-based information in order to support scientific research and policy-making in the fields of environmental management, climate change and civil protection (ESA, 2015). To achieve the main goals of Copernicus Program, ESA is developing a constellation of satellites called Sentinel, which will be launched over time until 2021 (Figure 3). Regarding this Sentinel satellites constellation, Sentinel 1 (acquiring and providing high-resolution Synthetic Aperture Radar data) and Sentinel 2A (acquiring and providing high-resolution multispectral data) are already operational and sending information to the Earth. Sentinel 2B will be launched in 2016 and together with Sentinel 2A they will both provide a global coverage of the Earth's land surface every 5 days.

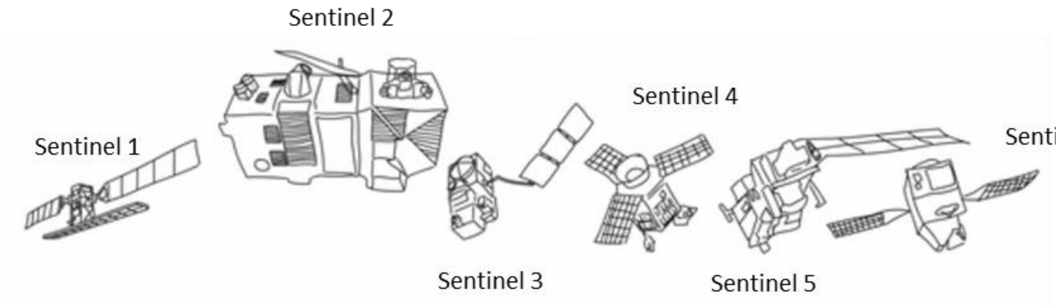

Figure 3 – Sentinel satellites constellation (Source: http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2)

Concerning the national participation in the European Space and Earth Observation sectors, Portugal contributed to ESA programmes with a total value of 111,5 M€ between 2000 and 2009 (Clama Consulting, 2011), demonstrating the strategic importance of these sectors for Portuguese authorities. Indeed, to increase the use of Sentinel satellites data in different sectors and domains, the Directorate-General for the Territory (DGT) and the Portuguese Institute for Sea and Atmosphere (IPMA) recently announced the projection and development of the IPSentinel digital infrastructure (DGT, 2015). This infrastructure will constitute a strategic and multifunctional platform for consulting and accessing both Copernicus ground truth data and Sentinel satellites data acquired for the whole national territory.

Regarding the *montado* ecosystem, which is the case study addressed in this Doctoral project, it is expected that Sentinel 2A and 2B will bring together new research opportunities due to their high spatial, spectral and temporal resolutions (e.g. detailed analysis of ecophysiological responses of *montado* trees to drought events). With the upcoming Sentinel data and with more than 30 years of archived data from the US Landsat Earth-observing satellites, both provided free of charge, a deeper understanding of the past, present and future of *montado* landscape dynamics may be boosted, as well as a relevant improvement of the knowledge related to *montado*'s resilience regarding the synergistic effects of unsustainable land management and climate changes.

Theoretically, spatio-temporal *montado* landscape change analysis can be performed at a spatial resolution of 30 meters since 1982, by using remote sensing information acquired by the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Landsat Operational Land Imager (OLI). Spatial and spectral resolutions of multispectral and thermal data acquired by these Landsat sensors make it suitable for mapping, quantifying and monitoring land cover and land surface biogeophysical properties, and also for better understanding how changes in land surface can affect local and regional climate (Hansen and Loveland, 2012; Wulder et al., 2012; Bonan, 2008). These sensors have been collecting imagery data in the visible, near infrared (NIR), and shortwave infrared (SWIR) portions of the electromagnetic spectrum, making them appropriate for vegetation studies across a wide range of environments (Bhandari et al., 2012; Cohen and Goward, 2004; Jia et al., 2014; Li et al., 2014). However, deriving *montado* land cover information from satellite-based remote sensing data is a complex and challenging task. Nevertheless it constitutes an effort that needs to be widely undertaken in order to produce more accurate spatial information of this ecosystem. The spatial fuzziness of *montado* caused by its tree density variability (Doorn and Pinto-Correia, 2007) associated with dry climate and the occurrence of bare soils, determine the spectral separability between *montado* and other Mediterranean land cover types. The high reflectance from bare soils can overwhelm the reflected components from sparse vegetation such as some *montado* areas (Berberoglu et al., 2000, 2007; Rodriguez-Galiano and Chica-Olmo, 2012). Multi-seasonal images and vegetation indices have been successfully included in the classification process in order to increase the separability between land cover types with similar spectral behaviour (Dash et al., 2007; Gartzia et al., 2013; Li et al., 2011; Oetter et al., 2001; Rodriguez-Galiano et al., 2012a; Senf et al., 2015).

The potential of moderate resolution EOS for periodically and consistently producing accurate *montado* spatial information to support long-term monitoring studies in southern Portugal, has never been specifically addressed by the scientific community. Considering the spatial, spectral and radiometric resolutions of Landsat data; and considering also the existence of more than 30 years of archived information as a strategic asset, a relevant research question must be addressed: it is possible to produce accurate *montado* land cover maps using such data? This Doctoral project aims to address this specific question by testing the integration of multi-seasonal images and vegetation indices into a remote sensing-based methodological approach including also the application of an advanced machine learning algorithm.

1.3.3. Biogeophysical effects of *montado* cover changes

Climate changes due to the increasing concentration of greenhouse gases and aerosols in the atmosphere have attracted the attention globally from a diverse community including both politicians and scientists. However, crucial issues focused on the research of the climatic impact of land cover and land use changes through biogeophysical processes is far from resolved (Deng et al., 2014).

Land cover and land use changes have an impact on the climate through changes in biogeochemical (e.g. atmospheric CO_2 concentrations) and biogeophysical (e.g. land surface albedo, land surface temperature, roughness length, evapotranspiration) processes (Betts et al, 2007; Devaraju et al., 2015; Li et al., 2015). These two processes regulate the fluxes and exchanges of energy, water, momentum, and chemical components between Earth surface and atmosphere, shaping meteorological conditions (Bonan, 2008). Regarding the effects of land cover change in these processes, recent studies have been arguing that changes in biogeophysical processes play a more regional/local role than biogeochemical ones (Li et al., 2015; Pongratz et al., 2010). Land surface albedo (LSA), land surface temperature (LST) and evapotranspiration (ET) are considered as the three most important biogeophysical factors in the whole surface energy and water balance (Dirmeyer and Shukla, 1994; Friedl, 2002; Lu et al., 2011; Mallick et al., 2014). Reduction in vegetation cover due to natural and/or human causes may lead to an increase in surface albedo and consequently to a shrinking in net radiation, energy fluxes (sensible and latent), convective clouds and precipitation, leading therefore to drier atmosphere conditions (Figure 4) (Pitman, 2003). Moreover, a reduction in vegetation cover will also decrease surface roughness, latent and sensible heat fluxes, rooting systems and evapotranspiration rate, leading to land surface warming (Figure 5) (Doughty, 2012; Lejeune et al., 2015; Pitman, 2003).

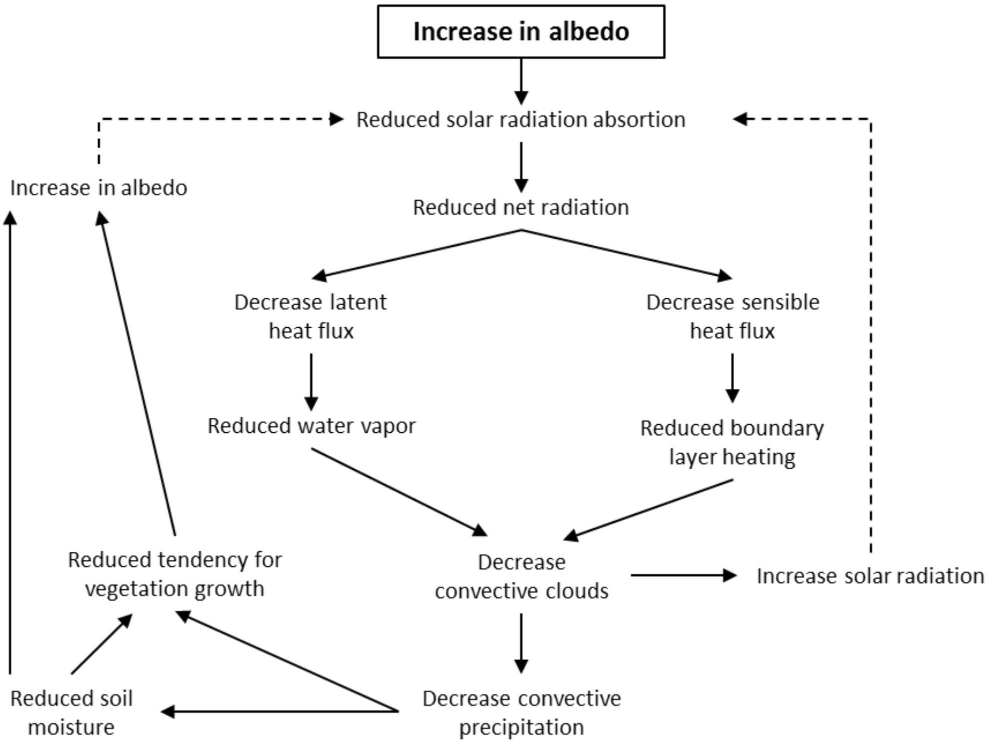

Figure 4 – Conceptual diagram of possible impacts derived from an increase in surface albedo. Solid lines represent positive feedback and the dashed lines represent negative feedback. Adapted from Pitman (2003).

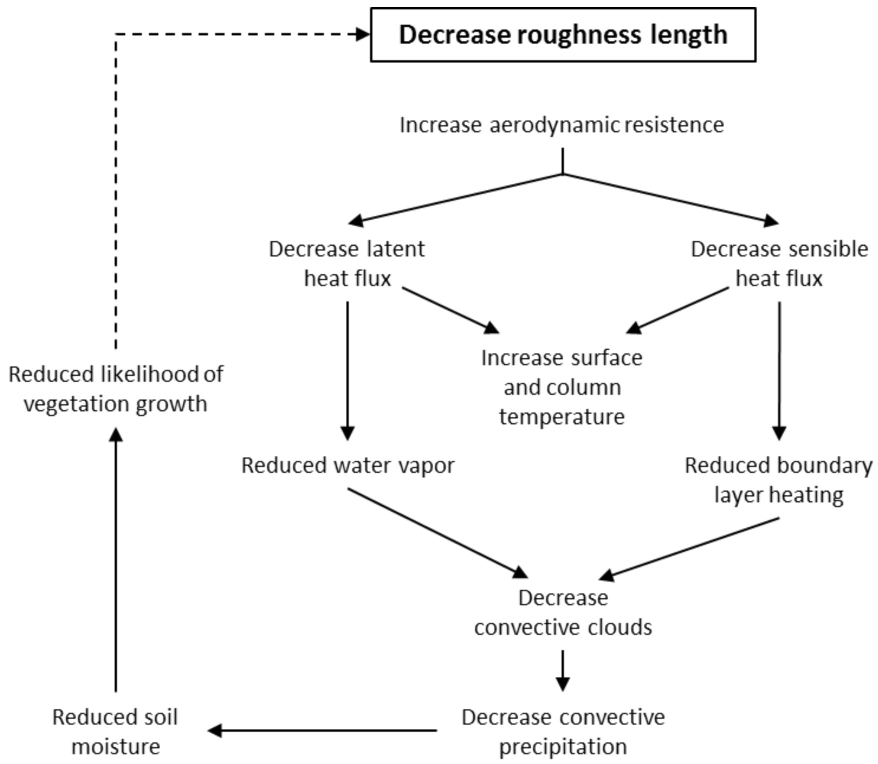

Figure 5 - Conceptual diagram of possible impacts derived from a decrease in surface roughness. Solid lines represent positive feedback and the dashed lines represent negative feedback. Adapted from Pitman (2003).

European and African Mediterranean regions have received particular attention from the ecological and climate point of view due to the extensive deforestation over the past 2000 years, mainly as a result of the geographical expansion of the Roman Empire (Blondel and Aronson, 2006; Bonan, 2008). According to the research carried out by Reale and Dirmeyer (2000), the Mediterranean region was moister in Roman times. Climate model simulations show that this huge deforestation process across the Mediterranean region over the times contributed to the dryness of the current climate (Arribas et al., 2003; Gates and Lieβ, 2001; Reale and Dirmeyer, 2000; Reale and Shukla, 2000). These studies mostly support the thesis that the greater forest cover during the Roman Era induced higher summer precipitation. Transformation of native Mediterranean forests into crops or grasslands over the times has significantly altered several biogeophysical processes affecting energy and water cycles, which in turn changed temperature and precipitation regimes in this region. Given that, Mediterranean region has been considered highly vulnerable to climate changes (Navarra, 2013). Indeed, the last report of the Intergovernmental Panel on Climate Change (IPCC) is projecting a decreasing trend in precipitation and an increasing trend in temperature for the Mediterranean region. Consequently, this region will be much drier and warmer than today, especially in the warm seasons (Hewitson et al., 2014).

It is understood that land cover changes can alter the environment, causing therefore significant impacts on ecosystems functioning at local, regional and global scales, and consequently greatly influencing global climate changes (Foley et al., 2005; Pachauri and Reisinger, 2007). Local changes gradually extend to regional, inter-regional and even larger scales, leading to global environmental effects. Therefore, in order to determine and assess the main impacts of land cover and land use changes on climate modifications at the global scale, it is mandatory to first understand in detail both local and regional processes (Deng et al., 2014).

Montado/*dehesa* landscape is one of the most important and widespread ecosystems in the Mediterranean region. As thoroughly described in the previous section 1.3.1, this ecosystem is in sharp decline, which has been evidenced by a progressive decrease in tree cover (Plieninger and Schaar, 2008). Effects of *montado* tree canopy cover changes on biogeophysical processes must be addressed at a local scale in order to be identified, assessed and understood (e.g. what are the effects on land surface albedo and temperature values resulting from a decrease of 50% in tree cover?). This information is extremely important as a starting point to understand how these changes in surface albedo and temperature can influence and/or modify local climate; how *montado*/*dehesa* tree productivity and resilience are affected by local climate changes; and how strong are the negative feedbacks presented in the Pitman´s diagrams (Figures 1 and 2) in the case of the *montado* ecosystem. All these answered questions will contribute to a more efficient and cost-effective *montado* planning and management decision-making process.

Chapter

2

Assessment of environment, land management, and spatial variables on recent changes in montado land cover in southern Portugal

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2.1. Abstract

Montado decline has been reported since the end of the 19th century in southern Portugal and increased markedly during the 1980s. Consensual reports in the literature suggest that this decline is due to a number of factors, such as environmental constraints, forest diseases, inappropriate management, and socioeconomic issues. An assessment on the pattern of montado distribution was conducted to reveal how the extent of land management, environmental variables, and spatial factors contributed to montado area loss in southern Portugal from 1990–2006. A total of 14 independent variables, presumably related to montado loss, were grouped into three sets: environmental variables (ENV), land management variables (LMA), and spatial variables (SPA). From 1990–2006, approximately 90,054 ha disappeared in the montado area, with an estimated an annual regression rate of 0.14% y-1. Variation partitioning showed that the land management model accounted for the highest percentage of explained variance (51.8%), followed by spatial factors (44.6%) and environmental factors (35.5%). These results indicate that most variance in the large-scale distribution of recent montado loss is due to land management, either alone or in combination with environmental and spatial factors. The full GAM model showed that

different livestock grazing is one of the most important variables affecting montado loss. This suggests that optimum carrying capacity should decrease to 0.18–0.60 LU ha-1 for livestock grazing in montado under current ecological conditions in southern Portugal. This study also showed that land abandonment, wildfire, and agricultural practices (to promote pastures, crops or fallow lands) were three significant variables influencing montado loss.

Keywords: Landscape change · livestock grazing intensity · *montado*/*dehesa* · Mediterranean · *Quercus* spp. · spatial distribution

2.2. Introduction

The Portuguese *montado* (such as the *dehesa* land cover type in Spain) is an agro-silvo-pastoral system in which cork oak (*Quercus suber*) and/or holm oak (*Quercus* [*ilex*] *rotundifolia*) are the dominant tree species with varying densities usually in combination with livestock grazing and agriculture in the herbaceous layer (Aronson et al. 2009; Pinto-Correia et al. 2011b; Vicente and Alés 2006). *Montado*/*dehesa* areas account for about 3.5–4.0 Mha in the southwestern Iberian Peninsula, assuming great importance in southern Europe (Olea and San Miguel-Ayanz 2006).

The *montado* is characterised as an agroforestry multifunctional system, as it produces a range of goods and services currently in demand (Pinto-Correia et al. 2011a; Surová et al. 2011, 2014), including the following: cork; charcoal; firewood; acorns and pasture for livestock; wild game, aromatic, and medicinal plants; and recreational services, such as ecotourism (Bugalho et al. 2009; Coelho and Campos 2009; Joffre et al. 1999; Sá-Sousa 2014). According to Aronson et al. (2009), Coelho et al. (2012), Godinho et al. (2011), Plieninger (2007), and Pulido et al. (2001), the *montado* also supports other important ecosystems services, such as carbon sequestration, soil conservation, groundwater recharge and quality protection, and biodiversity conservation. Given their environmental and socioeconomic importance, *montado*/*dehesa* systems are regarded as High Nature Value Farmlands (HNVF), according to European classification criteria (Almeida et al. 2013; Paracchini et al. 2008; Pinto-Correia and Godinho 2013), and are included in Annex I of the European Union Habitats Directive (92/43/CEE).

A decline in *montado*/*dehesa* area has been reported throughout the Mediterranean region, especially in Portugal, Spain, Morocco, France, and Italy (Brasier 1996; Cano et al. 2006; Gallego et al. 1999; Linaldeddu et al. 2013). As far as Portugal is concerned, *montado* decline has been reported since the end of the 19th century and is related to the intensive tree exploitation for charcoal and firewood production, man-made fires to promote open areas for crops and pastures for livestock grazing, failure in juvenile tree regeneration due to livestock browsing, and poorly understood diseases (Carvalho 1870). Surprisingly, most factors indicated in 1870 as threatening the *montado* continue to pose a threat today. The significance of such factors in the past is not known, but as they were highlighted at the time, it is assumed they must have been relevant. Paradoxically, references to threats in the past actually demonstrate the overall continuing resilience of the system, since it has survived the long term despite a number of pressures. Nevertheless, this raises the question of the limits of the *montado* in terms of sustainability: so far it has survived, but is it sustainable in the future in the face of a range of pressures of various kind (e.g. Bugalho et al. 2009; Cabral et al. 1992; Costa et al. 2010; Leitão 1902; Pinto-Correia and Mascarenhas 1999; Natividade 1950)?

Despite the observed trend of *montado* decline during the past century, the seriousness of the problem increased markedly during the 1980s (Brasier and Scott 1994; Cabral et al. 1992). A similar increase in the trend toward decline has been reported for the *dehesa* in Spain (Brasier and Scott 1994; Cano et al. 2003; Moreira et al. 2006; Plieninger 2006). Review of the literature suggests that this decline is mainly related to the following: environmental constraints, such as soil type and hydrological conditions (Costa et al. 2008; Costa et al. 2010; Cubera and Moreno 2007); drought (David et al. 1992; Pelegrín et al. 2008); and wildfires (Catry et al. 2012; Díaz-Delgado et al. 2002; Silva and Catry 2006). In addition, some known diseases (e.g., *Phytophthora cinnamomi* fungus) and insect attacks also favour this decline because their effects are amplified by the already stressed conditions of the *montado* (Brasier 1996; Camilo-Alves et al. 2013; Linaldeddu et al. 2013; Moreira and Martins 2005; Pérez-Sierra et al. 2013). Furthermore, there are other factors leading to *montado* change, including the following: inappropriate management, with a sharp increase in mechanisation and unsustainable livestock stocking rates (Acácio et al. 2010; Cadima et al. 1995; Costa et al. 2010; Del Pozo 2004; Plieninger 2006, 2007); vulnerability of the agricultural economy (Pinto-Correia 2000); rural depopulation; and the abandonment of traditional agricultural activities (Pinto-Correia 1993; Pinto-Correia and Vos 2004; Sheffer 2012). Briefly, such factors are mainly associated with changes in public policies (national and European), market mechanism and other socio-economic factors.

Several studies have examined long-term *dehesa* change in Spain (Cano et al. 2003; Plieninger 2006) and long-term *montado* change in Portugal (Acácio et al. 2009, 2010; Costa et al. 2009, 2011), but the focus was always on the local area and/or a single municipality. To support policy decisions regarding *montado* management, large-scale analyses of changes are needed to understand the overall process and to assess the role of policy.

Thus, the goal of this study is to present the changes detected in the *montado* distribution pattern for southern Portugal as a whole from 1990–2006 and determine the relative effects of selected environment, land management, and spatial factors on *montado* land cover change. According to the previous considerations regarding *montado* decline trends, we hypothesise that land management factors play more of a major role in causing recent *montado* change than environmental factors.

2.3. Material and Methods

2.3.1. Study area

This study was conducted in southern Portugal (Figure 1), a region with vegetation dominated by cork oak (*Q. suber*) and holm oak (*Q.* [*ilex*] *rotundifolia*) species (Bugalho et al. 2009; Pinto-Correia et al. 2011b). The study area covered approximately 4.1 x 10^6 ha (Figure 1), which accounts for 46% of mainland Portugal. The selected area is in accordance with published biogeographic boundaries (Costa et al. 1998), which consist of the following several layers: phytogeographic (flora and vegetation), geomorphologic, lithologic, and pedologic, as well as bioclimate. In fact, about 72% of the area selected is located in the so-called 'Luso-Extremadurense' province, one of the largest biogeographic provinces in the Iberian Peninsula. Its soils originate from palaeozoic siliceous material, and the original vegetation associations of Mesomediterranic cork oak (*Sanguisorbo agrimoniodis-Quercetum suberis*), holm oak (*Pyro bourgaenae-Quercetum rotundifoliae*), and pyrenean oak (*Arbuto unedonis-Quercetum pyrenaicae*) have been converted almost entirely into *montado* systems.

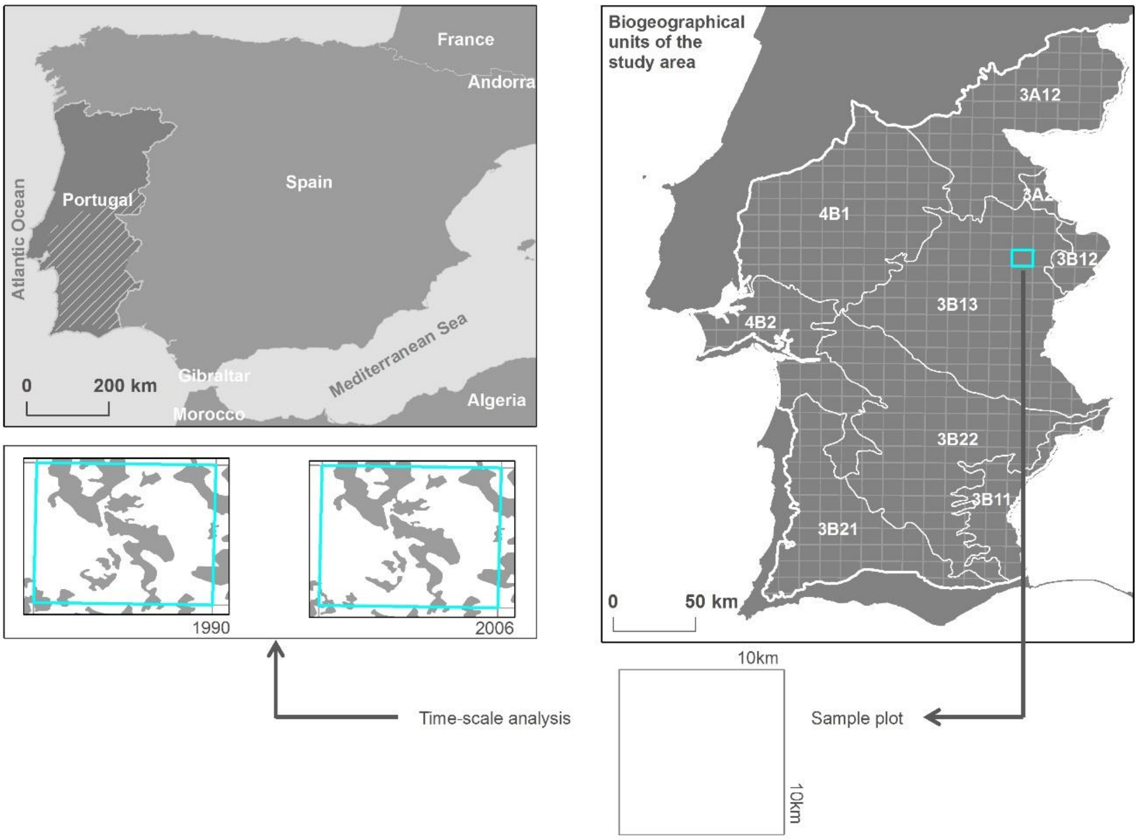

Figure 1 - Study area, biogeographic boundaries and 10x10 km UTM squares

2.3.2. *Cartographic data sources*

The areas and distributions of *montado* land cover in 1990 and 2006 in the study area were obtained from the CORINE land cover (CLC) (scale 1:100,000) of 1990 and 2006. Due to the degree of heterogeneity of tree density and the understory uses of the *montado*, this multifunctional system does not entirely fit into a single CLC category (Doorn and Pinto-Correia 2007). In fact, for the calculation of the CLC-1990 and CLC-

2006 *montado* areas, the following land cover categories were used: '244-agroforestry areas', '311-broadleaved forest', and '313-mixed forest'. For this procedure, spatial analyses were conducted to accurately extract *montado* areas using auxiliary geo-referenced data, such as the national land cover map of 1990 (LCM-1990) and the second level of the national land cover map of 2007 (LCM-2007-N2) (both at 1:25,000 scales), produced by the National Centre for Geographic Information and the Portuguese Geographic Institute, respectively. Additionally, data from the National Forest Inventories (IFN-1995 and IFN-2005) produced by the Portuguese Forestry Services as well as high-resolution true-colour orthophotomaps (2005) were also used in particular situations where uncertainty remained after the previously described processes. Thus, for 1990, all patches categorised as '*montado*' in the LCM-1990 were used, and they were intersected with the 244-, 311-, and 313-land cover categories from the CLC-1990 to extract only the proportion that corresponded to *montado* areas maintaining the cartographic characteristics of the CLC project. Finally, the same three land cover categories (244, 311, and 313, extracted from CLC-2006) were used to produce the *montado* map for 2006. These patches were overlaid with all patches classified as 'heterogeneous agricultural areas' in the LCM-2007-N2 and the *montado* areas mapped within each category. The IFN-1995 and IFN-2005 were used to reduce uncertainty in the final classification; visual interpretation and screen-digitised processing of the very high-resolution orthophotomaps served the same purpose.

Trends regarding changes in *montado* land cover during the 1990–2006 period were estimated using the UTM grid (with 10 × 10-km cell size) overlapped on each *montado* map to determine the *montado* area for each year and 10 × 10-km cell (henceforth simply referred to as cells). A total of 487 cells were examined in the study area, for which *montado* loss and gain were quantified by comparing the two maps.

2.3.3. Factors affecting montado land cover change

In the period of study (1990–2006), most of the change in *montado* land cover was attributed to loss processes, while observed gain values were insignificant throughout the study area. Thus, the analysis of recent patterns of *montado* land cover change only focusses on the loss processes.

Factors influencing *montado* loss were divided into three sets of explanatory variables: environmental (ENV), land management (LMA), and spatial (SPA) (Table 1). The stratification of these factors allows for the study of their combined effects as well as the relative influence on the spatial distribution of *montado* loss. Furthermore, the SPA set allows whether to quantify SPA influence on distribution of *montado* loss values or to correct the possible presence of spatial autocorrelation in the data (Borcard et al. 1992; Legendre 1993; Plant 2012).

Table 1 - Variables sets and correspondent explanatory variables description

Variable code	**Description**	**Unit**	**Source**
Spatial set			
AC	Autocovariate term	-	*autocov_dist* function of *Spdep* R package
X	X coordinates centered	-	GIS analysis
Y	Y coordinates centered	-	GIS analysis
XY	Multiplication of centered X and Y	-	-
X^2	Square of X coordinates centered	-	-
Y^2	Square of Y coordinates centered	-	-
Environmental set			
FIRE	Burned area due to wildfire 1990-2006	Proportion	Portuguese National Forestry Authority
SOIL1	Infertile soil	Proportion	CEEM, 1996.
SOIL2	Moderately fertile soil	Proportion	
SOIL3	Fertile soil	Proportion	
Land management set			
UAA_NU	Useful Agricultural Area not used	Proportion	Portuguese General Census of Agriculture 1999 (GCA99)
LSTOCK	Livestock units: cattle, goats and sheep	Livestock units	
NPAST	Improved natural pasture lands under *montado* cover	Proportion	
PCFL	Pasture, crops and fallow land under *montado* cover	Proportion	
NCROP	*montado* under cover without crops	Proportion	

Environmental set

The environmental set is composed of four variables: one of these (FIRE) represents the burnt area from 1990–2006, and the other three correspond to different soil fertility levels (SOIL1, SOIL2, and SOIL3) (Table 1). The GIS shapefile 'burnt areas' was provided by the Institute for Nature Conservation and Forests (ICNF). Soil fertility levels were obtained and adapted from the classification produced for the STRIDE-Amb. 12 final report (CEEM 1996). Fire and soils variables were superimposed on the 10 × 10-km grid layer using GIS software (ArcGis 10 and ESRI 2011), and proportional values for each variable were extracted for each 10 × 10-km cell.

Land management set

The five variables comprising the land management set were obtained from the Portuguese General Census of Agriculture (GCA) carried out in 1999 (Table 1). The GCA information is provided at the parish level. Indeed, data of the five variables were extracted for each 10 × 10-km cell by calculating the proportional area by parish within each 10 × 10-km cell. These five variables include the following: UAA_NU, the proportion of useful agricultural area not used in each 10 × 10-km cell, which was used as an indirect measure of rural abandonment; LSTOCK, the estimated grazing intensity obtained by converting cattle, goat, and sheep numbers into livestock units (LU), while the LU of each livestock type was summarised to obtain total LU per 10 × 10-km cell; NPAST, the proportion of area under *montado* cover occupied by improved natural pasture land; PCFL, the proportion of area under *montado* cover occupied by pasture, crops, and/or fallow land; and NCROP, the proportion of area under *montado* without crops.

Spatial set

The spatial set is composed of six variables: three basic (X, Y, and AC) and three derived variables (XY, X^2, and Y^2) (Table 1). It is well known that land cover data exhibit spatial autocorrelation, meaning that closest pairs of points have the tendency to be more similar than points at larger distances (Overmars et al. 2003). Therefore, regarding land cover change analysis is crucial to understand and incorporate the spatial correlations of the dependent variables in statistical models. Before statistical modelling, the existence of any autocorrelation in *montado* loss (dependent variable) was assessed using Moran's *I*. To capture the spatial autocorrelation of *montado* loss values, an autocovariate term (AC) (Dormann et al. 2007) was calculated using the R package *spdep* (Bivand 2010). Moreover, for this set of variables, a second-order polynomial of centred spatial coordinates (X^2 and Y^2) was computed to capture a larger-scale spatial variation (Legendre and Legendre 1998; Miller et al. 2007).

2.3.4. Statistical analysis

To understand the underlying causes of recent tendencies for *montado* change, the amount of *montado* area lost in each 10×10-km cell from 1990–2006 was defined as a dependent variable. The relationships between the dependent variable (*montado* loss) and the independent variables were analysed by means of a three-stage statistical analysis involving: 1) exploratory analysis; 2) model building; and 3) variance partitioning. The first stage was performed using exploratory plots and linear regression models for screening the response curve shape (Zuur et al. 2009). This procedure was useful for verifying if the *montado* loss values increased (or decreased) linearly with a specific independent variable. Exploratory analysis revealed that the main relationships between the dependent and independent variables were unlikely to be linear. Consequently, it was decided that the generalised additive model (GAM) (Hastie and Tibshirani 1990) should be used to assess the relationships between the covariates and *montado* loss. The GAM is more flexible than the generalised linear model (GLM), allowing for both linear and complex additive response shapes as well as a combination of the two within the same model (Wood and Augustin 2002). As with the GLM method, GAM models use a link function to establish a relationship between the mean of the response variable and a 'smoothed' function of explanatory variables.

The second statistical stage (model building) started with a univariate GAM analysis for all independent variables and predictors (Table 1). This analysis was appropriate for verifying the significance of each independent variable in explaining the *montado* loss values. Only variables with univariate significance p-values < 0.25 were used in posterior analyses (Tabachnick and Fidell 2001). To check multicolinearity, pairwise Pearson correlations among all predictors were computed, and pairs with r > 0.7 were excluded from further analyses (Tabachnick and Fidell 2001). Multivariate models were then constructed independently for each set of predictors (SPA, ENV, and LMA) using a GAM with an identity link function and Gaussian error term (Wood 2006) to select the most parsimonious models to be used in further analyses. Generalised cross validation (GCV) was used as a criterion for estimating the smoothing parameters (Wood 2006). For each set of predictors, models with all possible combinations of remaining variables (following univariate analysis) were devised and compared with Akaike information criteria corrected for small samples (AIC_c) (Burnham and Anderson 2002). Models with $\Delta AIC_c < 4$ are considered to have great relevance as candidate models (Burnham and Anderson 2002). Akaike weights (w_i) were also calculated as model selection criteria (Burnham and Anderson 2002), where the highest w_i represents the best model for ecological interpretations. The goodness-of-fit for each model was measured by means of deviance statistics (D^2) (Venables and Ripley 2002).

In the third stage, variance partitioning was used to specify which proportion of the variation in *montado* loss values is explained by each of the three factor sets exclusively as well as which proportions are attributable to interactions between factors (Borcard et al. 1992; Legendre 1993). The effects of different factors on the distribution of *montado* loss values may coincide with each other or counteract one another; therefore, the sum of the amount of explained variation by each set of variables usually differs from the total amount explained by the three sets together. Thus, seven fractions representing explained variation were obtained by means of the partitioning method: 1) the pure effect of ENV; 2) the pure effect of SPA; 3) the pure effect of LMA; 4) the shared effect of ENV + SPA; 5) the shared effect of ENV + LMA; 6) the shared effect of SPA + LMA; and 7) the shared effect of ENV + SPA + LMA. The D^2 was used as a measure of variance explained by each GAM model (Guisan and Zimmermann 2000).

All statistical analyses were conducted using R 2.14.2 (R Development Core Team 2012) software, using the *mgcv* package for GAMs (Wood 2006).

2.4. Results

2.4.1. Factors affecting montado land cover change

In the study area, it was estimated that *montado* covered approximately 1,310,756 ha in 1990, while, in 2006, it decreased to 1,220,702 ha (Figs. 2a and 2b). In 1990, approximately 16.3% (from a total of 487 cells) had more than 60% of *montado* area, while, in 2006, there was only 13.2%, reflecting a sharp decrease during the 16-y period (Figs. 2c and 2d). From 1990–2006, no cells showed a gain in *montado* area greater than 500 ha (Figure 2e). At the same time, 42 cells exhibited *montado* loss values ranging from 500–1000 ha, while 143 cells showed a loss of 100–500 ha (Figure 2e). During the 1990–2006 period, an area of 90,054 ha of *montado* was lost, corresponding to an annual regression rate of 5628.4 ha y^{-1}. In total, the rate of *montado* regression estimated for the period from 1990–2006 was, on average, 1.4% $cell^{-1}$ $decade^{-1}$.

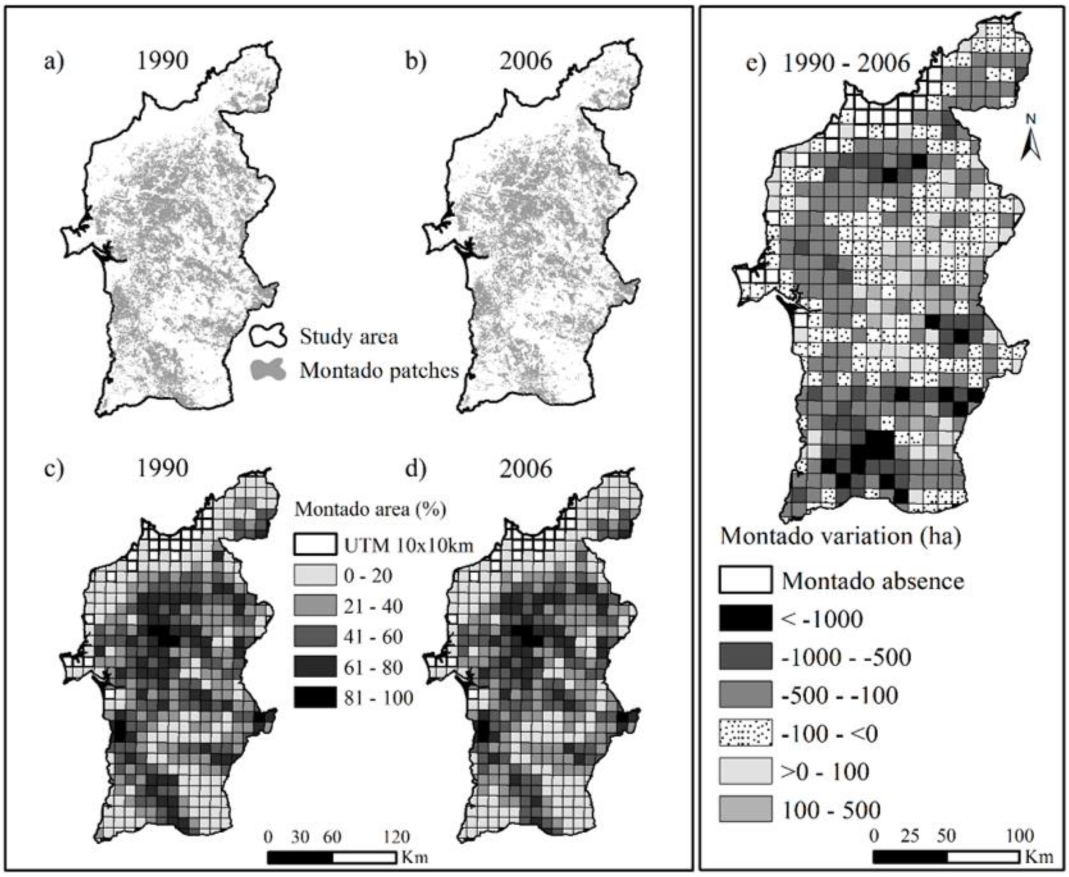

Figure 2 - Spatial-temporal patterns of *montado* landscape between 1990 and 2006. a) *montado* area in 1990 (1,310,756 ha), b) *montado* area in 2006 (1,220,702 ha), c) and d) % of *montado* area in each UTM square in 1990 and 2006, respectively, e) *montado* area variation (in ha) between 1990 and 2006 in each 10x10 km cell.

2.4.2. Model selection

After univariate analysis, multicollinearity inspection, and model selection, the number of predictors in the spatial set was reduced to three (AC, X, and Y). The five land management set predictors (UAA_NU, LSTOCK, NPAST, PCFL, and NCROP) were retained. For the environmental set, the four original predictors (FIRE, SOIL1, SOIL2, and SOIL3) were also retained.

To gauge the influence of spatial variables on *montado* loss values, seven possible additive models were used with the three other variables. Of these models, only one was considered plausible (Δ_i < 4), which selected with high probability the autocovariate term (AC), X, and Y coordinates, showing that the spatial distribution of *montado* loss values is also influenced by spatial factors (AIC_c [w_i] = 0.96) (Table 2). In the model selected, the AC term plays a crucial role in the spatial distribution of *montado* loss values ($p < 0.001$) (Table 3) due to the spatial autocorrelation verified in these values (Moran's I = 0.09, $p < 0.001$). During the environmental modelling procedure, 15 candidate models were tested, of which only five plausible models were found to explain the variability of *montado* loss values ($\Delta_i < 4$) (Table 2). The best model shows that *montado* loss values are optimally explained by the additive effect of FIRE and SOIL2 (AIC_c [w_i] = 0.24) (Table 2). Finally, in the case of land management variables, out of 31 candidate-adjusted models, only three models were selected as being plausible for explaining the variability contained in the dataset ($\Delta_i < 4$) (Table 2). Based on Akaike weights, the model with the additive effect of UAA_NU + LSTOCK + PCFL + NCROP (model 1) presented the highest value (AIC_c [w_i] = 0.45) (Table 2).

Table 2 - Best candidate models for spatial, environmental and land management sets for explaining *montado* loss data

Model Set	**Model**	**Variables contained in the model**	**AIC**	**AICc**	**Δi**	**AICc (w_i)**
Spatial	1	AC + X + Y	-102.15	-102.11	0.00	0.96
Environmental	1	FIRE + SOIL2	-110.72	-110.63	0.00	0.24
	2	FIRE + SOIL1 + SOIL2	-110.72	-110.59	0.05	0.23
	3	FIRE + SOIL2+SOIL3	-110.44	-110.30	0.33	0.20
	4	FIRE + SOIL1 + SOIL2+SOIL3	-110.27	-110.06	0.58	0.18
	5	FIRE + SOIL1+SOIL3	-109.97	-109.84	0.80	0.16
Land Management	1	UAA_NU + LSTOCK + PCFL + NCROP	-129.98	-129.81	0.00	0.45
	2	UAA_NU + LSTOCK + PCFL + NCROP+NPAST	-129.98	-129.74	0.07	0.43
	3	UAA_NU + LSTOCK + PCFL+NPAST	-126.11	-125.94	3.87	0.06

Note: Δi is the AICc differences and AICc weight (w_i) is the estimated probability that a model is the best model in the set.

The spatial model explained 44.6% of total variation, showing a close association of the autocovariate term with the observed *montado* loss values (Tables 3 and 4). The environmental model explained 35.5% of the variation, indicating that *montado* loss values were significantly influenced by burnt area and soil quality (Tables

3 and 4). The loess curve of the burnt area plot (Figure 3a) exhibited a sharp increase in *montado* loss values, ranging from 0.40–0.65 of burnt area.

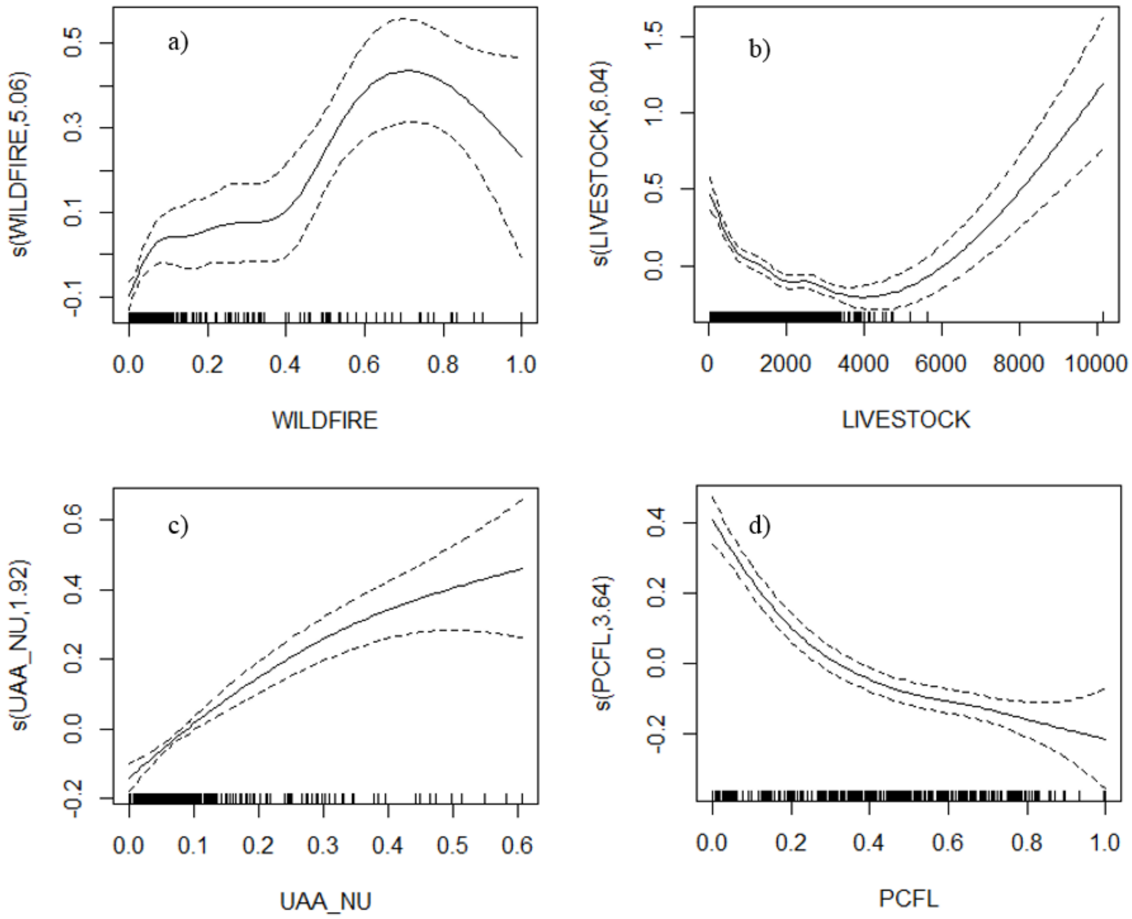

Figure 3 - Response curve shapes of (a) burned area, (b) livestock units (c) useful agricultural areas not used, (d) Pasture, crops and fallow lands under *montado* cover in the GAM models for *montado* loss values. *X* axis represent: (a) proportion of burned area in each 10x10km cell; (b) Livestock Units calculated per each 10x10 km cell; (c) proportion of Useful Agricultural Area not used in each 10x10 km cell; (d) proportion of area under *montado* cover occupied by pastures, crops and fallow lands in each 10x10 km cell. Dashed lines are approximate 95% pointwise confidence intervals, and tick marks show the sample plots (10x10 km cells) along the variable range.

The land management model showed the highest percentage of explained variance (51.8%) (Table 4). *Montado* loss values were markedly influenced by LSTOCK, PCFL, UAA, and NCROP variables (Table 3). The shape of the loess curve of the LU plot shows that *montado* loss values are close to zero when the number of LU per cell ranges from 1,800 to approximately 6,000, which corresponds to a grazing intensity of 0.18–0.60 LU ha^{-1}, and rapidly increases in cells where the LU is greater than 6,000 LU cell^{-1} (Figure 3b). Figure 3c shows that UAA_NU has a positive effect on *montado* loss values, indicating that loss values increase in cells where the percentage of UAA_NU is higher. This suggests that the abandonment of agricultural land, in particular in marginal areas, such as mountain regions, has a negative impact on the *montado* system. Finally, the loess curve of the PCFL plot shows that *montado* loss is negatively influenced by an increase in the proportion of pasture, crops, and/or fallow land under *montado* cover (Figure 3d).

The full model accounted for 61.0% of the explained variation (Table 4). The largest proportion of *montado* loss was accounted for by the shared effects of the land management, environmental, and spatial sets (27.3%). The greatest pure effect was associated with the land management model (9.7%), whereas spatial (4.7%) and environment (3.0%) sets had moderate influences on *montado* loss values (Figure 4). Other shared pair effects were 1.5% and 3.7% for ES and EL, respectively (Figure 4). Furthermore, the shared effect of the land management and spatial set (11.1%) indicates that the combined effects of these two sets had a considerable influence on *montado* loss values.

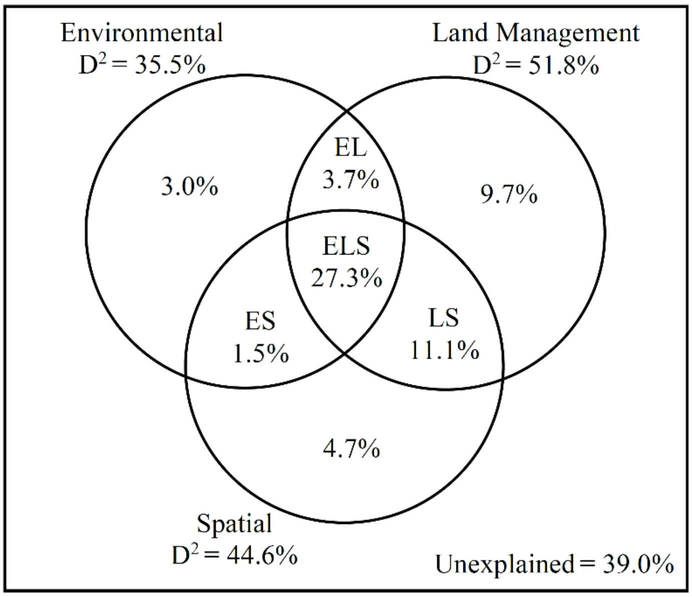

Figure 4 - Results of the variation partitioning for the *montado* loss values in terms of fractions of the variation explained. Variation in the montado loss values is explained by three sets of explanatory variables: spatial, environmental, and land use and management, and by their interactions (EL- Environment and Land Management (3.7%); ES – Environment and Spatial (1.5%); LS- Land Management and Spatial (11.1%); ELS- Environment, Land Management and Spatial (27.3%). Unexplained is the percentage of unexplained variation.

Table 3 - Coefficients and their significance for partial and full models for *montado* loss data.

	Variables	Partial models			Full model		
Spatial Set		Linear term			Linear term		
		β	**s.e.**	***p*-Value**	***β***	**s.e.**	***p*-Value**
	Intercept	0.125	0.023	0.001***	0.231	0.025	0.000***
	AC	0.635	0.064	0.001***	0.219	0.081	0.011*
		Smoother terms			Smoother terms		
		edf	***F*-Value**	***p*-Value**	***edf***	***F*-Value**	***p*-Value**
	s (X)	2.042	3.670	0.016*	4.147	1.830	0.104
	s (Y)	4.718	2.787	0.013*	8.173	1.008	0.391
Environmental Set		Linear term					
		β	**s.e.**	***p*-Value**			
	Intercept	0.294	0.011	0.000***			
		Smoother terms			Smoother terms		
		edf	***F*-Value**	***p*-Value**	***edf***	***F*-Value**	***p*-Value**
	s (FIRE)	5.357	14.619	0.000***	3.847	4.583	0.000***
	s (SOIL2)	4.229	7.761	0.000***	$8.004e^{-09}$	0.055	0.997
Land Management Set		Linear term					
		β	**s.e.**	***p*-Value**			
	Intercept	0.331	0.010	0.000***			
		Smoother terms			Smoother terms		
		edf	***F*-Value**	***p*-Value**	***edf***	***F*-Value**	***p*-Value**
	s (UAA_NU)	5.723	2.519	0.018*	5.541	2.399	0.026*
	s (LSTOCK)	6.424	10.871	0.000***	7.089	2.707	0.007**
	s (PCFL)	6.225	7.844	0.000***	2.079	2.102	0.120
	s (NCROP)	2.956	3.429	0.069	$5.358e^{-09}$	0.133	0.999

Table 4 - Summary of explained deviance (D^2) of all models for *montado* loss data.

Models	D^2	**AIC**	**AICc**
ENV	0.355	-110.98	-110.68
SPA	0.446	-102.15	-102.11
LUM	0.518	-129.98	-129.95
ENV + SPA	0.513	-188.37	-188.30
ENV + LUM	0.563	-188.99	-188.92
SPA + LUM	0.580	-184.05	-183.98
ENV + SPA + LUM	0.610	-215.48	-215.37

2.5. Discussion

As indicated previously, this study had one key objective: to analyse the comparative importance of environment, land management, and spatial factors on recent *montado* changes.

2.5.1. The influence of environment, land management, and spatial factors on recent montado change

For the period of 1990–2006, the estimated regression rate of *montado* (0.14% y^{-1}) obtained in this study falls within ranges previously reported by Costa et al. (2011), which were 0.16–0.22% and 0.26% y^{-1} for cork oak and holm oak, respectively, and those of Plieninger (2006), who reported with 0.04–0.27% y^{-1} for holm oak. These results apparently point to an overall trend toward *montado*/*dehesa* decline throughout the western Iberian Peninsula, regardless of different spatial-temporal scales of analysis. The hypothesis is that decline in different parts of this area may be accounted for by the same causes.

This study demonstrates that most of the variation in recent large-scale *montado* loss is explained by land management either alone or in combination with environmental and spatial effects. Considering only pure effects, land management variables account for most of the variability in *montado* loss. An important land management and spatial component effect on *montado* loss was also observed.

Variation partitioning showed that spatial variables were also important in explaining recent *montado* loss. Spatial data, such as land cover data, have a tendency to be dependent (spatial autocorrelation), which means that when using spatial models, some variance may be explained by neighbouring values (e.g. Overmars et al. 2003; Plant 2012; Wu et al. 2009). The great spatial effect on recent *montado* loss (spatial, ES, and LS in Figure 4) may be attributed to human disturbances not taken into account in this study (e.g., soil degradation due to the intensification of agriculture during the 'wheat campaign' that occurred during the 1930s–1960s [Baptista 1995; Stoate et al. 2001]), seed dispersal and natural regeneration, and intrinsic processes at landscape scales (relief, local water balance, etc.) (e.g. Hubbell et al. 2001; Rutherford et al. 2008). Another reason for spatially autocorrelated patterns of *montado* loss values may be spatial interactions between *montado* and other land cover/use types not examined in this study (e.g. Ramírez and Díaz 2008; Rivest et al. 2011). As indicated by the results of this study and by others on land cover change, statistical models that do not account for autocorrelation in spatial data might overestimate the importance of covariates (Lichstein et al. 2002; Plant 2012). This also might include variables that have only slight or no relevance on dependent variables (Overmars et al. 2003) and thus could lead to erroneous ecological conclusions and inappropriate management recommendations (Wu et al. 2009).

This study showed that using different intensities in livestock grazing is one of the most important variables for determining *montado* loss, as other authors have argued (e.g. Berrahmouni et al. 2007; Blondel 2006; Blondel et al. 2010; Bugalho et al. 2011; Gaspar et al. 2008; Plieninger 2007). As seen in Figure 3b, the U-shaped curve response reflects the intrinsic relationship between the *montado* system and the different intensities of livestock grazing. This is clear evidence that ungrazed cells are associated with higher *montado* loss values, probably because these cells tend to have a more developed understory, which may have caused physiological stress due to the competition between oak trees and the understory for soil water content (Costa et al.

2010; David et al. 2007; Moreno et al. 2007). Furthermore, the water-deficit stress in *montado* trees could have been enhanced by the climatic conditions that occurred during the research period with long sequences of drier years (Costa et al. 2009; Mourato et al. 2010). Additionally, quick overgrowth of flammable shrubs (e.g., *Cistus* spp.) promotes an increased risk of severe wildfires in the absence of livestock grazing (Joffre et al. 1999). Furthermore, it was verified in the U-shaped curve that *montado* loss values were close to zero when LU per hectare ranged from 0.18–0.60. This suggests that the optimum *montado* carrying capacity for livestock grazing is 0.18–0.60 LU ha^{-1} in the current ecological conditions for southern Portugal. However, the selected livestock variable did not consider the duration of grazing, which is an important factor that should be considered for a more precise assessment (Calvo et al. 2012). Nevertheless, several authors showed that the carrying capacity in drier areas of the south-eastern Iberian Peninsula is close to 1.0 animals ha^{-1} or less (Baeza, 2004; Calvo et al. 2012; Correal et al. 1992). Indeed, the obtained results show that *montado* loss values promptly increase when the livestock grazing intensity is greater than 0.60 LU ha^{-1}, likely indicating that a frequent overgrazing situation exists above this value. Too much grazing pressure leads to soil compaction (4.20 kg cm^{-2} in heavily grazed oak stands), which reduces water infiltration, increases water run-off, and promotes soil erosion, and leads to soil degradation (Lima et al. 2000; Pulido and Díaz 2002; Coelho et al. 2004). Furthermore, overgrazing eliminates natural regeneration of oaks due to livestock acorn predation and browsing or trampling of seedlings (Pulido and Díaz 2005).

The partial and full multivariate models used in this study also demonstrate that UAA_NU and wildfires are two important variables influencing *montado* loss. Indeed the UAA_NU is an indirect measure of rural abandonment and reflects some stress-producing socioeconomic factors that contribute to *montado* loss. In the study area, both the Algarve hills and the southern littoral Alentejo exhibited the highest UAA percentages and significant *montado* loss values. This can be explained by high depopulation rates in these areas, leading to the abandonment of agricultural land and, therefore, to gradual shrub encroachment dominated by *Cistus* spp., which can result in increased fire risk (Bernaldez 1991). These results clearly show that wildfires are a significant *montado* loss predictor, and a close positive relationship was found between burnt area percentage and *montado* loss, mainly in the Algarve hills and northern area of the study. This agrees with previous findings reported for southern Portugal, and a significant proportion of national burnt *montado* area, from 1990–2005, occurred in this region (Silva and Catry, 2006). Particularly, during the 2003–2005 period, a total of more than 48,000 ha of burnt *montado* area was located in the Algarve hills (Moreira et al. 2009; Silva and Catry 2006).

Finally, analysis of statistical models also showed that *montado* loss is best explained when PCFL is included in models. This variable represents land management under *montado* cover promoting pasture, crops, and/or fallow land associated with livestock production. In cells with low percentages of pasture, crops, or fallow land, high *montado* loss values were observed. This probably occurred due to the absence of land management under the *montado* and/or the combination of livestock grazing leading to greater shrub encroachment. Thus, wildfire hazard and soil water competition may cause disturbance and degradation to these ecosystems (Acácio et al. 2009; Cubera and Moreno 2007; Schaffhauser et al. 2011). Furthermore, some studies focussing on water dynamics in the *montado* system have shown that pasture and crops promoted under *montado* cover do not compete more strongly than shrubs with oak trees for available soil water resources (Cubera and Moreno 2007; Montero et al. 2004). Indeed, soil fertilisation for pastures and crops seems to favour an increase in the water-use efficiency of oak trees and an improvement of their photosynthetic rate and hydric status during the dry period (Cubera and Moreno 2007; Montero et al. 2004). To sum up, the results of this study demonstrate that the progressive disappearance of grazing at sustainable livestock levels and cereal cultivation in long rotation cycles result in shrub encroachment and subsequent *montado* decline.

Chapter

3

Using a stochastic gradient boosting algorithm to analyse the effectiveness of Landsat 8 data for *montado* land cover mapping: application in southern Portugal

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3.1. Abstract

The *montado* is a multifunctional agro-silvo-pastoral system dominated by cork oak (Quercus suber) and/or holm oak (Q. [ilex] rotundifolia) in varying densities. The availability of accurate and updated spatial information of *montado* ecosystems is crucial to understanding their spatial patterns and trends. This study aims to develop and propose a thorough and effective methodological approach for *montado* ecosystem mapping by using Landsat 8 multispectral data, vegetation indices, and the Stochastic Gradient Boosting (SGB) machine learning algorithm. Three research goals are directly addressed in this study: 1) assessing the overall suitability and effectiveness of Landsat 8 imagery for m*ontado* ecosystem mapping; 2) assessing the improvement of *montado* classification accuracies by adding vegetation indices; and 3) evaluating the performance of the SGB classifier for *montado* land cover classification. Two Landsat 8 scenes (spring and summer 2014 images) of the same area in southern Portugal were acquired. For each scene, six different vegetation indices were calculated: the Enhanced Vegetation Index (EVI), the Short Wave Infrared Ratio (SWIR32), the Carotenoid Reflectance Index 1 (CRI1), the Green Chlorophyll Index (CIgreen), the Normalised Multi-band Drought Index (NMDI), and the Soil-Adjusted Total Vegetation Index

(SATVI). Based on this information two datasets were prepared: i) Dataset I including only multi-temporal Landsat 8 spectral bands (LS8), and ii) Dataset II including the same information as Dataset I plus vegetation indices (LS8 + VIs). Integration of the vegetation indices into the classification scheme caused a significant improvement in the accuracy of Dataset II's classification product when compared to Dataset I, leading to a difference of 5.6% in overall accuracy and 0.07 in the Kappa value. For the *montado* ecosystem, adding vegetation indices in the classification process showed a relevant increment in producer's, user's, and Kappa accuracies of 1.19%, 8.53%, and 0.11, respectively. By using the variable importance function from the SGB algorithm, it was found that the six most relevant variables (from a total of 24 tested variables) were the following: EVI_summer; CRI1_spring; SWIR32_spring; B6_summer; CIgreen_summer; and SATVI_summer. These results constitute a pioneering and accurate remote sensing-based *montado* mapping product developed by using Landsat 8 OLI imagery.

Keywords: vegetation indices; *dehesa*; remote sensing; Mediterranean; multi-seasonal data; *Quercus spp*; LULC mapping

3.2. Introduction

The distinctive character of the wood-pastures and agro-silvo-pastoral land use systems throughout the world (McEwan and McCarthy, 2008; Plieninger et al., 2011; Slimani et al., 2014), as well as their natural value (Plieninger et al., 2015) and the increasing concern about its current vulnerability (Bergmeier et al., 2010; Lindenmayer et al., 2014), raises the need to understand its dynamics in order to design new and well-adapted policies to maintain these cultural landscapes. The long-term pressure on these landscapes has resulted in regeneration failure and woodland-ageing (Russell and Fowler, 1999; Lindenmayer et al., 2014) and consequently in an increase in vulnerability to new disturbances (e.g. Acácio et al., 2009; Guiomar et al., 2015). Prime examples of these multifunctional systems are the cork and holm oaks' woodlands of the Iberian Peninsula.

The so-called "*montado*" in Portugal and "*dehesa*" in Spain constitute an agro-silvo-pastoral system dominated by cork oak (*Quercus suber*) and/or holm oak (*Q.* [*ilex*] *rotundifolia*) showing high spatial variability in tree densities, usually with an understory mosaic of annual crops, grasslands, and shrublands (Joffre et al., 1999; Pinto-Correia and Mascarenhas, 1999). According to Olea and San Miguel-Ayanz (2006), the *montado* and *dehesa* ecosystems cover an area of about $3.5x10^4$ to $4.0x10^4$ km^2 in the south-western Iberian Peninsula, and are thus of great relevance in the Mediterranean biogeographical region.

The *montado* is described as a multifunctional system, as it supports a variety of goods and services that are nowadays valued by society (Pinto-Correia et al., 2011; Surová et al., 2011). Aside from cork, firewood, and charcoal, this system may also provide acorns and pastures for livestock feeding, aromatic and medicinal plants, wild game, and cultural services such as ecotourism (Bugalho et al., 2009; Coelho and Campos, 2009; Joffre et al., 1999). Furthermore, the *montado* ecosystem can also supply other ecosystem services, such as soil conservation, groundwater recharge and quality protection, carbon sequestration, and biodiversity conservation (Blondel and Aronson, 1999; Coelho et al., 2012; Godinho et al., 2011; Plieninger, 2007; Pulido et al., 2001). The *montado* is one of highest biodiversity-rich ecosystems of the western Mediterranean Basin. More than 135 vascular plants per 1,000 square metres can be identified in the *montado* (Díaz-Villa et al., 2003), as well as endangered and critically endangered species such as the Iberian imperial eagle (*Aquila adalberti*), the black vulture (*Aegypius monachus*), the Iberian lynx (*Lynx pardinus*), and the black stork (*Ciconia nigra*) (Branco et al., 2010). In addition, the *montado* ecosystem provides refuge for several other animal species that are listed in the annexes of the European Union (EU) Habitats and Birds Directives (Branco et al., 2010).

Changes in *montado* landscapes are mainly related to environmental constraints (Brasier, 1996; Costa et al., 2010; Cubera and Moreno, 2007), ineffective land management, the vulnerability of the agricultural economy, and also modifications in the organisation of labour in farming (Pinto-Correia, 2000). These alterations in *montado* landscapes result in contrasting trends of change between intensification and abandonment. Monitoring these changes is therefore a pressing concern for society and governmental institutions, and also for the scientific community.

The availability of accurate and up-to-date spatial information on the *montado* is crucial to understanding the patterns and trends of this ecosystem. Consistent and regular *montado* land cover information at high spatial resolution is required to support the decision-making process on ecosystem management and conservation. Established methods, such as field inventories and aerial photo interpretation, can be used for land cover mapping, however these tasks are often time consuming, too expensive, and limited in providing spatially continuous information over large territories (Xie et al., 2008). Satellite Earth Observation (EO) permits repeated and consistent assessment and monitoring of the environment. Using remote sensing technology, considered as a valuable source of Earth's surface information, land cover mapping can be gathered utilising a reduced amount of field data, making it more cost-effective (Bhandari et al., 2012; Franklin et al., 2000; Rogan and Chen, 2004).

The Landsat sensor family has been acquiring images of Earth's surface since 1972. In February 2013 the National Aeronautics and Space Administration (NASA) launched the eighth satellite from the Landsat program, the so-called Landsat 8, which is a significantly improved satellite. Spatial and spectral resolutions of the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 sensors' multispectral imagery makes it suitable for generating land cover maps. These sensors have been collecting imagery data in the visible, near infrared (NIR), and shortwave infrared (SWIR) portions of the electromagnetic spectrum, making them appropriate for vegetation studies across a wide range of environments (Bhandari et al., 2012; Cohen and Goward, 2004; Jia et al., 2014; Li et al., 2014). Landsat 8 includes two sensors: the Operational Land Imager (OLI), collecting data from nine bands, and the Thermal Infrared Sensor (TIRS), with two thermal bands. Compared with its predecessors (TM and ETM+), Landsat 8 OLI has some new features, in which the refined spectral range for some bands (e.g. NIR and SWIR bands) and the radiometric quantisation of 12 bits are two of the most relevant improvements. The narrowing of Landsat 8 OLI bands avoids atmospheric absorption features, which is evident for the NIR band (0.845–0.885 μm), which was refined to avoid the effects of water vapour absorption at 0.825 μm that occurs in ETM+ band 4 (0.775–0.900 μm), as a result allowing for a better land cover characterisation across a wide range of environments (Irons et al., 2012; Roy et al., 2014).

Given the land cover characteristics and the dominance of dry climate and soil conditions, the Mediterranean landscape shows a low inter-class separability (Berberoglu et al., 2000; Rodriguez-Galiano and Chica-Olmo, 2012; Salvador and Pons, 1998). These climate conditions also determine soil moisture, vegetation diversity, and its density over the landscape. Therefore, in this type of landscape, bare soils have a significant spatial occurrence, showing high reflectance that can mask reflected components from sparse vegetation (Berberoglu et al., 2007; Rodriguez-Galiano and Chica-Olmo, 2012). As a Mediterranean ecosystem, obtaining *montado* cover maps constitutes a difficult and complex task due to the spatial fuzziness caused by its tree density variability (van Doorn and Pinto-Correia, 2007) (Figure 1).

Figure 1 - Spatial variation in tree *montado* density (scale 1:5000)

To deal with these constraints, several approaches have been tested and applied in order to increase the separability between land covers that show similar spectral behaviour, such as the integration of multi-seasonal images and vegetation indices in the classification process (Dash et al., 2007; Gartzia et al., 2013; Li et al., 2011; Oetter et al., 2001; Rodriguez-Galiano et al., 2012a; Senf et al., 2015). Using multi-seasonal images in land cover classification improves the discrimination between vegetation types due to their capability to capture variations in their phenological state (Julien et al., 2011; Prishchepov et al., 2012; Rodriguez-Galiano and Chica-Olmo, 2012). The integration of vegetation indices in classification schemes has been widely used in land cover mapping to increase map accuracy (Carrão et al., 2008; Dash et al., 2007; Gartzia et al., 2013; Li et al., 2011). Due to the arithmetic combination of two or more original bands, vegetation indices are more clearly related to key biophysical parameters of vegetation than any original bands (Jones and Vaughan, 2010). This new information has the ability to enhance the electromagnetic behaviour of several vegetation properties. Therefore, vegetation indices are useful for reliable spatial and temporal comparisons of variations in canopy structural, phenological, and biophysical parameters, which can facilitate vegetation inter-class separability (Huete et al., 2002). However, the accuracy of these indices in quantifying vegetation parameters is affected by their sensitivity to atmospheric water vapour content, particularly those that use the NIR band in their computation (Kerekes, 1994). As stated above, one of the most relevant changes in the Landsat 8 OLI sensor is a narrower NIR band, which can avoid water vapour absorption. Recently, two studies (Li et al., 2014; Xu and Guo, 2014) reported that, depending on the land cover type, there are subtle differences of vegetation indices derived from ETM+ and OLI sensors. Therefore, further research is needed to evaluate the robustness of vegetation indices extracted from the new Landsat sensor in specific remote sensing applications, such as evaluating their performance in improving land cover classifications.

Statistical analysis of remote sensing data is a challenging process due to image features, such as pixel's high dimensionality, inherent non-linear nature, and also the high spatial and spectral redundancy (Camps-Valls et al., 2011). In the last decade, machine learning algorithms have gained relevance in improving the performance of classification and regression problems. Support Vector Machines (SVM), Random

Forest (RF), and Stochastic Gradient Boosting (SGB) have been recognised as powerful machine learning algorithms in the remote sensing field (Chirici et al., 2013; Gislason et al., 2006; Huang et al., 2002; Knorn et al., 2009; Lawrence et al., 2004; Rodriguez-Galiano et al., 2012b). Nevertheless, the SGB algorithm has mostly been used in problems aimed at predicting spatial data (e.g. forest biomass estimation and tree basal area) (Carreiras et al., 2012; Moisen et al., 2006). To our knowledge, only a few studies have reported applications of SGB for remote sensing classification purposes (Chirici et al., 2013; Lawrence et al., 2004). Therefore, more research is needed to assess the potential and effectiveness of the SGB algorithm for land cover mapping, especially using Landsat 8 OLI data.

Despite the environmental and socio-economic importance of *montado* and its geographic representativeness in the Mediterranean Basin, the development of remote sensing-based approaches for mapping this ecosystem with the use of medium spatial and spectral resolution imagery is rarely addressed in the scientific literature (Carreiras et al., 2006; Godinho et al., 2014; Joffre and Lacaze, 1993; Salvador and Pons, 1998). Thus, this study aims to develop and propose a thorough and effective methodological approach for *montado* ecosystem mapping by using a classification scheme which integrates Landsat 8 OLI multispectral data, vegetation indices, and an advanced machine learning algorithm. Three research goals are directly addressed in this study:

1. Assessing the overall suitability and effectiveness of Landsat 8 OLI imagery for *montado* ecosystem mapping;
2. Assessing the improvement of *montado* classification accuracy by adding vegetation indices as proxy variables of plant physiological processes;
3. Evaluating the performance of the SGB classifier for *montado* land cover classification.

3.3. Material and Methods

3.3.1. Study area

This study was conducted in southern Portugal (Figure 2), a region with a markedly Mediterranean climate characterised by hot and dry summers (August: 31–32ºC T_{max}) and wet and cold winters (January: 6–7ºC T_{min}). Mean annual precipitation varies from 550 mm to 650 mm. Elevation range varies from 40 m to 645 m, and the mean slope is 3.52º, corresponding to a low roughness zone. The study area, covering roughly 8,567 km^2 (centre of the study area: 38º 44' 27.60" N; 7º 41' 31.20" W), is mainly located in the biogeographic Luso-Extremadurense Province, one of the largest in the Iberian Peninsula, whose soils are derived from Palaeozoic siliceous materials. Mesomediterranic cork oak (*Sanguisorbo agrimoniodis–Quercetum suberis*), holm oak (*Pyro bourgaenae–Quercetum rotundifoliae*), and Pyrenean oak (*Arbuto unedonis–Quercetum pyrenaicae*) phytosociological systems are characteristic of this province. *Montado* covers about 44.8% of the study area, being the dominant land use system in the region, followed by arable land (27.9%).

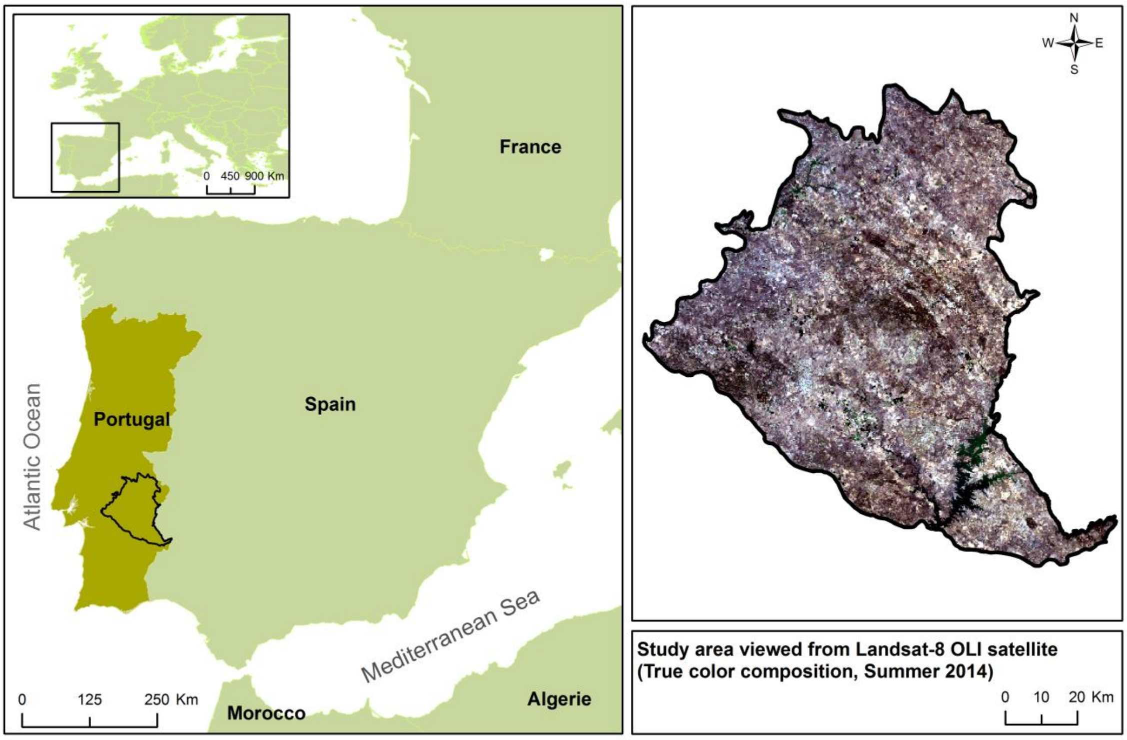

Figure 2 - Study area

3.3.2. Satellite data and pre-processing

Two Landsat 8 scenes of the same area in southern Portugal were acquired in order to develop a multi-seasonal-based classification scheme. One scene was acquired in spring (15^{th} May 2014) and the other one was acquired in summer (19^{th} August 2014), to ensure that inter-class separability benefits from the phenological variation of the vegetation cover. This approach was proved to be accurate (with Kappa values ranging from 0.65 to 0.94) in several land cover mapping studies (Pax-Lenney and Woodcock, 1997; Rodriguez-Galiano and Chica-Olmo, 2012; Schriever et al., 1995). May and August represent peaks in productivity and are also relevant seasons in the phenological development of the major vegetation types in the study area. In summer, annual crops (e.g. tomato and corn) can be confused with evergreen vegetation. The same is expected to occur between urban areas and bare soils due to the high reflectivity of urban surfaces (Rodriguez-Galiano and Chica-Olmo, 2012). Thus, using spring imagery allows for better discrimination in these situations. On the other hand, summer imagery is powerful for distinguishing, for example, vineyards from pastures, which is not possible using only spring imagery. Additionally, large portions of *montado* understorey are occupied by crops and pastures, which are dry during the summer season. Therefore, it is imperative to use the summer imagery to achieve better spectral contrast between the *montado* overstorey and the understorey (Carreiras et al., 2006).

Landsat 8 imagery acquired under path 203 and row 33 entirely covers the study area. The processing level of the acquired images corresponds to the "Standard Level 1 Terrain Corrected" (L1T) which configures a systematic radiometric and geometric correction through the incorporation of ground control points and a digital elevation model. Both acquired scenes are cloud-free images. For the image classification procedure, only OLI VNIR and SWIR bands 2–7 were used in this study (Table 1). As an additional pre-processing task, an atmospheric correction was applied to both images on selected bands by using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) method. FLAASH is an ENVI atmospheric correction algorithm based on MODTRAN4 radiative transfer code (FLAASH, 2009).

Table 1 - Landsat 8 OLI spectral bands

#	Band name	Band width (μm)	Band centre (μm)	Pixel size (m)
2	Blue	0.450 – 0.515	0.483	30
3	Green	0.525 – 0.600	0.563	30
4	Red	0.630 – 0.680	0.655	30
5	Near infrared	0.845 – 0.885	0.865	30
6	Shortwave infrared 1	1.560 – 1660	1.610	30
7	Shortwave infrared 2	2.100 – 2.300	2.200	30
8	Panchromatic	0.500 – 0.680	0.590	15

3.3.3. Vegetation Indices

Vegetation indices were calculated from the selected Landsat 8 multispectral bands of both the spring and summer images. For each scene, six different vegetation indices were calculated: the Enhanced Vegetation Index (EVI), the Short Wave Infrared Ratio (SWIR32), the Carotenoid Reflectance Index 1 (CRI1), the Green Chlorophyll Index (CI_{green}), the Normalised Multi-band Drought Index (NMDI), and the Soil-Adjusted Total Vegetation Index (SATVI) (Table 2). These vegetation indices were selected based on their respective sensitivity and effectiveness for monitoring vegetation cover and for retrieving vegetation parameters in semi-arid environments, wherein water scarcity, soil background effects, and the predominance of senescent plant species are the main characteristics (e.g. Cabello et al., 2012; Hill, 2013; Marsett et al., 2006; Sauceda et al., 2008).

Table 2 - Spectral vegetation indices calculated from Landsat 8 to be used in this study.

Vegetation Index	Band Formula	Reference
Green Chlorophyll Index	$\mathrm{CIgreen} = \frac{\rho\mathrm{NIR}}{\rho\mathrm{Green}} - 1$	Gitelson et al. 2003, 2005
SWIR32*	$\mathrm{SWIR32} = \frac{\rho\mathrm{SWIR2}}{\rho\mathrm{SWIR1}}$	Guerschman et al., 2009
Carotenoid Reflectance Index 1	$\mathrm{CRI1} = \left(\frac{1}{\rho\mathrm{Blue}}\right) - \left(\frac{1}{\rho\mathrm{Green}}\right)$	Gitelson et al. 2002
Enhanced Vegetation Index	$\mathrm{EVI} = 2.5 \times \left(\frac{\rho\mathrm{NIR} - \rho\mathrm{Red}}{1 + \rho\mathrm{NIR} + 6 \times \rho\mathrm{Red} - 7 \times \rho\mathrm{Blue}}\right)$	Huete et al. 1997
Normalized multi-band drought index	$\mathrm{NMDI} = \frac{\rho\mathrm{NIR} - (\rho\mathrm{SWIR1} - \rho\mathrm{SWIR2})}{\rho\mathrm{NIR} + (\rho\mathrm{SWIR1} - \rho\mathrm{SWIR2})}$	Wang and Qu, 2007
Soil-Adjusted Total Vegetation Index	$\mathrm{SATVI} = \left(\frac{\rho\mathrm{SWIR1} - \rho\mathrm{Red}}{\rho\mathrm{SWIR1} + \rho\mathrm{Red} + L}\right) \times (1 + L) - \left(\frac{\rho\mathrm{SWIR2}}{2}\right)$	Marsett et al., 2006

Note: *L* in SATVI index represents a constant related to the slope of the soil-line. In this study *L*= 0.5 was applied. *SWIR1 and SWIR2 bands in the case of Landsat 8. Original configuration corresponds to SWIR2 and SWIR3 bands of MODIS sensor (Guerschman et al., 2009).

EVI and SATVI were used as complementary indices. EVI was designed to enhance green vegetation reflectance, while minimizing canopy background influence, and is sensitive to high biomass conditions (Huete et al., 1997). SATVI index is sensitive to both green and senescent vegetation and thus suitable for semi-arid regions (Marsette et al., 2006). As a limitation, EVI tends to present relatively low values in all biomes and also lower ranges on semi-arid regions (Jiang et al., 2008). When used to retrieve vegetation fractional cover, SATVI index overestimates in high density canopy cover conditions (Marsett et al., 2006). Leaf pigment content (e.g. chlorophylls and carotenoids) vary over the seasons and within vegetation types (Dash et al., 2007; Lewandowska and Jarvis, 1977; Peterson et al., 1988; Suaceda et al., 2008). Therefore, CIgreen and CRI1 vegetation indices were used to quantify the spatio-temporal variability of pigment contents in order to increase the separability between vegetation types (Gitelson et al. 2002, 2003, 2005; Wu et al., 2010). However, CIgreen and CRI1 may be affected by canopy architecture, shadow and soil background effects (Gitelson et al., 2005; Verrelst et al., 2008). The SWIR32 index was used as a surrogate of the Cellulose Absorption Index (CAI), which has been reported as a useful index to detect and distinguishing bare soils from dry vegetation (Guerschman et al., 2009, Hill et., 2014). Given the water scarcity in Mediterranean region, soil and vegetation moisture are a very important factor in determining spectral behaviour of land cover types. Bare soils can have similar reflectance features to urban areas and similar NIR reflectance to dry crops/pastures (Berberoglu et al., 2000). Therefore, to increase the separability between these land cover types, NMDI was used due to its capacity to quantify the water content of soil and vegetation, where high values of NMDI indicate the presence of dry bare soils. However, NMDI index seems to saturate whit leaf area index values up to 5 (Wang and Qu, 2007).

3.3.4. Training and validation data

A dataset including 1,903 sample points covering the study area was produced using a stratified approach in order to ensure a thorough and representative reference dataset constituted by eleven land cover categories (Table 3).

Table 3 – List of land cover classification categories and their respective number of sample points

Class code	Class Name	Number of sample points	Class code	Class Name	Number of sample points
MO	*montado*	420	IA	Irrigation Agriculture	101
EF	Eucalypt Forest	117	C/P	Dry crops/pastures	213
SL	Shrubland	221	BS	Bare soil	81
PF	Pine Forest	80	UB	Urban	80
WT	Water	89	VI	Vineyards	235
OG	Olive Grove	266			

All of these points were chosen through a photo-interpretation and posterior cross-validation process using a set of high-resolution (0.5 m) true-colour orthophotomaps (produced in 2005 by IGP – the Portuguese Geographic Institute), and also by using the true-colour composition of the summer Landsat 8 OLI image. This true-colour composition was pansharpened with panchromatic band 8 in order to increase spatial detail and thus improve the photo-interpretation process. To guarantee the overall quality of the final dataset of the sample points, a field validation was performed in June 2014 to validate all the points that presented less certitude in their classification via photointerpretation. For each sample point, vegetation indices and reflectance values from the 12 bands (6 spring and 6 summer bands) were extracted from both Landsat 8 OLI images. Posteriorly, all available sample points were split into training (80%) and validation (20%) datasets using the *createDataPartition* function from the *caret* package (Khun, 2014) implemented in the R statistical software (R Development Core Team, 2014). This function is useful for creating balanced splits in the data. It ensures that random sampling occurs within each class while also preserving the overall class distribution over the dataset (Kuhn and Johnson, 2013). The SGB models were constructed using the training dataset, while the accuracy assessment of final models was performed using the validation dataset.

3.3.5. Image classification using Stochastic Gradient Boosting

The third objective of this study was the implementation and assessment of the SGB classifier performance when using multi-seasonal Landsat 8 OLI data. SGB is a hybrid machine learning algorithm that combines both the advantages of bagging and boosting procedures (Friedman, 2001, 2002). This algorithm uses the steepest gradient method in order to emphasise the misclassified training data that is close to the correct classification (Lawrence et al., 2004). Several advantages have been highlighted regarding the use of the SGB algorithm, including low sensitivity to outlier effects, the ability to deal with inaccurate training and unbalanced datasets, the stochastic characteristic in modelling non-linear relationships, robustness in dealing with interaction effects among predictors, and also the capability to quantify variables' importance (Friedman, 2001). Moreover, the stochasticity component of the SGB algorithm is a powerful property for improving classification accuracy and also for reducing the occurrence of the over-fitting phenomenon (Friedman, 2002).

Analytically, the SGB algorithm involves a parameter tuning process to maximise predictive accuracy. These parameters are: (i) bag fraction (*bf*), which is the random fraction of the training data used to perform each classification tree; (ii) tree complexity (*tc*), which represents the number of splits that should be performed in each tree; (iii) learning rate (*lr*), which determines the contribution of each tree to the growing model and helps to control over-fitting by controlling the gradient steps; and (iv) number of trees (*nt*) (Elith et al., 2008). To determine the optimal combination among these parameters for achieving the highest overall model accuracy, a set of SGB models were tested using different values for *bf* (0.50, 0.60, and 0.75), *tc* (1, 3, 5, 9, and 11), *lr* (0.001, 0.01, 0.05, and 0.07), and *nt* (50–1,500). The optimal bag fraction value was assessed testing *tc* = (1, 3, 5, 9, 11), *lr* = 0.01, and *nt* ranging from 50 to 1,500 trees, in order to reduce the number of candidate models. Therefore, a total of 30 candidate SGB models were evaluated through the *gbm* R package version 2.1 (Ridgeway, 2013). The training dataset (Section 2.4) was used to tune and train SGB classification models by applying a repeated (three times) 10-fold cross validation resampling method, which is considered to be an appropriate approach when large amounts of data are not available (Khun and Johnson, 2013). In this technique the samples are randomly partitioned into *k*-sets (folds) with roughly equal sizes. From this stage a model is fitted using the remaining *k*-1 subset, and the first subset to be held out is used to estimate model performance measures. This process is repeated with the second subset held out, and so on. After this procedure, results from each fold are summarised (using mean and standard error) to select the model with the highest average accuracy (Khun and Johnson, 2013).

Optimal values for SGB tuning parameters were selected using only multi-seasonal Landsat 8 OLI spectral bands (Dataset I: LS8). The best combination of tuning parameters was then used to assess the improvement in the classification accuracies that resulted from adding vegetation indices to the multi-seasonal Landsat 8 OLI spectral bands (Dataset II: LS8 + VIs). Finally, to implement the whole SGB procedure (e.g. tuning parameters, graphs, confusion matrix, model comparability, and prediction) an R code was developed and implemented by using the *caret* package.

3.3.6. Performance assessment

Accuracy is the most commonly used criteria for evaluating the performance of a classifier algorithm and the effectiveness of specific remote sensing data for producing accurate land cover data. It also allows diagnosis of the improvement in classification quality resulting from adding ancillary information to the classification scheme. In this context, a validation dataset (Section 2.4) containing an independent set of sample points was used to provide an unbiased estimate of SGB classifications. Therefore, a confusion matrix was computed and four traditional accuracy assessment measures were calculated for both Dataset I and II: overall classification accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and the Kappa coefficient (K) (Congalton and Green, 2009). In addition, quantity and allocation disagreement were also calculated (Pontius and Millones, 2011). Quantity disagreement is defined as the amount of difference between the reference land cover categories and the classified categories. This difference results from obtaining less than an optimum matching among the proportions of the categories, corresponding therefore to errors in the proportions of classes. Allocation disagreement corresponds to the amount of difference between the reference layer and the classified categories. This difference results from obtaining less than a maximum matching in the spatial allocation of the categories, given the proportions of the categories in the reference and comparison layers. Allocation disagreement deals with errors in spatial allocation of land cover classes.

To investigate if separate vegetation indices differ between land cover types, several Kruskal–Wallis and Tukey–Kramer tests (post hoc pairwise comparisons) were performed. This approach is useful for analysing the degree of dissimilarity of vegetation indices among land cover types. This is therefore an indirect way of measuring the importance of these indices for the separability of land cover categories.

3.4. Results and Discussion

3.4.1. Identifying the optimal SGB parameters

Based on the repeated 10-fold cross-validation results, the highest overall accuracy was achieved with a bag fraction value of 0.50. Indeed, no significant differences were observed among the overall accuracies determined for the three tested bag fractions ($bf_{0.50}$: OA = 80.02%; $bf_{0.60}$: OA = 79.91%; $bf_{0.75}$: OA = 79.96%). Similar results have been reported regarding the establishment of the optimal value for this SGB parameter, where bag fractions in the range of 0.50–0.75 produce, in general, high overall accuracies for different analytical purposes (e.g. Carreiras et al., 2012; Elith et al., 2008). As shown in Figure 3, the tuning procedure for assessing the optimal SGB parameters between selected *lr*, *tc*, and *nt* values determined that the lowest overall accuracy was obtained with *lr* = 0.001, reaching a maximum overall accuracy value of 77.38% with *tc* = 11 and *nt* = 1,500. The highest overall accuracies were achieved when *tc* = 11, *lr* = 0.07, and *nt* = 1,150 and when *tc* = 9, *lr* = 0.05, and *nt* = 1,300 parameter values were used (OA = 80.67% and 80.59%, respectively). However, the overall accuracies achieved by both 0.05 and 0.07 learning rates show some instability (peaks and valleys in the *tc* curves) in the classification accuracies over each tree, which may have important practical implications related to SGB classification performance (Elith et al., 2008). According to Elith et al. (2008) it is preferable to use slower learning rates (i.e. low values of *lr*) to control this instability in the models' accuracy. The results shown in Figure 3 reveal that a more stable model also with high overall accuracy (OA = 80.22%) was achieved when *lr* = 0.01 was used. Therefore it can be concluded that for the data used in this study, *lr* = 0.01 is the optimal value for this SGB parameter. In summary, the best combination of tuning parameters achieved during the tests, i.e. *bf* = 0.50, *lr* = 0.01, and *tc* = 11, were used in the subsequent image SGB classifications.

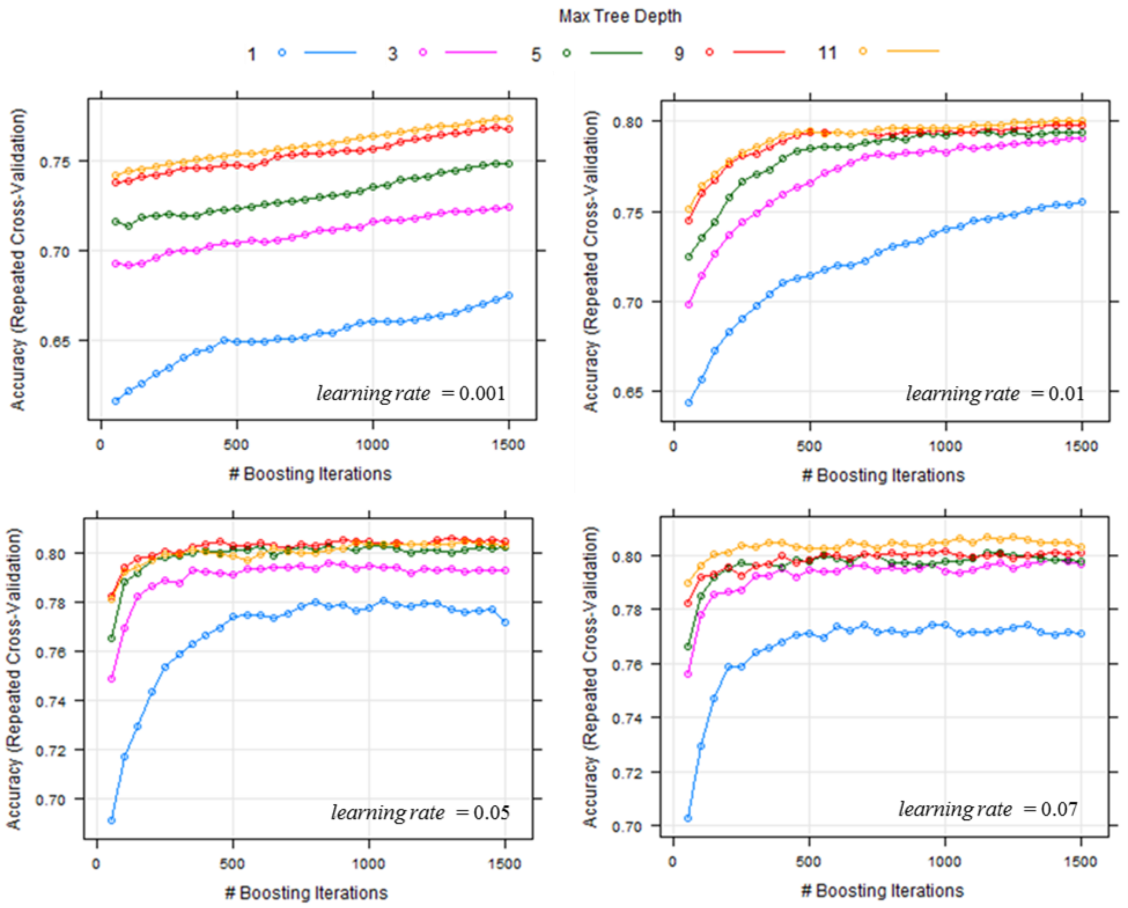

Figure 3 - Overall accuracies for tested tree complexity (*tc*) and learning rate (*lr*) values using bag fraction 0.50.

3.4.2. Effectiveness of Landsat 8 OLI multispectral imagery for montado ecosystems mapping

Considering the Mediterranean landscape heterogeneity of this study area and the overall spatial complexity of the *montado* ecosystem (van Doorn and Pinto-Correia, 2007), the accuracy assessment results produced by applying the SGB algorithm are positive. The performed SGB classification using only the selected multi-seasonal Landsat 8 OLI spectral bands (Table 4) showed overall strong agreement and good accuracy (OA = 80.16%; K = 0.77), revealing that this sensor is suitable for generating land cover maps for these Mediterranean ecosystems. At the land cover/vegetation class level, *montado* ecosystem classification was reasonably accurate (70.19% and 86.90% of user's and producer's accuracy, respectively). Indeed, it can be seen through the confusion matrix that some areas of dry crops/pastures, vineyards, and olive groves were classified as *montado*, and vice versa. These errors occurred due to the spatial variability of tree density in the *montado* ecosystem, contributing therefore to a lower inter-class separability between these land cover categories. Some low density *montado* areas (tree cover between 10% and 30%) showed a wrong classification by having been mapped as dry crops/pastures and vineyards. In these areas, the vegetation cover density is generally sparse and, therefore, the high reflectance of the bare soil may have masked small components reflected from sparse vegetation (Berberoglu et al., 2000; Rodriguez-Galiano and Chica-Olmo, 2012). On the other hand, when *montado* areas are characterised by dense vegetation (tree density > 50%), classification confusions may occur with olive groves and shrubland, showing some limitation when only original Landsat 8 OLI bands are used in the classification scheme.

Table 4 - Confusion matrix obtained with SGB algorithm applied to selected multi-seasonal Landsat 8 OLI multispectral bands (Dataset I).

		Reference data												
		MO	EF	SL	PF	WT	OG	IA	C/P	BS	UB	VI	Total	User´s acc.
Classified data	MO	**73**	1	1	2	0	16	1	3	0	0	7	104	70.19
	EF	0	**18**	0	4	0	0	0	0	0	0	0	22	81.82
	SL	2	3	**42**	1	0	1	0	0	0	0	0	49	85.71
	PF	0	0	1	**8**	0	0	0	0	0	0	0	9	88.89
	WT	0	0	0	0	**17**	0	0	0	0	0	0	17	100.00
	OG	2	1	0	0	0	**32**	0	3	1	1	1	41	78.05
	IA	0	0	0	0	0	0	**18**	1	0	0	0	19	94.74
	C/P	4	0	0	0	0	3	1	**34**	5	0	0	47	72.34
	BS	0	0	0	0	0	0	0	1	**10**	3	0	14	71.43
	UB	0	0	0	0	0	1	0	0	0	**12**	0	13	92.31
	VI	3	0	0	1	0	0	0	0	0	0	**39**	43	90.70
	Total	84	23	44	16	17	53	20	42	16	16	47	**378**	
	Producer´s acc.	86.90	78.26	95.45	50.00	100.00	60.38	90.00	80.95	62.50	75.00	82.98		
	Overall acc.	**80.16**		Kappa	**0.77**									

Note: acc. – accuracy.

3.4.3. *Assessing the improvement of montado classification accuracy by adding vegetation indices to the classification scheme.*

The Kruskal–Wallis tests revealed that each vegetation index value was significantly different over the land cover types (p values were < 0.001 for all vegetation indices). The variability values of the six vegetation indices among the land cover categories are shown in Figure 4. Water and irrigation agriculture were intentionally excluded from this analysis due to their high and implicit separability potential when compared to the remaining land cover types. The patterns illustrated in the boxplot graphs clearly show the high degree of dissimilarity of the vegetation indices among land cover categories, which is a desirable factor for increasing the separability between them (Tolpekin and Stein, 2009). Among the indices, the dissimilarity patterns related to EVI (summer), CRI1 (spring), and CI_{green} (summer) demonstrate their usefulness for discriminating fractional cover of photosynthetic vegetation (e.g. Hill, 2013). Discrimination of pine forest, eucalypt forest, *montado*, and also vineyards from the remaining categories was evident when the EVI index was used (Figure 4a). In addition, EVI was also suitable for increasing the separability between olive grove and *montado* areas. Both land cover types constitute one of the most confused pairwise when using only the original Landsat 8 OLI bands (Table 4). According to the Tukey–Kramer tests, non-significant differences were found only for *montado*–vineyards and bare soils–urban land cover pairs when using the EVI index (p values > 0.05). The non-detected significant differences between bare soils and urban areas with EVI was not a surprise, as there is no green vegetation in these areas, and EVI was especially featured for detecting and monitoring vegetation greenness (Cho et al., 2014; Huete et al., 1997).

The use of leaf pigments such as the CRI1 and CI_{green} resulted in an increase in class separability. These vegetation indices were very useful, for example, for distinguishing *montado* from vineyards (CRI1) and from olive groves (CI_{green}), and also for enhancing the differences between eucalypt and pine forests (Figure 4b and 4d). However, neither index was suitable for discriminating urban–crops/pastures and urban–bare soils land cover pairs (Tukey–Kramer pairwise comparisons show p values > 0.05).

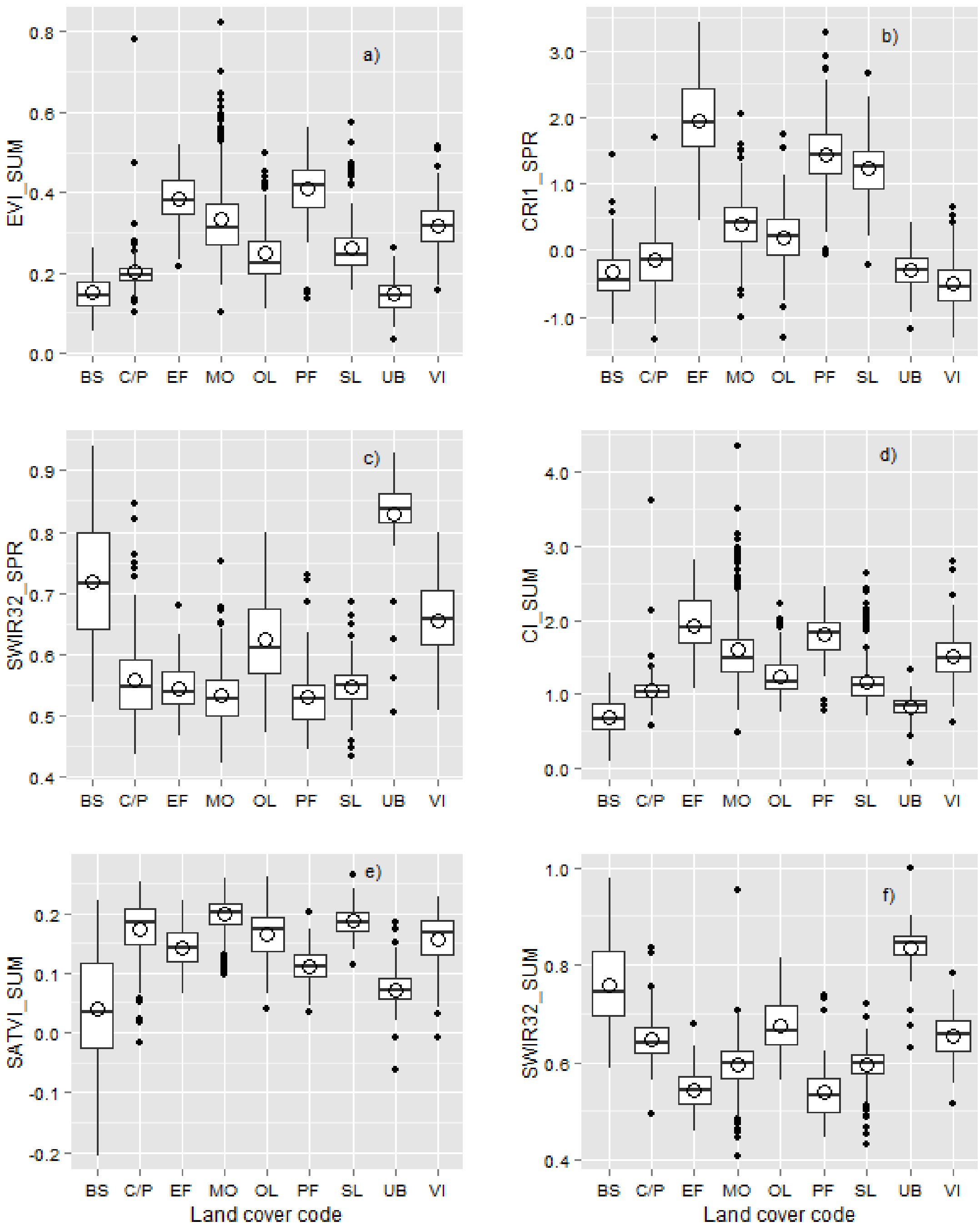

Figure 4 - Distribution of spectral vegetation indices values over land cover categories. The central solid line represents the median and the circle the mean, bars shows the 95% confidence intervals, and dots represent outliers. Code represent land cover classes: BS- Bare soil; C/P- Dry crops/pastures; EF- Eucalypt Forest; MO- *montado*; OG- Olive Grove; PF- Pine Forest; Sl- Shrubland, UB- Urban; VI- Vineyards.

It was reported by several authors (Dash et al., 2007; Lewandowska and Jarvis, 1977; Peterson et al., 1988; Sauceda et al., 2008) that leaf pigment content (e.g.

chlorophylls and carotenoids) in arid and semi-arid landscapes vary over the seasons and between vegetation types, therefore providing valuable information that can enhance land cover spectral differences. The results of the present study also corroborate that CI_{green} and CRI1 vegetation indices are suitable for quantifying the spatio-temporal variability of chlorophyll and carotenoid contents. The determination and integration of these indices is therefore very useful for increasing the separability between vegetation types (Dash et al., 2007; Gitelson et al., 2002, 2003, 2005; Wu et al., 2010).

A particular characteristic in arid and semi-arid regions is the presence of bare soils and vegetation with non-photosynthetic tissues during long periods (Goirán et al., 2012). The spectral separability among bare soils and senescent plants is ambiguous in the VIS-NIR wavelength region (Nagler et al., 2000). The contrasting behaviour presented by the SWIR32 and SATVI indices (Figure 4c, 4e, and 4f), which are both short-wave infrared-derived indices, emphasises their effectiveness in dealing with non-photosynthetic vegetation, bare soil, and green vegetation fractions (Guerschman et al., 2009, Hill, 2013; Marsett et al., 2006). High values of the SWIR32 index (spring and summer) were found mainly in urban areas, bare soils, and vineyards. The dissimilarity between these three land cover types was quite significant (p value < 0.001). The SATVI index was useful for distinguishing dry crops/pastures, *montado* areas, and shrubland from the other categories by minimising soil spectral signal effects, which constitute a particular feature of this index (Marsett et al., 2006). Finally, the inclusion of the NMDI index in the classification scheme has also proved useful for supporting a more effective differentiation of land cover classes. Sparsely vegetated areas, such as vineyards and some *montado* areas (tree density 10–30%) were distinctively separated from bare soils and urban areas when the summer NMDI index was included (p values < 0.001). As reported by Wang and Qu (2007), using the NMDI index may be effective for detecting significant differences in vegetation moisture. In fact, the differentiation between shrubland and the remaining vegetation classes in this study was quiet evident (p value < 0.001) given the extremely low NMDI value observed.

Figure 5 shows the results obtained by applying the repeated 10-fold cross validation procedure to Dataset I (LS8) and Dataset II (LS + VIs). As it can be seen, the highest classification accuracy was achieved when vegetation indices were used in combination with the multi-seasonal Landsat 8 OLI bands, reaching an overall accuracy of 84.20%.

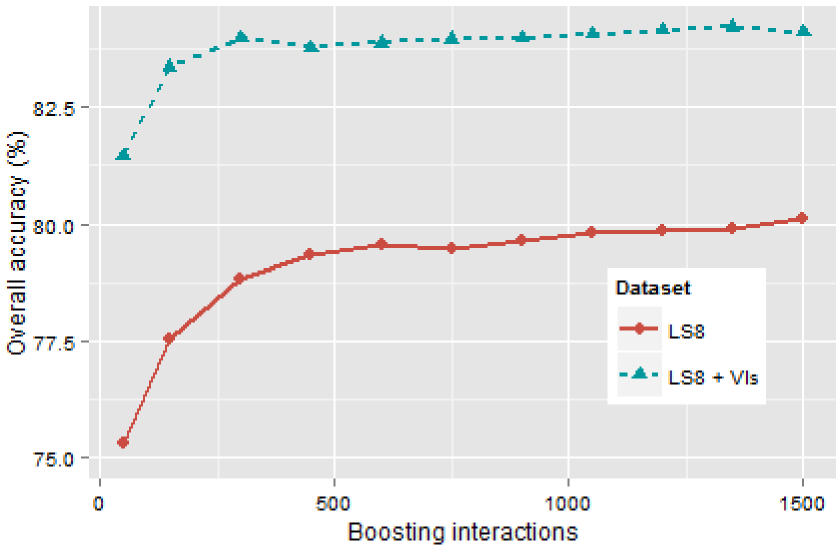

Figure 5 - Relationships among the results of overall accuracy (when using repeated 10-fold cross validation), tree complexity (*tc*) and number of trees (*nt*). Note: LS8 represents the Dataset I and LS8+VIs represents the Dataset II.

Table 5 presents the confusion matrix produced for the accuracy assessment of the SGB model when vegetation indices were included in the classification process. The confusion matrix was obtained using an independent validation dataset. Overall, strong agreement and good accuracy (OA = 85.71% and K = 0.84) were observed. For the land cover/vegetation class level, all classes also showed a strong agreement and a good accuracy (UA > 78%). Regarding the main goal of this study, i.e. accurately mapping the spatial distribution of *montado* ecosystems in the study area, the results were very positive (PA = 88.10%; UA = 78.72%). The combination of vegetation indices with Landsat 8 OLI multispectral bands provided the best classification performance, with overall accuracy and the Kappa coefficient increased by 5.6% and 0.07, respectively, when compared with the same accuracy measures obtained by applying SGB to the Landsat 8 OLI multispectral bands (Tables 4 and 5).

Table 5 - Confusion matrix obtained with SGB algorithm applied to selected multi-seasonal Landsat 8 OLI multispectral bands and Vegetation Indices (Dataset II).

	Reference data												User´s acc.
Classified data	MO	EF	SL	PF	WT	OG	IA	C/P	BS	UB	VI	Total	
MO	**74**	1	0	2	0	11	0	2	0	0	4	94	78.72
EF	1	**21**	0	2	0	0	0	0	0	0	0	24	87.50
SL	2	1	**43**	2	0	1	0	0	0	0	0	49	87.76
PF	0	0	1	**9**	0	0	0	0	0	0	0	10	90.00
WT	0	0	0	0	**17**	0	0	0	0	0	0	17	100.00
OG	2	0	0	1	0	**39**	0	3	1	0	1	47	82.98
IA	0	0	0	0	0	0	**19**	1	0	0	0	20	95.00
C/P	2	0	0	0	0	1	1	**35**	4	0	0	43	81.40
BS	0	0	0	0	0	0	0	1	**11**	2	0	14	78.57
UB	0	0	0	0	0	1	0	0	0	**14**	0	15	93.33
VI	3	0	0	0	0	0	0	0	0	0	**42**	45	93.33
Total	84	23	44	16	17	53	20	42	16	16	47	378	
Producer´s acc.	88.10	91.30	97.73	56.25	100	73.58	95.00	83.33	68.75	87.50	89.36		
Overall acc.	**85.71**		Kappa	**0.84**									

Note: acc. – accuracy.

Table 6 shows an exhaustive comparison of the accuracy values obtained by applying SGB classification to both Dataset I (LS8 – selected multi-season Landsat OLI spectral bands) and Dataset II (LS8 + VIs). The Kappa coefficient value improvement resulting from the difference between both classification accuracy measurements was also calculated for each land cover/vegetation class. Integration of vegetation indices into the classification scheme caused a significant accuracy improvement in the Dataset II classification product when compared with Dataset I (Table 6), leading to remarkable differences in the producer's accuracy values for olive groves (13.21%), eucalypt forest (13.04%), and urban areas (12.50%). Considering the user's accuracy results, a significant increase was also observed, mainly for dry crops/pastures (9.05%), *montado* (8.53%), and bare soils (7.14%). The most significant improvements in classification accuracy were observed in both *montado* ecosystems (Kappa value from 0.62 in Dataset I to 0.73 in Dataset II) and dry crops/pastures (Kappa value from 0.69 in

Dataset I to 0.79 in Dataset II). Considering the two accuracy measures proposed by Pontius and Millones (2011), it was found that the total disagreement is dominated by an allocation error. However, the allocation disagreement was very low in both cases, below 12% for Dataset I and below 10% for Dataset II. At the class level, the allocation disagreement values range from 0.00% to 5.82% for maps produced with the LS8 dataset, whereas when using the LS8 + VIs dataset the maximum value decreased to 5.29%. The highest quantity and allocation disagreement values were found in *montado* patches, while the lowest ones were found in water patches (Figure 6). These results contrast with those obtained by Li et al. (2011), who argued that vegetation indices had a limited role in improving overall classification performance. For instance, by performing a visual interpretation of the resulting SGB classification maps derived from both Datasets I and II, it can be seen that in the first case (Dataset I-derived), some *montado* areas were classified as dry crops/pastures areas. Nevertheless, this misclassification did not occur when using Dataset II, which included a combination of selected vegetation indices (Figure 7a and 7b).

Table 6 - Comparison of SGB classification accuracies obtained by using Dataset I (LS8) and Dataset II (LS8+VIs)

Class Name	PA using Dataset I	PA using Dataset II	Imp. of PA	UA using Dataset I	UA using Dataset II	Imp. of UA	K using Dataset I	K using Dataset II	Imp. of K
montado	86.90	88.10	1.19	70.19	78.72	8.53	0.62	0.73	0.11
Eucalypt Forest	78.26	91.30	13.04	81.82	87.50	5.68	0.81	0.87	0.06
Shrublands	95.45	97.73	2.27	85.71	87.76	2.04	0.84	0.86	0.02
Pine Forest	50.00	56.25	6.25	88.89	90.00	1.11	0.88	0.90	0.01
Water	100.0	100.0	0.00	100.0	100.0	0.00	1.00	1.00	0.00
Olive Grove	60.38	73.58	13.21	78.05	82.98	4.93	0.74	0.80	0.06
Irrigation agriculture	90.00	95.00	5.00	94.7	95.00	0.26	0.94	0.95	0.00
Dry crops/pastures	80.95	83.33	2.38	72.34	81.40	9.05	0.69	0.79	0.10
Bare soil	62.50	68.75	6.25	71.43	78.57	7.14	0.70	0.78	0.07
Urban	75.00	87.50	12.50	92.31	93.33	1.03	0.92	0.93	0.01
Vineyards	82.98	89.36	6.38	90.70	93.33	2.64	0.89	0.92	0.03

Note: PA – Producer´s accuracy; UA – User´s accuracy; K – Kappa coefficient; Dataset I= LS8; Dataset II = LS8+VIs; Imp. – Improvement from Dataset I to Dataset II.

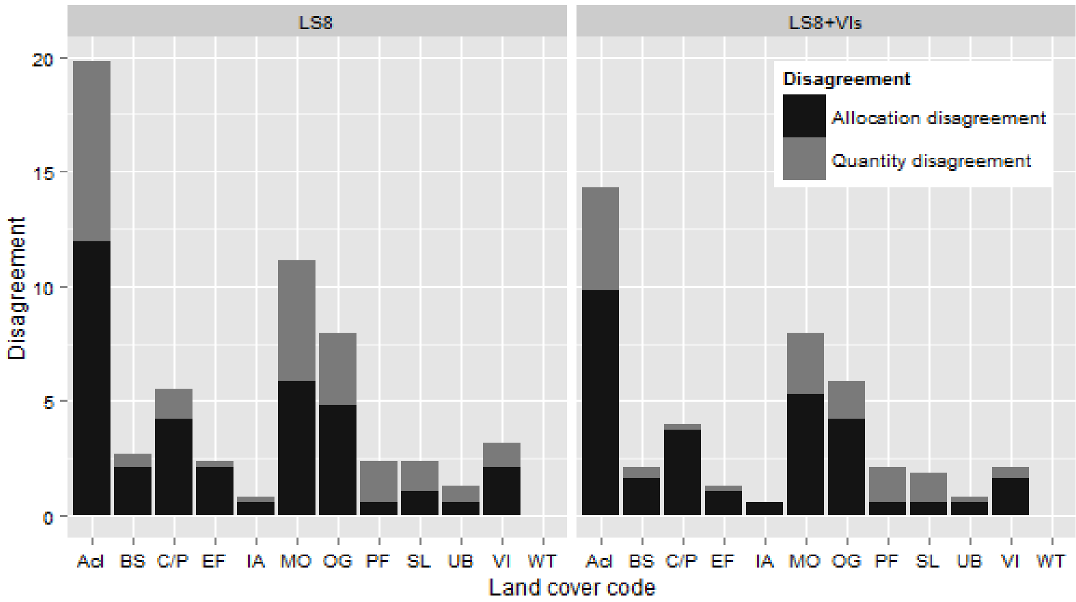

Figure 6 - Quantity disagreement and allocation disagreement for Datasets I (LS8) and II (LS8+VIs). Y axis represents disagreement in percentage. X axis represents the land cover category code: Acl- All land cover classes; BS- Bare soil; C/P- Dry crops/pastures; EF- Eucalypt Forest; IA- Irrigation Agriculture; MO- *montado*; OG- Olive Grove; PF- Pine Forest; Sl- Shrubland, UB- Urban; VI- Vineyards; WT- Water.

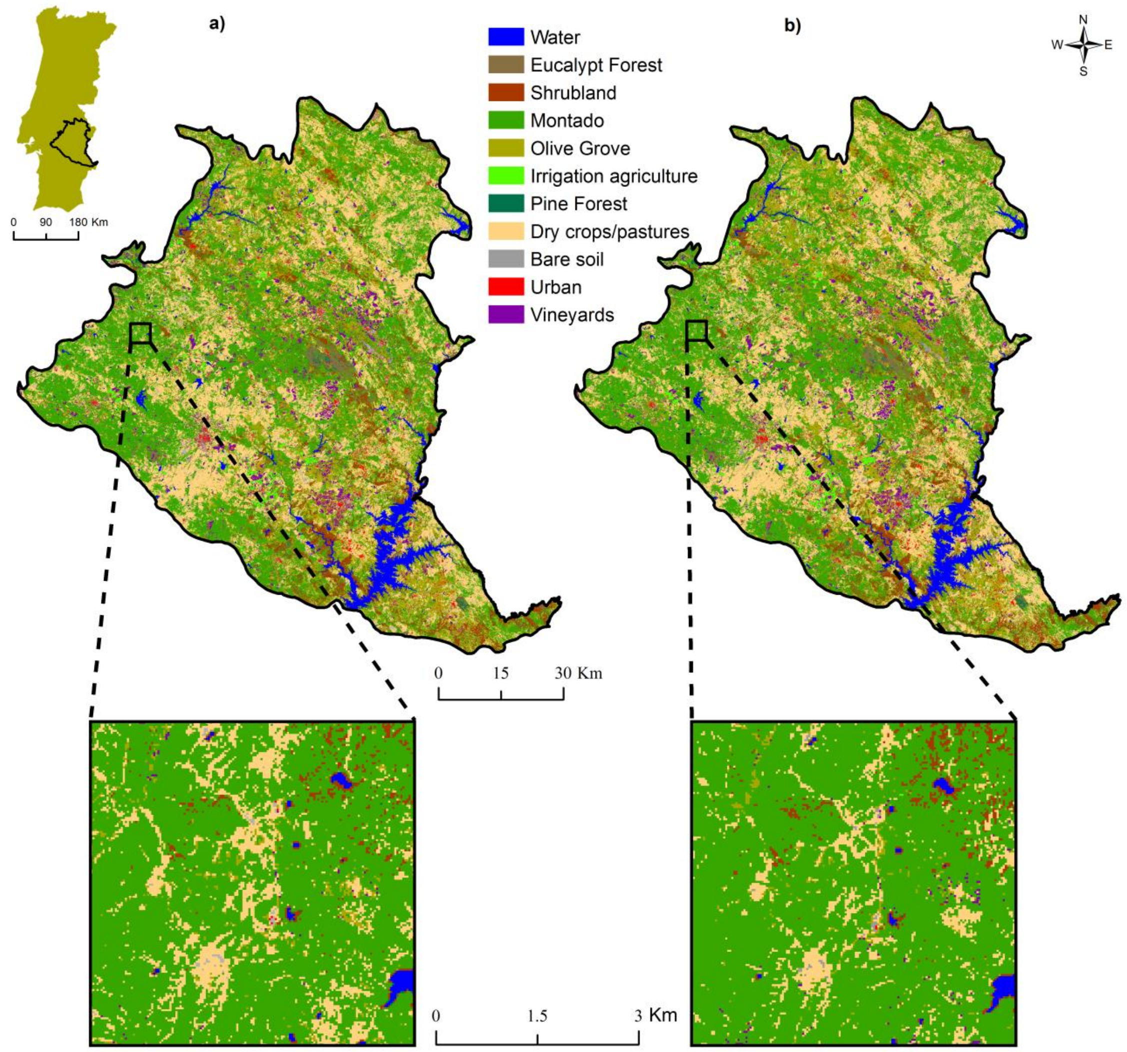

Figure 7 - Comparison of Land Cover products derived from SGB classification applied to Dataset I (LS8) – at left - and Dataset II (LS8+VIs) – at right.

Figure 8 shows the relative contribution of the 24 variables used, and it is clear that vegetation indices had the highest relative importance for discriminating among land cover/vegetation classes. Based on these results, EVI, CRI1, SWIR32, CI_{green}, SATVI, and NMDI were positioned in the top 10 of the most significant variables for classification, with EVI (Summer), CRI1 (Spring), and SWIR32 (Spring) being the three most relevant discrimination variables. As reported by Dash et al. (2007), the results obtained in this study support the conclusion that data acquired in the summer season appear to provide a larger degree of discrimination than data acquired in the spring. In fact, seven variables from the top 10 of those most significant for classification were derived from summer season data (Figure 8).

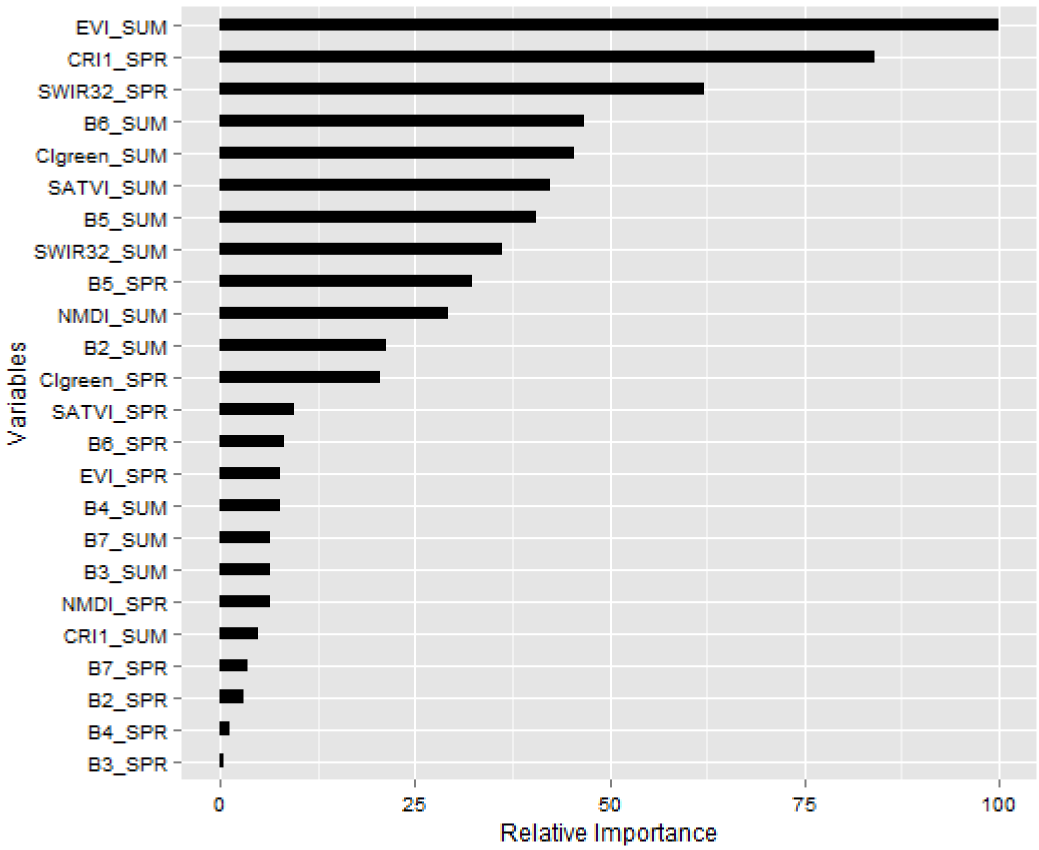

Figure 8 - Relative importance of each one of the 24 variables used in the SGB classification model applied to Dataset II. SUM: Summer, SPR: Spring.

In summary, the results reported by this study may be of great relevance for land cover classification in the context of the Mediterranean region. It has been shown that the use of vegetation indices as ancillary information can markedly enhance the biophysical differences between land cover/vegetation categories, and therefore may increase their spectral inter-separability.

Chapter

4

A remote sensing-based approach to estimating *montado* canopy density using the FCD model: a contribution to identifying HNV farmlands in southern Portugal

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4.1. Abstract

Mapping the land-cover pattern dominated by complex Mediterranean silvo-pastoral systems with an accuracy that enables precise monitoring of changing tree-cover density is still an open challenge. The main goal of this paper is to demonstrate the implementation and effectiveness of the Forest Canopy Density (FCD) model in producing a remote sensing-based and detailed map of *montado* canopy density over a large territory in southern Portugal. This map will make a fundamental contribution to accurately identifying and assessing High Nature Value (HNV) farmland in *montado* areas. The results reveal that the FCD model is an effective approach to estimating the density classes of *montado* canopy (overall accuracy = 78.0%, kappa value = 0.71). The study also shows that the FCD approach generated good user's and producer's accuracies for the three *montado* canopy-density classes. Globally, the results obtained show that biophysical indices such as the advanced vegetation index, the bare soil index, the shadow index and the thermal index are suitable for estimating and mapping *montado* canopy-density classes. These results constitute the first remote sensing-based product for mapping *montado* canopy density that has been developed using the FCD model. This research clearly demonstrates that this approach can be used in the context of Mediterranean agro-forestry systems.

Keywords: canopy density · FCD · agroforestry · *montado* · *dehesa* · advanced vegetation index

4.2. Introduction

The existence of traditional agricultural landscapes in Europe is considered to be a reflection of their rich cultural and natural heritage. The huge variety of natural conditions and traditional farming practices in Europe has created unique landscapes that have provided living conditions for a large number of plant and animal species (EEA/UNEP 2004; Doxa et al. 2010; Plieninger and Bieling 2013). This is the case for the extensive agro-forestry systems in southern Iberia, which are now acknowledged as being unique landscapes and hotspots of biological diversity. In recent decades, however, it has been reported that the biodiversity of European agro-ecosystems is in a clear and worrying state of decline (Billeter et al. 2008; Oppermann and Beaufoy 2012; Stoate et al. 2009).

To prevent the loss of farmland biodiversity, several relevant conservation efforts at the European level have been implemented, such as habitat and bird directives and the biodiversity action plan for agriculture. Another initiative that is relevant to conserving the biodiversity of farmland is the identification of High Nature Value Farmlands (HNV) at European, national and regional levels (Andersen et al. 2003; EEA/UNEP 2004; Paracchini et al. 2008). According to Andersen et al. (2003) HNV 'can be defined as those areas in Europe where agriculture is a major (usually the dominant) land use and where that agriculture supports or is associated with either a high species and habitat diversity or the presence of species of European conservation concern or both'.

Some of the largest HNV areas are found in southern Europe. They consist of habitats such as the *montado* (in Portugal), *dehesa* (in Spain), semi-natural grasslands and steppe areas (EEA/UNEP 2004; Pinto-Correia and Carvalho-Ribeiro 2012). The *montado* is an agro-silvo-pastoral system dominated by cork oak (*Quercus suber*) and/or holm oak (*Q.* [*ilex*] *rotundifolia*) in varying densities, usually with a systematic undercover combination of livestock grazing, agriculture and forestry uses (Aronson et al. 2009; Pinto-Correia et al. 2011; Vicente and Alés 2006). The *montado* is one of the most biodiversity-rich ecosystems in the western Mediterranean Basin and is broadly classified as HNV (Branco et al. 2010; Diaz et al. 2003; Pinto-Correia and Carvalho-Ribeiro 2012). However, because it presents a degree of spatial fuzziness determined by the variability in cover density, which in turn has been shaped by decisions made by farmers, different intensities of management practices, and also by biophysical constraints, biodiversity values might also vary between different *montado* patches. Thus, not all areas where *montado* occurs can be classified as HNV farmlands (Almeida et al. 2013) and the need for a precise classification underlies the extended use of the HNV classification in carrying out targeted management of *montado* areas.

As stated above, *montado* is spatially characterized by the variability of its tree-cover density. In turn, this tree-cover variability creates different ecological features by altering the local climate conditions, water balance, and nutrient cycling (Joffre and Rambal 1993; Marañón et al. 2009; Plieninger et al. 2004; Plieninger 2006). On the other hand, the gradient between low and high tree-cover density over *montado* landscape can provide different structural heterogeneity and habitat diversity, determining the composition of species communities (Diaz et al. 1997, 2003; Marañón et al. 2009). Studies carried out in Portugal and Spain have identified *montado* tree-cover density as one of the most important variables in determining bird diversity (Diaz et al. 2003; Godinho and Rabaça 2011). In summary, and as observed in other agricultural landscapes, *montado* tree-cover density plays an important role in maintaining ecosystem functions and farmland biodiversity (Fisher et al. 2010; Harvey et al. 2006; Manning et al. 2006; Morelli et al. 2014).

To date, the identification of HNV farmlands has most often been based on spatial data from various data sources such as land-cover maps, agricultural statistics and biodiversity datasets (Oppermann et al 2012). Nevertheless, when an HNV classification is required at a regional/local scale to support, for example, regional planning and conservation policies, the main limitations that are faced stem from the availability of some of the above-mentioned datasets and also their spatial resolution. In order to overcome these limitations, which can significantly compromise the accuracy of HNV classifications, some interesting approaches have been taken to improve the effectiveness of HNV classification methodologies using a remote sensing-based approach, mainly at a regional/local scale (Almeida et al. 2013; Hazeu et al. 2014).

Given the existing relationship between tree cover, biodiversity and management intensities in the *montado*, it is essential to integrate information on tree-cover density in order to achieve more effective results through approaches to HNV identification. In this sense, the availability of accurate and up-to-date geographic information on *montado* tree-cover density with a high spatial resolution is an important factor in moving towards more accurate identification of *montado* areas as HNV farmlands. Traditional methods like field inventories and aerial photo interpretation can be used for the density mapping of land cover and tree cover. However, these tasks are often time-consuming, too expensive and limited in their ability to provide spatially continuous information over large territories (Xie et al. 2008). When supported by remote-sensing technology, land-cover mapping can be performed with a lower amount of field data and therefore becomes more cost-effective (Bhandari et al. 2012; Franklin et al. 2000; Rogan and Chen 2004).

In recent decades, mainly due to significant improvements in the spatial and spectral resolutions of satellite sensors and in image-processing techniques, several methods of producing forest-cover maps from remotely sensed data have been proposed (Boyd et al. 2002; Carreiras et al. 2006; Cross et al. 1991; Dorren et al. 2003; Defries et al. 1997; Gong et al. 1994; Joshi et al. 2006; Levesque et al. 2003; Rikimaru et al. 2002). One of the most widely used methods for forest-cover estimation using satellite imagery is the Forest Canopy Density Model (FCD) (Baynes 2004; Chandrashekhar et al. 2005; Deka et al. 2013; Joshi et al. 2006; Mon et al. 2012), which was presented by Rikimaru et al. (2002). Forest-canopy density is closely related to stem density (James et al. 2012; Jennings et al. 1999). The FCD model quantifies the degree of forest density and expresses it as a percentage (0-100%). Most of the studies that have used the FCD model were conducted in tropical forests, revealing that this model is highly effective at extracting information on forest-canopy density (Chandrashekhar et al. 2005; Deka et al. 2013; Joshi et al. 2006; Nandy et al. 2003). Although the FCD model has been widely used in several studies, only one reference to its use in the Mediterranean agro-forestry systems has been identified (Vinué and Gómez 2012).

The main goal of this paper is to demonstrate the implementation and effectiveness of the FCD model in producing a detailed, remote sensing-based map of *montado* canopy density over a large territory. It will be possible to use this map as a fundamental variable in accurately identifying and assessing HNV farmland in *montado* areas.

4.3. Material and Methods

4.3.1. Study area

This study was conducted in southern Portugal (Figure 1), a region that has a long history of occupation by cork oak and holm oak species (Bugalho et al. 2009; Pinto-Correia et al. 2011). The study area comprises the *Alto Alentejano Superdistrict*, which occupies an area of 856,720 ha (centre of the study area: 38º 44´ 27.60´´N; 7º 41´ 31.20´´W) (Fig. 1). It was selected in accordance with the published biogeographic boundaries defined by Costa et al. (1998). Elevation values vary from 40 to 645 m, corresponding to a low-roughness zone. The dominant soil types are luvisols (ortic, vertic and ferric) and lithosols. Eutric cambisols and calcic luvisols are less common but are also represented. The mean annual temperature ranges from 15.4ºC to 15.9ºC while annual precipitation presents larger spatial variability, varying between 542.2 and 808.1 mm. With the exception of the western boundary, which is surrounded by the upper thermomediterranean thermotype, all of the remaining area is included within the lower mesomediterranean belt. The majority of the study area is upper dry except for the south-eastern boundary, which is lower dry, and both main hills present a lower sub-humid ombrotype (Mesquita and Sousa 2009). Phytosociologically speaking, both *Pyro-Quercetum rotundifoliae* and *Sanguisorbo-Quercetum suberis montados* on siliceous soils are dominant in the landscape while *Lonicero implexae-Querceto rotundifoliae* is a characteristic series associated with areas of marble (Costa et al. 1998). *Montados* occupy about 44.8% of the study area, being the dominant land-use system in the region, followed by arable land (27.9%). Therefore, this biogeographic region is a representative area in terms of *montado* cover dominance and is also a suitable region in which to assess the effectiveness of the FCD method due to its high spatial variability in terms of *montado* tree density.

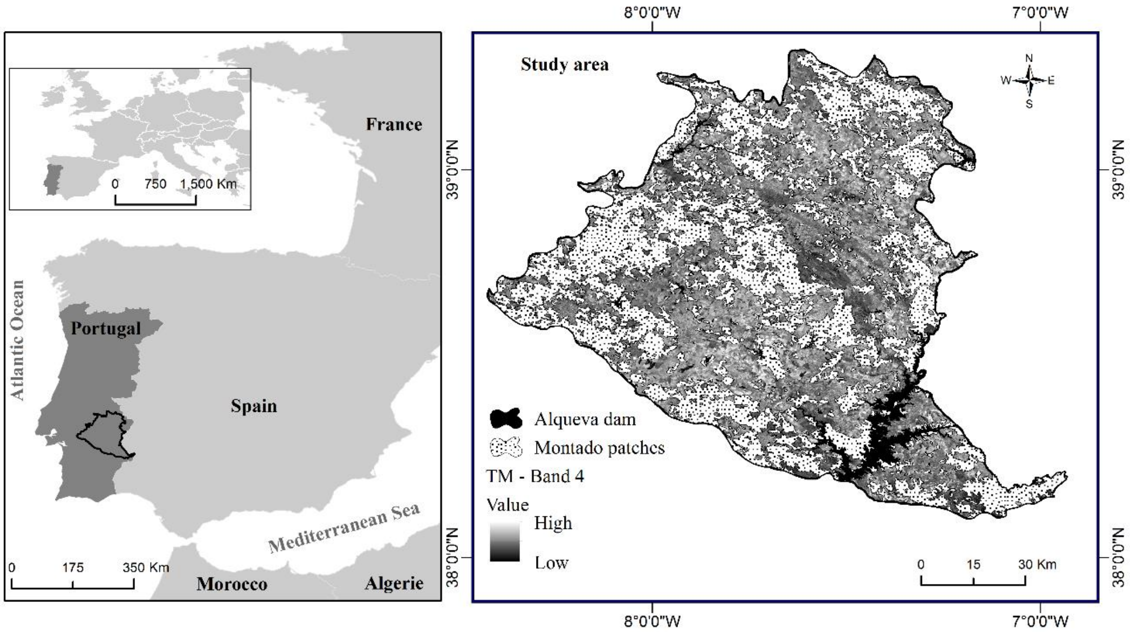

Figure 1 - Location of the study area and representation of the area using Landsat TM imagery band 4 as background and study site represented by *montado* patches.

4.3.2. Data used and image pre-processing

This study aims to use Landsat-5 TM multispectral data to apply and assess the FCD model in order to estimate and map *montado* canopy density. The TM sensor was used to acquire six visible and near-infrared (VNIR) and short-wave infrared (SWIR) spectral bands (bands 1-7) with a spatial resolution of 30 m and one thermal-infrared (TIR) band (band 6) with a spatial resolution of 120 m. TM VNIR and SWIR bands 1 – 5 (B1, B2, B3, B4 and B5, respectively) and TIR band 6 (B6) were used in this study. A Landsat-5 TM scene covering the case study area (Fig. 1) in southern Portugal was acquired on 20 July 2003. This summer-season acquisition ensured that most of the croplands and pastures were dry and would therefore provide a better spectral contrast between the overstorey and the understorey (Carreiras et al. 2006).

The image location corresponds to path 203 and row 33 of the Landsat Worldwide Reference System (WRS). The processing level of the acquired image corresponds to “Standard Level 1 Terrain Corrected” (L1T), which configures a systematic radiometric and geometric correction through the incorporation of ground control points (GCP) and a digital-elevation model (DEM). The acquired scene is a free cloud cover image (Figure 1). As an additional pre-processing task, an atmospheric correction was applied to selected multispectral bands by using the Quick Atmospheric Correction (QUAC) method. This method determines the atmospheric compensation parameters directly from the information contained within the scene using the observed pixel spectra. The approach is based on the empirical finding that the spectral standard deviation of a collection of diverse material spectra, such as the endmember spectra in a scene, is essentially spectrally flat (Bernstein et al. 2005).

4.3.3. Estimation of montado canopy density

To avoid misclassifications between other land-cover types and *montado* canopy density classifications, a mask of *montado* areas that occur over the study area was built using the *montado* map produced by Godinho et al (2014). This *montado* map was produced for the whole of southern Portugal by following the cartographic specifications of the Corine Land Cover project (*e.g.* map scale = 1:100 000, minimum map unit = 25 ha, minimum distance between lines = 100 m, and several generalization rules). Therefore, the created *montado* mask was selected as our study site and was used to limit image processing and calculation tasks involving biophysical indices only for the *montado* areas.

4.3.4. Forest Canopy Density Model (FCD)

The FCD model developed by Rikimaru et al. (2002) is comprised of biophysical variable modelling and analysis supported by information derived from four remote sensing-based biophysical indices: the advanced vegetation index (AVI), the bare soil index (BI), the shadow index (SI) or scaled shadow index (SSI), and the thermal index (TI). Once the Landsat TM bands have been normalized (except for band 6), it is possible to combine these four indices in order to calculate the canopy density expressed as a percentage for each pixel (0-100%). The relationship between the biophysical indices and the spatial patterns of the FCD conditions is established by using the conceptual model expressed in Figure 2 (adapted from Rikimaru et al. 2002).

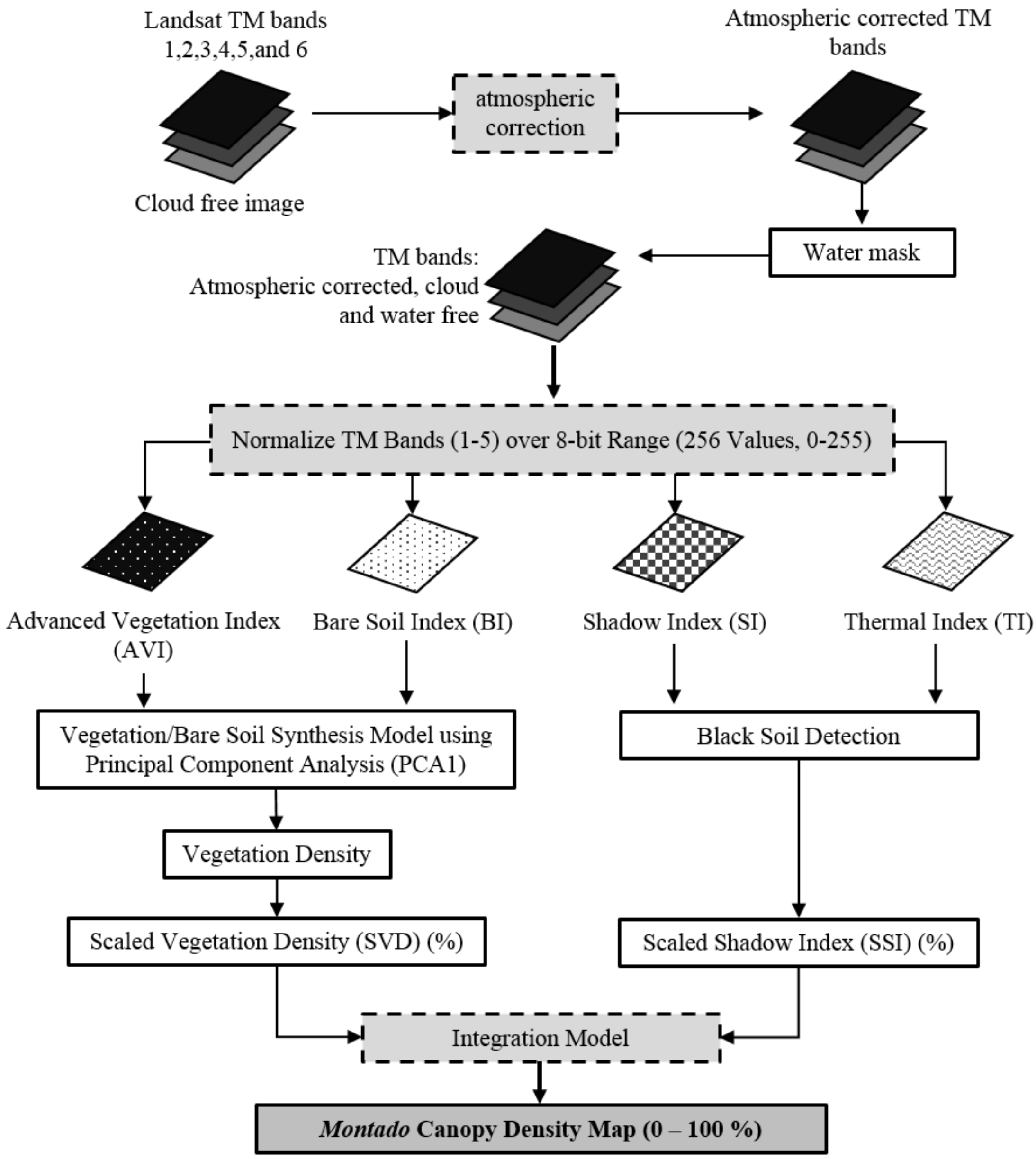

Figure 2 - Conceptual model used to estimate *montado* canopy density classes (adapted from Rikimaru et al, 2002).

4.3.4.1. Advanced Vegetation Index (AVI)

The advanced vegetation index (AVI) responds sensitively to vegetation quantity when compared to the NDVI. In fact, the NDVI is unable to highlight subtle differences in canopy density. The AVI was calculated using equation 1:

$$\mathrm{AVI} = [(\mathrm{B4}+1) \times (256-\mathrm{B3}) \times (\mathrm{B4}-\mathrm{B3})]^{1/3} \qquad \text{Equation 1}$$

AVI = 0 if B4 < B3 after band normalization

The AVI has a positive relationship with the amount of vegetation. Consequently, its value is high for high forest density and grassland and low for low forest density and bare land.

4.3.4.2. Bare Soil Index (BI)

Vegetation types with a marked background response, such as the *montado* agro-forestry system, are enhanced by using the bare soil index (BI). This index is a normalized index of the difference sums of two reflective (near-infrared and blue) and absorption (short-wave infrared and red) bands. This index is suitable for differentiating between several vegetation *strata* with different backgrounds, such as completely bare soil, sparse canopy and dense canopy. The BI was calculated using equation 2.

$$BI = \frac{(B5+B3)-(B4+B1)}{(B5+B3)+(B4+B1)} \times 100 + 100 \qquad \text{Equation 2}$$

Where: $0 < BI < 200$.

The BI increases as forest density decreases and the degree of soil exposure increases (Rikimaru et al. 2002; Baynes 2004).

4.3.4.3. Shadow Index (SI)

The shadow index (SI) is a function of the number of tree crowns: if there are more trees, there is consequently more shadow. Thus, this index increases as the forest canopy cover increases and its value is higher for high forest density and lower for grasslands and bare soil. However, when forest density is very high, shadows cannot be accurately measured using this remote sensing-based approach and the canopy density might therefore be underestimated. To deal with this constraint, the SI is scaled using a linear transformation, resulting in a scaled shadow index (SSI) (Rikimaru et al. 2002; Mon et al. 2012). Based on this transformation, SSI=0 corresponds to forests which have the lowest SIs (0%) while sites where the SSI=100 represent forests with the highest possible shadow value (100%). The SI was calculated using equation 3.

$$\mathrm{SI} = [(256 - \mathrm{B1}) \times (256 - \mathrm{B2}) \times (256 - \mathrm{B3})]^{1/3} \qquad \text{Equation 3}$$

4.3.4.4. Thermal Index (TI)

The thermal index is also an important component in FCD process computation due to its strong but negative relationship with forest density. High-density forest stands reveal low temperatures because tree canopies block and absorb solar energy and evaporation takes place from the leaf surface, which mitigates warming. The TI therefore increases as vegetation density decreases. However, in sites where the soil is black (or very dark), low irradiant data from these soils may confuse shadow phenomena with black soil conditions. In these situations, SI values are high and may lead to shadows being misclassified as vegetation instead of bare soil. Despite the high shadow values in these conditions, the TI is also high. Therefore, this misclassification can be avoided by overlaying these two variables to combine the TI and SI, since shadows decreases soil temperatures (Rikimaru et al. 2002). Consequently, the TI can be used as a previous step in the FCD method for detecting black soils and differentiating them from grassland and forest, thereby improving the SI variable. To achieve this, an overlay process was carried out using shadow and thermal indices to identify pixels with higher values of both variables. Once these pixels had been identified, a reclassification process was performed only on the shadow-index variable, where these pixels were reclassified to zero values in terms of SI.

To incorporate temperature information into the FCD procedure, the ground temperature was extracted from a non-normalized thermal band (B6) by means of two steps: (1) calculating the spectral radiance L_b from the digital number of band 6; and (2) performing a spectral radiance conversion to ground temperature T. These two steps were performed using the following equations (Jamallabad and Abcar 2004; Joshi et al. 2006):

$$L_b = L_{min} + (L_{max} - L_{min}) \times DN_6/255 \qquad \text{Equation 4}$$

$$T = \frac{K2}{Ln\left(\frac{K1}{L_b}+1\right)} \qquad \text{Equation 5}$$

Where L_{max} and L_{min} are the maximum and minimum thermal radiation energies, which for Landsat 5 TM is L_{min} =1.238W / (m^2 sr) and L_{max} =15.600W / (m^2 sr); DN_6 is

Band 6 digital number; T is the effective at-satellite temperature in K, K1 = 607.76 W/ (m^2 *sr μm*) and K2 = 1260.56 K.

4.3.4.5. Computing the FCD model

In order to apply the FCD model, both the AVI and BI were primarily integrated into a Vegetation Density (VD) index by performing a Principal Component Analysis (PCA1). The VD obtained was scaled to values from 0 to 100 in order to produce the scaled vegetation density (SVD) (Rikimaru et al. 2002; Deka et al. 2013). Finally, with both the SVD and SSI expressed as percentage scale units, it was possible to calculate the *montado* canopy density for each pixel using the following equation:

$$\mathrm{FCD} = (SVD \times \mathrm{SSI} + 1)^{1/2} - 1 \qquad \text{Equation 6}$$

Based on the FCD model, four classes were obtained: non-*montado* areas (N*m*) (<10%); low *montado* canopy density (L*m*) (11-40%), moderate *montado* canopy density (M*m*) (41-70%) and high *montado* canopy density (H*m*) (71-100%). The non-*montado* class was included in the classification scheme due to the existence of some open areas covered by the *montado* mask shapefile.

4.3.5. Ground-truth data and assessing the accuracy of the FCD

To ensure that representative and reliable ground-truth data was obtained for the four classes, a dataset of 200 sample pixels (50 pixels for each class) covering the *montado* mask was created. All of these pixels resulted from photo-interpretation and subsequent cross-validation processes that used as their cartographic bases a set of very high-resolution (0.5 m) true-colour orthophotomaps produced in 2005 by the CNIG – Portuguese National Centre of Geographic Information (scale 1:10,000). The 200 pixels were used to assess the accuracy of *montado* canopy density estimations obtained by the FCD model.

The accuracy of classifications of remote-sensing images is usually analysed by using error matrices and kappa statistics (Congalton and Green 2009). Hence, in order to assess the accuracy of *montado* canopy-density estimations obtained by the FCD model, a confusion matrix was computed and four accuracy-assessment measures were calculated: overall classification accuracy (OA), producer´s accuracy (PA), user´s accuracy (UA) and Kappa coefficient (K) (Congalton and Green 2009). The accuracy measures obtained were subsequently analysed in order to verify the effectiveness of the FCD model in estimating *montado* canopy density.

4.4. Results and Discussion

4.4.1. Spatial patterns of montado canopy-density classes

The spatial patterns of *montado* canopy-density classes over the study site, which were estimated by applying the FCD method, are shown in Figure 3. Based on this map, it can be observed that the percentage of area occupied by each *montado* canopy-density class is noticeably different. Specifically, the application of the FCD model revealed the low-density class to be the most representative, occupying 54.1% of the total *montado* area, followed by the moderate-density and high canopy-density classes, which respectively occupied 33.3% and 12.6% (Figure 4). The results derived from the application of the FCD model reflect the same trend as that reported by the National Forestry Inventory’s results, which demonstrated a decreasing percentage area from low to high *montado* density classes (AFN 2010; Tomé 2006). Therefore, the results obtained show that the reliability of the FCD model is not area-dependent because they reveal the same trend (low-density classes occupy a greater percentage area than moderate and high-density classes) as that observed in other regions of Portugal.

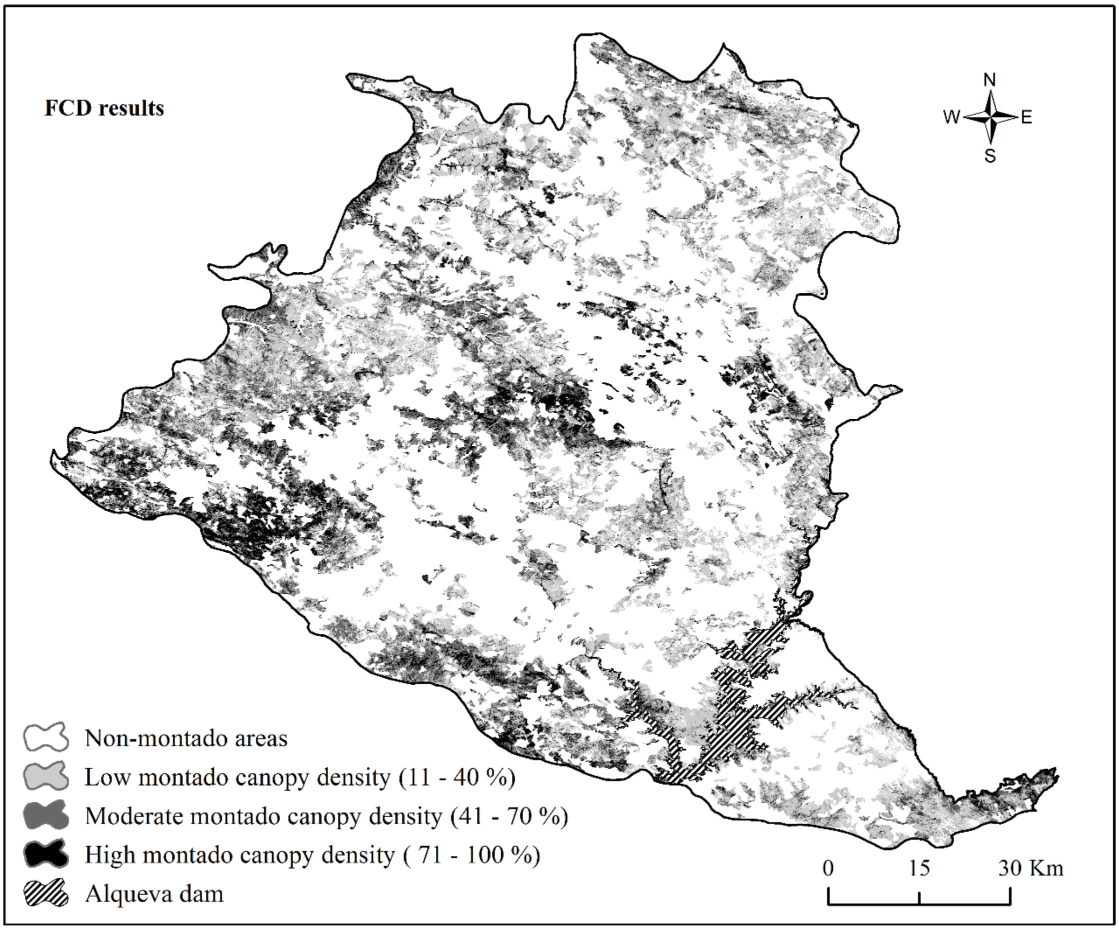

Figure 3 - *Montado* canopy-density map produced by the Forest Canopy Density model (FCD).

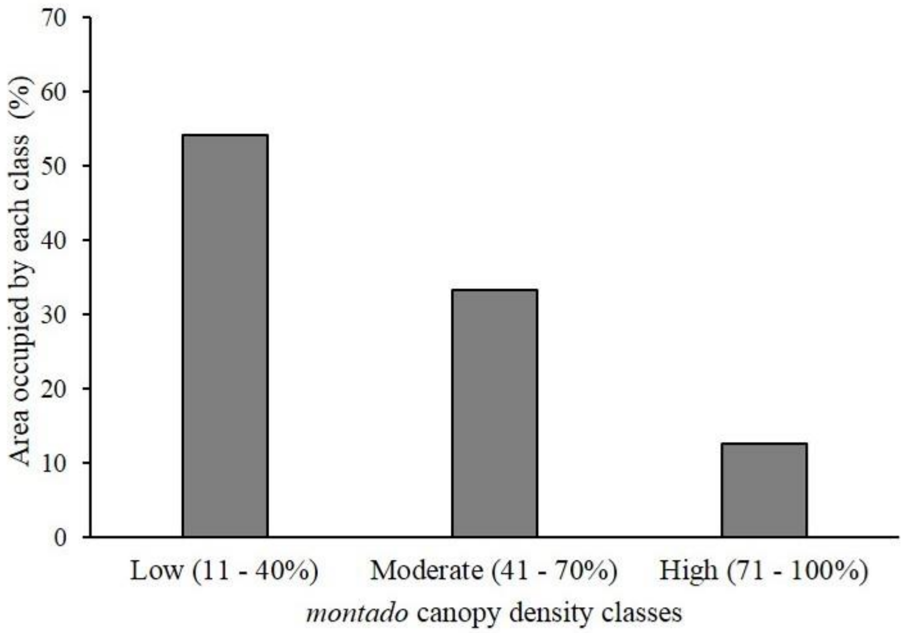

Figure 4 - Percentage area covered by each *montado* canopy-density class over the study site, obtained from the FCD method.

4.4.2. Accuracy and performance of the FCD in estimating montado canopy density

Considering the spatial complexity of the *montado* ecosystem (Doorn and Pinto-Correia 2007), the accuracy-assessment results produced by applying the FCD approach are positive. The cartographic accuracy of the map produced shows an overall accuracy (0-100%) and kappa value (0-1) of 78.0% and 0.71, respectively. The confusion matrix computed in this study (Table 1) revealed that the FCD approach generated good user's and producer's accuracies for the three *montado* canopy-density classes and also showed that the accuracy of these assessment measures tends to increase from low to high-density classes. This could be explained by the variation in spectral reflectance from heterogeneous (and sparser) to more homogeneous (and denser) *montado* canopy-density classes (Chandrashekhar et al. 2005; Joshi et al. 2006; Mon et al. 2012). More heterogeneous *montado* classes generate more complex patterns of spectral reflectance due to their spatial variability in *montado* tree density, leading to slightly lower accuracies for low *montado* density classes, such as those observed in other studies of forestal canopy density (Mon et al. 2012; Panta et al. 2008).

Table 1 - Confusion matrix of the montado canopy-density classes estimated by the FCD method

		Reference data					
		Nm	Lm	Mm	Hm	Total	User´s accuracy
Classified data	N*m* (<10%)	**46**	4	0	0	50	0.92
	L*m* (11-40%)	14	**36**	0	0	50	0.72
	M*m* (41-70%)	0	14	**35**	1	50	0.70
	H*m* (71-100%)	2	1	8	**39**	50	0.78
	Total	62	55	43	40	200	
	Producer´s accuracy	0.74	0.65	0.81	0.98		
	Overall accuracy	**78.00**		Kappa	**0.71**		

Note: N*m* = Non-*montado*; L*m*= Low *montado* canopy density; M*m* = Moderate *montado* canopy density; H*m* = High *montado* canopy density.

The overall producer´s accuracy over the three canopy density classes was 81.3%, revealing that the four biophysical indices (AVI, SI, BI and TI) used in the FCD method were suitable for accurately differentiating between all three *montado* canopy-density classes. Using the FCD model (which incorporates the BI in its calculations), the component of soil reflectivity - a very important spatial characteristic of *montado* landscape - is selectively distinguished from the existing *montado* canopy cover, leading to a more accurate classification (Rikimaru et al. 2002). On the other hand, sites where the soil seems to be black (showing low irradiant data), and which therefore present a high SI value, may lead to areas being misclassified as dense vegetation rather than bare land. When using the FCD model, this issue is tackled by combining both the SI and TI. This technique will allow black soil conditions to be detected, thereby avoiding misclassifications when the SI, TI and BI are high for the same location (Rikimaru et al. 2002; Mon et al. 2012).

Although the FCD method is effective in dealing with complex reflectance of vegetation because it incorporates biophysical information on vegetation in its computational framework, we obtained a slightly lower producer´s accuracy for the L*m* density class (0.65 - see Table 1). This result may reveal some of the limitations of applying this method in very sparse Mediterranean vegetation. The scarcity of water resources in these regions gives rise to the presence of bare soils with high reflectance, which may overwhelm the small component reflected by sparse vegetation (Rodríguez-Galiano and Chica-Olmo 2012). The *montado* canopy-density range of L*m* (11 – 40%) represents a sparser *montado* type than M*m* and H*m*. Therefore, the high reflectivity of the bare-soil component is higher in L*m* than in the M*m* and H*m* classes. Consequently, a relatively low level of accuracy characterises the spectral separability of bare soils and sparse vegetation in Mediterranean areas, as it occurs in areas of low *montado* canopy density (Berberoglu et al. 2000, 2007). In addition, it has already been stated that the FCD model may have some limitations because this method requires knowledge of ground conditions in order for threshold values to be defined (Baynes 2004; Chandrashekhar et al. 2005). Overall, however, the FCD model showed strong agreement and good accuracy (OA= 78.0%; K= 0.71), thereby resulting in good overall estimations of the density of *montado* canopy.

Chapter

5

Detecting the effects of Mediterranean forest canopy cover decrease in land surface albedo and temperature using Landsat-5 TM data

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5.1. Abstract

The Mediterranean region has undergone huge levels of forest destruction and transformation over the past millennium. Modifications in vegetation cover can have an impact on the climate through changes in biogeochemical and biogeophysical processes. In this paper, the tree canopy cover percentage of a savannah-like ecosystem (*montado*/*dehesa*) was estimated at Landsat pixel level for 1987 and 2011, and the effects of its decrease on land surface albedo (LSA) and land surface temperature (LST) were analysed. Canopy cover estimations using Stochastic Gradient Boosting (SGB) algorithm showed that the Enhanced Vegetation Index (EVI) and the Short Wave Infrared Reflectance 3/2 Ratio (SWIR32) were the most important variables contributing to a model with a high predictive capability (R^2 = 81.5%; RMSE = 12.4%). Overall, *montado* canopy cover estimations showed that between 1987 and 2011 canopy cover decreased on average 6.9% by pixel over this 24-year period. As a result, it was found that positive ΔLSA and ΔLST between 1987 and 2011 have a strong spatial correspondence with pixels that show the highest decrease in *montado* canopy cover. Actually, a canopy cover decrease in excess of 50% led to a huge increase of 0.037 in surface albedo, and 4.64º C in surface temperature. This research highlighted the role that change in *montado* canopy cover may play in local land surface albedo and temperature variations, as an increase in these two biogeophysical parameters may

potentially bring about, in the long term, local/regional climatic changes moving towards greater aridity.

Keywords: *montado*; *dehesa*; canopy cover; biogeophysical effects; surface albedo, surface temperature; Mediterranean; Landsat

5.2. Introduction

One of the most obvious human-induced impacts on the Mediterranean landscapes is the huge level of forest destruction and transformation seen over the past millennium. Scientific research using palaeo-botanical, archaeological, and historical records reveals that forest areas were once predominant across almost the entire Mediterranean Basin. Currently, Mediterranean forest cover has fallen to 9-10% of the region's total land area (Blondel and Aronson, 1999).

The effects of historical land cover change, not only in the Mediterranean region but also around the globe, are considered to be one of the major drivers contributing to widespread global environmental and climate changes (Devaraju et al., 2015; Reale and Dirmeyer, 2000; Turner et al., 2007). Land cover transformation, such as deforestation to promote agricultural lands and/or pastures for livestock production, have an impact on the climate through changes in biogeochemical (e.g., atmospheric CO_2 concentrations) and biogeophysical (e.g. land surface albedo, land surface temperature, roughness length, evapotranspiration) processes (Betts et al, 2007; Devaraju et al., 2015; Li et al., 2015). Regarding the effects of land cover change in these two processes, recent studies have posited that changes in biogeophysical processes play a more regional/local role than biogeochemical ones (Li et al., 2015; Pongratz et al., 2010).

The implications of land cover change on climate, by altering biogeophysical properties, have been researched in numerous studies (e.g. Davin et al., 2010; Zhu and Zeng, 2015; Kvalevag et al., 2010). These studies have found that surface albedo and evapotranspiration are the dominant biogeophysical forces of land cover change on climate. The key role played by vegetation cover in climate is mainly expressed through its influence on energy and water balances (Bonan, 2008; Pitman, 2003). It is as such that land surface albedo (LSA), land surface temperature (LST), and evapotranspiration (ET) are considered key biogeophysical factors in the entire surface energy and water balance (Dirmeyer and Shukla, 1994; Friedl, 2002; Lu et al., 2011; Mallick et al., 2014). Therefore, changing vegetation type and cover can modify LSA, LST, and ET parameters, and hence alter the micrometeorological conditions (Bonan, 2008).

Previous studies have shown that forest cover decrease in the Mediterranean region over the past 2000 years has contributed to the dryness of the present climate (Arribas et al., 2003; Gates and Lieβ, 2001; Reale and Dirmeyer, 2000). Forests have lower albedo levels than shrubs, dry crops, pastures and bare soils. As a result, the conversion of forests to these land cover types can lead to increases in surface albedo, and may potentially feed back into the local/regional climate (Bonan, 2008). An increase in surface albedo leads to a reduction in net radiation, energy fluxes (sensible and latent), convective clouds and precipitation, leading to a drier atmosphere (Pitman, 2003). On the other hand, the slight decrease in surface temperature due to albedo increase is outweighed by a surface warming associated with a decrease in surface roughness, latent heat flux, rooting systems and evapotranspiration rate (Doughty, 2012; Lejeune et al., 2015; Pitman, 2003).

In arid and semi-arid areas such as the Mediterranean region, tree canopy cover plays a fundamental role in several ecosystem processes (e.g. water recycling, surface cooling). Taking that into consideration, it is important to quantify the impacts of the decrease in Mediterranean tree cover in a set of key biogeophysical parameters that have a powerful effect on the magnitude and directions of local/regional climate changes. Indeed, Lindner et al. (2010) suggest that the annual mean temperature for the Mediterranean region will increase on average 4-5 ºC in summer. The same authors pointed out that a 50% decrease in rainfall during the summer season is expected to occur, which combined with an increase in temperature may lead to increased levels of dryness and arid conditions. A reduction in precipitation patterns due to climate change may reduce the vital ecophysiological conditions of trees, which may consequently contribute to forest decline. On the other hand, forest cover reduction due to land use changes can affect local hydrological processes by reducing evapotranspiration, thereby leading to drops in precipitation as well as to a decrease in forest cover (Gates and Lieβ, 2001).

Tree cover mapping has been recognized by the scientific community as an important task in studies focused on land surface and atmosphere interactions (e.g. Xiao et al., 2014). It is a core variable to understanding the fluxes between land surface and the lower boundary of the atmosphere, such as exchanges of radiation, heat, carbon, and water (Bonan, 2008; Davin et al., 2010). Therefore, the availability of accurate and up-to-date spatial information on the tree cover fraction and on its spatio-temporal patterns is essential to understanding the role of trees in regulating these land surface-atmosphere fluxes. Consistent and comprehensive tree cover information at high temporal and spatial resolutions is required to support more detailed studies on the effects of biogeophysical impacts of vegetation cover change. Established methods, such as plot-based studies and aerial photo-interpretation, can be used for tree cover mapping. However, these tasks are often time consuming, excessively expensive, and limited in providing spatially continuous information over large territories (Xie et al., 2008). Using remote sensing technology, tree cover mapping can be gathered with a lower level of field data, making it more cost-effective (Ahmed et al., 2015; Rogan and Chen, 2004). In addition to its cost-effectiveness, satellite remote sensing provides a potentially useful tool for simultaneously quantifying the spatio-temporal dynamics of tree cover changes and for assessing the resulting effects on biogeophysical properties (Xiao et al., 2014). Considerable efforts have been made to develop remote sensing-based approaches for different ecoregions and for distinct spatial scales based on high-medium spatial resolution satellite data, by extracting the fraction of tree canopy cover at pixel level (e.g. Carreiras et al, 2006; Leinenkugel et al., 2015; Yang et al., 2012). Moreover, remote sensing has also been widely used for estimating surface albedo and temperature with various satellite platforms in recent decades (Li et al., 2013; Qu et al., 2015).

In this study, a savannah-type evergreen oak woodland known as *montado* (in Portugal) or *dehesa* (in Spain), was used as a case study because it represents one of the most characteristic and important ecosystems existing in the Mediterranean basin.

Montado/*dehesa* woodlands constitute an agroforestry system dominated by holm oak (*Q.* [*ilex*] *rotundifolia*) and/or cork oak (*Quercus suber*) presenting high spatial variability in tree densities, usually with an understory mosaic of annual crops, grasslands, and shrublands (Joffre et al., 1999). It is estimated that this ecosystem covers an area of about $3.5x10^4$ to $4.0x10^4$ km^2 in the southwest of the Iberian Peninsula (Olea and San Miguel-Ayanz, 2006). Despite its socio-economic and environmental importance, *montado* ecosystems have been undergoing a severe decline (Godinho et al., 2014), which has been manifested by a progressive decrease in tree cover (Plieninger and Schaar, 2008). Therefore, this study aims to develop an effective remote sensing-based methodological approach which aims to demonstrate the direct role of *montado* canopy cover decrease in local land surface biogeophysical property modifications. Three research goals are directly addressed in this study:

4. To estimate the percentage of *montado* canopy cover at Landsat pixel scale for 1987 and 2011;
5. To identify *montado* canopy cover decrease between 1987 and 2011;
6. To estimate the impacts of *montado* canopy cover decrease on land surface albedo and land surface temperature.

5.3. Material and Methods

5.3.1. Study area

This study was conducted in southern Portugal (Figure 1), a region with a markedly Mediterranean climate characterised by warm and dry summers (August: 31–32ºC T_{max}) and wet and cold winters (January: 6–7ºC T_{min}). Mean annual precipitation varies from 550mm to 650mm. Elevation range varies from 40m to 645m, and the mean slope is 3.52º, corresponding to a low roughness zone. The study area, covering roughly 8,567km^2 (centroid of the study area located at 38º 44' 27.60" N; 7º 41' 31.20" W), is mainly located in the biogeographic Luso-Extremadurense Province, one of the largest in the Iberian Peninsula, whose soils are derived from Palaeozoic siliceous materials. *Montado* covers about 44.8% of the study area, being the dominant land use system in the region, followed by arable land (27.9%).

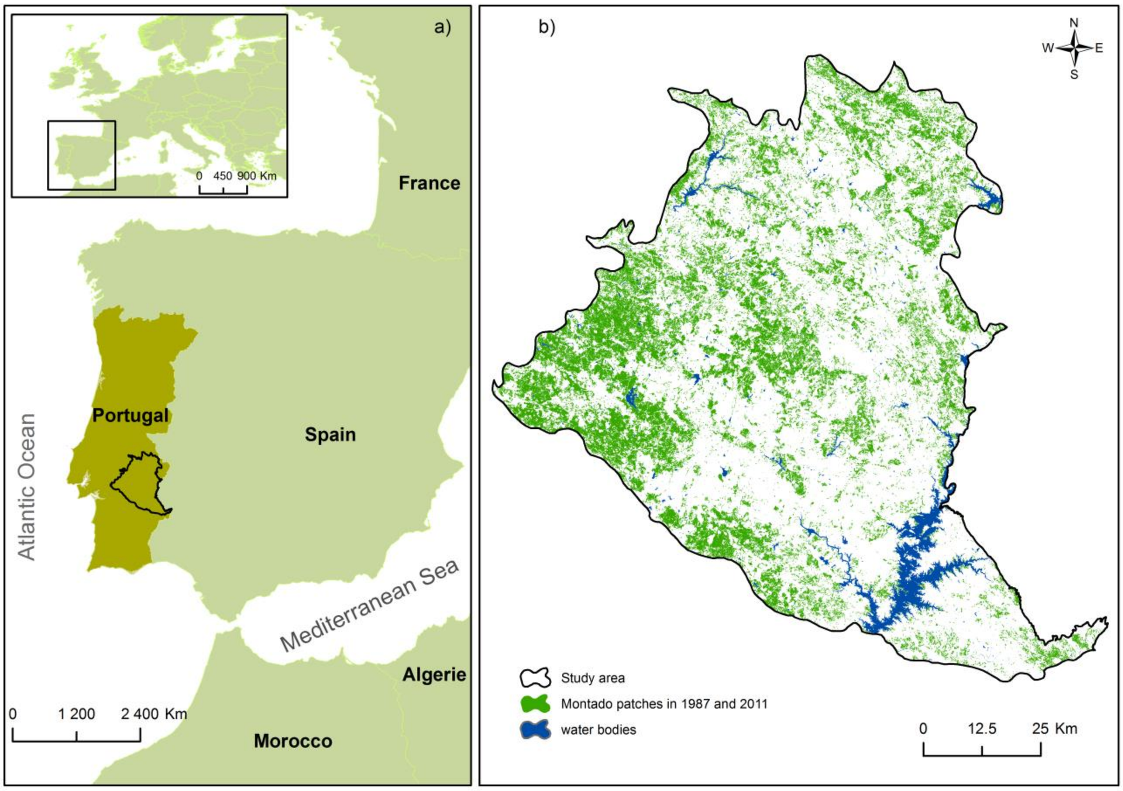


Figure 1 – Study area

5.3.2. Satellite data and pre-processing

To obtain the spatial distribution of *montado* patches for 1987 and 2011 over the study area, four Landsat-5 TM satellite scenes were acquired (path 203/row 33). For each year, a scene from spring (acquired from the 5th May of 1987 and 20th March of 2011, respectively) and another one from summer (acquired from the 25th and 28th August of 1987 and 2011, respectively) were used in the classification procedure to ensure that inter-class separability benefitted from the phenological variation of the vegetation cover. The processing level of the acquired imagery corresponds to "Standard Level 1 Terrain Corrected" (L1T) which configures a systematic radiometric and geometric correction through the incorporation of ground control points and a digital elevation model. The acquired scenes are cloud-free images. Landsat-5 TM optical bands were corrected for atmospheric effects using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) method (FLAASH, 2009). As an additional pre-processing task, a relative radiometric normalization was performed after atmospheric correction in order to ensure comparability between the 1987 and 2011 images. Relative radiometric normalization was carried out following the El Hajj et al.

(2008) procedure, which encompasses three main processes: the selection of a reference image, the invariant targets selection through a multi-band difference image, and the calculation of the linear regressions. The image acquired in 1987 was selected as the reference image.

5.3.3. Montado land cover maps for 1987 and 2011

Following the image classification procedure developed by Godinho et al. (in evaluation[1]), images from 1987 and 2011 were firstly classified into eleven land-cover types: *montado*, eucalyptus forest, shrublands, pine forest, water bodies, olive groves, irrigation agriculture, dry crops/pastures, vineyards, bare soil, and urban areas. Classifications were performed using 1,343 sample points from 1987, and 1,901 from 2011 (80% for training and 20% for validation), and using Stochastic Gradient Boosting (SGB) as an image classification algorithm. The overall classification accuracy corresponds to 82.87% for the 1987 data set, and 82.01% for the 2011 data set. The accuracy of *montado* areas stood at 81.14% for 1987 and 81.66% for 2011. As a second step, the classified images were compared and only those features representing *montado* patches from both the 1987 and 2011 periods were extracted from these outputs for the subsequent analysis. The m*ontado* maps obtained from 1987 and 2011 were then used to estimate the percentage of canopy cover at pixel level.

5.3.4. Estimation of montado canopy cover for 1987 and 2011

5.3.4.1. Determining response variable: montado canopy cover (%)

A set of 849 pixels distributed throughout the *montado* patches occurring over the study area were used to calculate the percentage of *montado* canopy cover using high-resolution aerial photographs. Aerial photographs from 2011 covering the study area were accessed through the Bing Maps© Aerial tool that runs on ArcMap© 10.1 software (ArcGis© 10.1, ESRI© 2012). The 849 pixels selected were converted from raster to polygonal vectorial format (shapefile) and then overlaid with the aerial photographs. For each pixel, the entire *montado* canopy intersected by the 30x30m

[1] Article submitted in the International Journal of Applied Earth Observation and Geoinformation.

polygon was screen-digitised and then the percentage of pixel area covered by *montado* canopy was calculated.

5.3.4.2. Predictor variables set

One of the main objectives of this study is the calculation of *montado* canopy cover by using remote sensing data. As such, Landsat-5 TM multispectral bands acquired during the summer of 2011 and their derived vegetation indices were used as predictor variables. The reflectance values of multispectral bands and vegetation indices were extracted for each one of the selected 849 pixels to be used subsequently in the regression analysis. Six different vegetation indices were calculated: the Enhanced Vegetation Index (EVI), the Short Wave Infrared Reflectance 3/2 Ratio (SWIR32), the Carotenoid Reflectance Index 1 (CRI1), the Green Chlorophyll Index (CI_{green}), the Normalised Multi-band Drought Index (NMDI), and the Soil-Adjusted Total Vegetation Index (SATVI) (Table 1). These vegetation indices were selected based on their respective sensitivity and effectiveness in retrieving and monitoring vegetation parameters in semi-arid environments (e.g. Hill, 2013; Marsett et al., 2006).

Table 1 – Spectral-based vegetation indices calculated from Landsat 8 to be used in this study.

Vegetation Index	Band Formula	Reference
Green Chlorophyll Index	$\mathrm{CIgreen} = \frac{\rho\mathrm{NIR}}{\rho\mathrm{Green}} - 1$	Gitelson et al. 2005
SWIR32*	$\mathrm{SWIR32} = \frac{\rho\mathrm{SWIR2}}{\rho\mathrm{SWIR1}}$	Guerschman et al., 2009
Carotenoid Reflectance Index 1	$\mathrm{CRI1} = \left(\frac{1}{\rho\mathrm{Blue}}\right) - \left(\frac{1}{\rho\mathrm{Green}}\right)$	Gitelson et al. 2002
Enhanced Vegetation Index	$\mathrm{EVI} = 2.5 \times \left(\frac{\rho\mathrm{NIR} - \rho\mathrm{Red}}{1 + \rho\mathrm{NIR} + 6 \times \rho\mathrm{Red} - 7 \times \rho\mathrm{Blue}}\right)$	Huete et al. 1997
Normalized multi-band drought index	$\mathrm{NMDI} = \frac{\rho\mathrm{NIR} - (\rho\mathrm{SWIR1} - \rho\mathrm{SWIR2})}{\rho\mathrm{NIR} + (\rho\mathrm{SWIR1} - \rho\mathrm{SWIR2})}$	Wang and Qu, 2007
Soil-Adjusted Total Vegetation Index	$\mathrm{SATVI} = \left(\frac{\rho\mathrm{SWIR1} - \rho\mathrm{Red}}{\rho\mathrm{SWIR1} + \rho\mathrm{Red} + L}\right) \times (1 + L) - \left(\frac{\rho\mathrm{SWIR2}}{2}\right)$	Marsett et al., 2006

Notes: L in SATVI index represents a constant related to the slope of the soil-line. In this study L= 0.5 was applied. *SWIR1 and SWIR2 bands in the case of Landsat 8. Original configuration corresponds to SWIR2 and SWIR3 bands of MODIS sensor (Guerschman et al., 2009).

5.3.4.3. Model Building and prediction using Stochastic Gradient Boosting (SGB)

SGB is a hybrid machine learning algorithm that combines both the advantages of bagging and boosting procedures. Numerous advantages have been highlighted regarding the use of the SGB algorithm, such as the stochastic characteristic in modelling non-linear relationships, robustness in dealing with interaction effects among predictors, and also the powerful property of the stochasticity component in reducing the occurrence of the over-fitting phenomenon (Friedman, 2001, 2002). Model-building using SGB requires parameter-tuning, namely the following: (i) bag fraction (*bf*); (ii) tree complexity (*tc*); (iii) learning rate (*lr*); and number of trees (*nt*). Detailed information about these parameters and their importance for the SGB algorithm performance can be found in Elith et al. (2008). To identify the best combination of these parameters for achieving the lowest root mean square error (RMSE), a set of SGB models were tested using *bf* =0.50, and also different values for *tc* (1, 3, 5, and 7), *lr* (0.001 and 0.01), and *nt* (50–2,500). Therefore, by using the percentage of *montado* canopy cover as a dependent variable, and the explanatory variables (see Section 5.3.4.2) calculated for every 849 pixels, several candidate SGB models were evaluated through the *gbm* R package version 2.1 (Ridgeway, 2013). The 849 sample pixels were split into training (80%) and validation (20%) datasets using the *createDataPartition* function from the *caret* package (Khun, 2014) implemented in the R statistical software (R Development Core Team, 2014). The training dataset was used to tune and train SGB models by applying a repeated (five times) 10-fold cross validation resampling method. The validation dataset containing an independent set of sample pixels (n= 169) was used to provide an unbiased estimation of SGB predictions and to evaluate the model performance through RMSE and coefficient of determination (R^2).

The best-fit SGB model between percentage of *montado* canopy cover and Landsat-5 TM bands and their derived vegetation indices was used to predict canopy cover values for all *montado* patches existing in the entire study area in 2011. Since the goal was also to generate a map with *montado* canopy cover values for the 1987 dataset, the same best-fit SGB model was used.

5.3.5. Estimation of Land Surface Albedo (LSA) and Land Surface Temperature (LST)

Some algorithms for estimating broadband surface albedo from Landsat TM/ETM+ satellite data have been developed (Liang 2001; Tasumi et al., 2008). In this study, the formula proposed by Liang et al. (2001) was used to calculate the land surface albedo and to identify its changes between 1987 and 2011. Therefore, for each Landsat-5 TM image (1987 and 2011) the LSA was calculated by applying the following equation:

$$LSA = 0.356b_1 + 0.13b_3 + 0.373b_4 + 0.085b_5 + 0.072b_7 - 0.0018 \quad (1)$$

where b_1, b_3, b_4, b_5 and b_7 are the atmospheric corrected reflectance values of the bands 1, 3, 4, 5 and 7 of the Landsat-5 TM sensor.

Land surface temperature (LST) was calculated for 1987 and 2011 by using the single-channel method proposed by Jimenez-Muñoz and Sobrino (2003). This method only requires atmospheric water vapour content (w) for atmospheric correction. As such, LST was estimated using the following equation:

$$T_s = \gamma[\varepsilon^{-1} (\Psi_1 L_{sensor} + \Psi_2) + \Psi_3] + \delta \quad (2)$$

with

$$\gamma = \left\{\frac{C_2 \; L_{sensor}}{T_{sensor}^2}\left[\frac{\lambda^4}{C_1} L_{sensor} + \lambda^{-1}\right]\right\}^{-1} \quad (3a)$$

$$\delta = -\gamma L_{sensor} + T_{sensor} \quad (3b)$$

where T_s is LST, L_{sensor} is at-sensor radiance or top of atmosphere radiance (TOA), T_{sensor} is at-sensor brightness temperature in K, λ is the effective wavelength (11.457 µm for Landsat 5-TM band 6), C_1 = 1.19104 10^8 W µm^4 m^{-2} sr^{-1}, C_2 = 14387.7 µm K. Surface emissivity ε was estimated by applying the NDVI method proposed by Sobrino et al. (2004) using the following equations:

$$\varepsilon_{TM6} = 0.004 * P_V + 0.986 \quad (4a)$$

$$P_V = \frac{(\mathrm{NDVI}-0.2)}{(0.5-0.2)} \tag{4b}$$

where P_v is the vegetation proportion defined by Carlson and Ripley (1997). Finally, Ψ_1, Ψ_2 and Ψ_3, are the atmospheric correction functions for Landsat-5 TM, which can be calculated using the following equations:

$$\Psi_1 = 0.14714w^2 - 0.15583w + 1.1234 \tag{5a}$$

$$\Psi_2 = -1.1836w^2 - 0.37607w - 0.52894 \tag{5b}$$

$$\Psi_3 = -0.04554w^2 + 1.8719w - 0.39071 \tag{5c}$$

where total atmospheric water vapour (w) is, respectively, 1.46 and 1.22g cm^{-2} for the 1987 and 2011 images. These values were obtained, for the centroid and acquisition time of each image, from the Modern-Era Retrospective Analysis for Research and Applications (MERRA) portal (http://gmao.gsfc.nasa.gov/research/merra/, last accessed on May 29 2015).

5.3.6. *Effects of montado canopy cover decrease on LSA and LST*

With the aim of examining the direct effects of canopy cover decrease on LSA and LST changes, only those pixels that presented losses in *montado* canopy cover between 1987 and 2011 were considered. Therefore, the impact of canopy cover decrease on local albedo and temperature can be expressed as the LSA and LST differences (ΔLSA and ΔLST) between 2011 and 1987 in these pixels:

$$\Delta\mathrm{LSA} = \mathrm{LSA}_{2011} - \mathrm{LSA}_{1987} \tag{6}$$

$$\Delta\mathrm{LST} = \mathrm{LST}_{2011} - \mathrm{LST}_{1987} \tag{7}$$

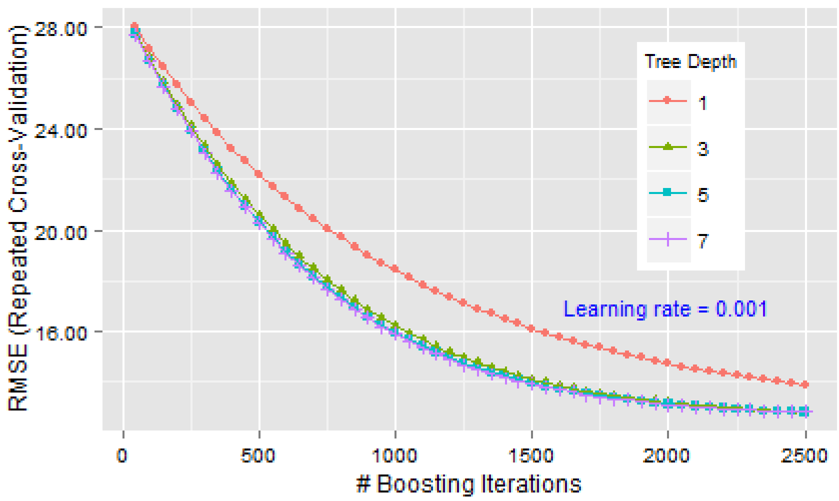
Positive ΔLSA indicates an increase in surface albedo and positive values of ΔLST indicate a local warming effect of *montado* canopy cover decrease. To better understand the effects of canopy cover decrease in ΔLSA and ΔLST, eleven classes (A to K) of canopy cover decrease were defined; 1-5% (A); 5-10% (B); 10-15% (C); 15-20% (D); 20-25% (E); 25-30% (F); 30-35% (G), 35-40% (H); 40-45% (I); 45-50% (J); 50-61% (K). For each class the average values of ΔLSA and ΔLST were estimated.

5.4. Results and Discussion

5.4.1. Estimation of montado canopy cover for 1987 and 2011

5.4.1.1. SGB model parameters, validation, and prediction

Results from the repeated 10-fold cross-validation process are shown in Figure 2. They reveal that parametrization is an important step in order to achieve the optimal SGB performance (e.g. Elith et al., 2008). The tuning procedure for assessing the optimal SGB parameters for learning rate (*lr*), tree complexity (*tc*), and number of trees *(nt*) values determined that the lowest RMSE and highest R^2 was obtained with *lr* = 0.01, *tc* = 1 and *nt* = 1,200, by attaining a minimum RMSE value of 12.4% and R^2= 81.5% (Figure 2). Results show that a greater value of *lr* (0.01) had the effect of reducing RMSE for all of the tested tree complexity values (1, 3, 5, and 7) and number of trees, which is particularly evident for *tc* = 1 when comparing both tested *lr* values (Figure 2). Therefore, it can be concluded that for the data used in this study, *bf* = 0.50, *lr* = 0.01, *tc* = 1, and *nt* = 1,200 constitute the best combination of SGB parameters. It was as such that these parameter values were used to estimate the percentage of *montado* canopy cover for 2011 and 1987.



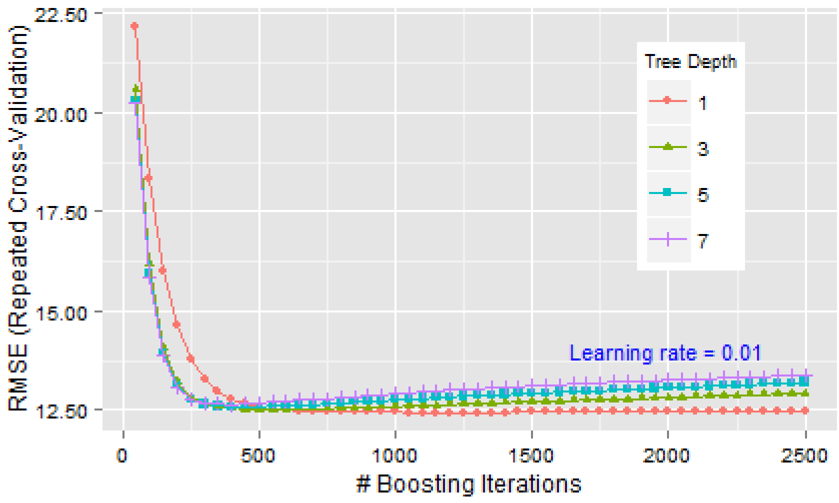


Figure 2 - Cross-validated RMSE for tree complexity (tc), learning rate (lr), and number of trees (nt) values tested using the bag fraction parameter as 0.50.

One of the most useful outputs of the SGB algorithm is the information regarding the relative importance of each predictor variable in the global fitted model (Friedman, 2001). Figure 3 shows the contribution of each variable to the best-fit SGB model considering the Landsat-5 TM multispectral bands and their derived vegetation indices. According to the relative importance measure, which ranges between 0 and 100%, the predictor variables that contributed most to the prediction capacity of the percentage of *montado* canopy cover were the EVI (34.9%), SWIR32 (30.6%), spectral bands B5 (13.2%) and B7 (10.7%). Overall, these results confirm the usefulness of EVI for determining fractional cover of photosynthetic vegetation in semi-arid environments, as well as the effectiveness of the short-wave infrared-derived index (SWIR32) in dealing with non-photosynthetic vegetation, bare soil, and green vegetation fractions (Carreiras et al., 2006; Guerschman et al., 2009, Hill, 2013; Marsett et al., 2006).

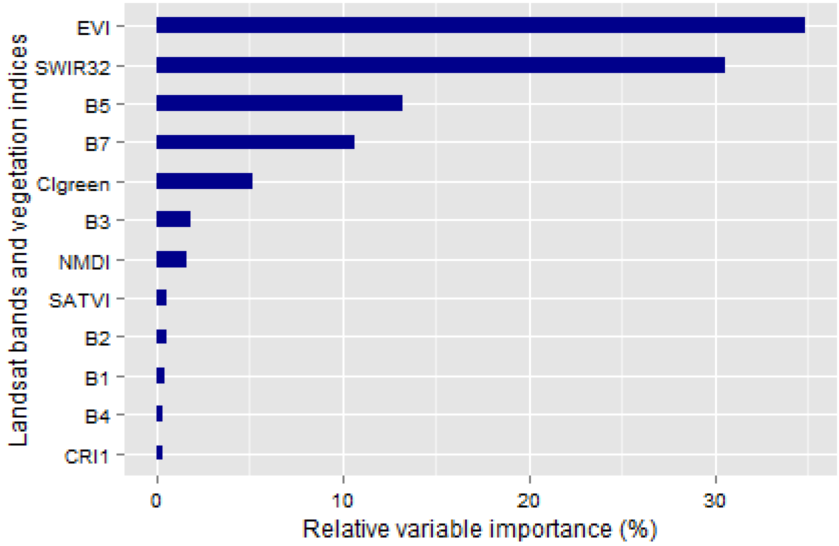


Figure 3 - Relative importance of the 12 predictor variables for estimating the percentage of montado canopy cover.

Regarding the *montado* ecosystem's spatial complexity determined by the tree density variability and the soil background effect (Carreiras et al., 2006), the results of canopy cover estimations produced by applying the best-fit SGB model are positive. Figure 4 shows a scatterplot of the observed versus predicted percentage of *montado* canopy cover in 2011 when using an independent dataset (n = 169). Overall, we can identify a high level of agreement between observed and predicted data (R^2 = 78.4%, RMSE = 14.9%), indicating, however, that the fitting statistics are slightly lower than those observed in the cross-validation process. These results are extremely similar to those reported by Carreiras et al. (2006) (R^2 = 74.0%) who also used Landsat multispectral bands and vegetation indices as predictor variables to estimate *montado* canopy cover.

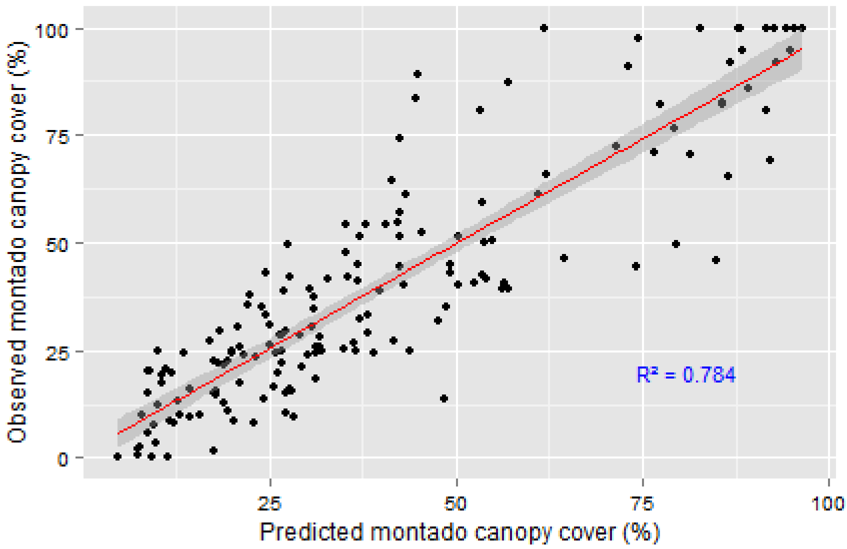


Figure 4 - Relationship between observed and predicted percentage of montado canopy cover

5.4.1.2. Mapping and identifying montado canopy cover decrease between 1987 and 2011

Based on the best-fit SGB model, two maps representing the estimation of *montado* canopy cover were produced. Figures 5a and 5b show the predictions of canopy cover (%) for 2011 and 1987, respectively. Spatial distributions of canopy cover values indicate that the *montado* ecosystem was much denser in 1987 than in 2011, which is particularly evident in the western and south-western regions of the study area (Figures 5a and 5b). These results reflect the same trend as has been reported by the National Forestry Inventory´s results, which reveal a decreasing trend in *montado* tree density (AFN, 2001, 2010). In the period between 1987 and 2011, it was found that 369,625 pixels, which correspond to 16.2% of the total of *montado* pixels in the study area, presented a decrease in percentage of tree canopy cover (Figure 5c). Overall, a mean decrease of 6.9% of *montado* canopy cover per pixel was calculated during this 24-year period. This declining trend in the *montado* ecosystem is mainly related to environmental constraints (e.g. drought) (Pelegrín et al. 2008), diseases (Camilo-Alves et al. 2013), and to inappropriate and ineffective management practices (Godinho et al., 2014).

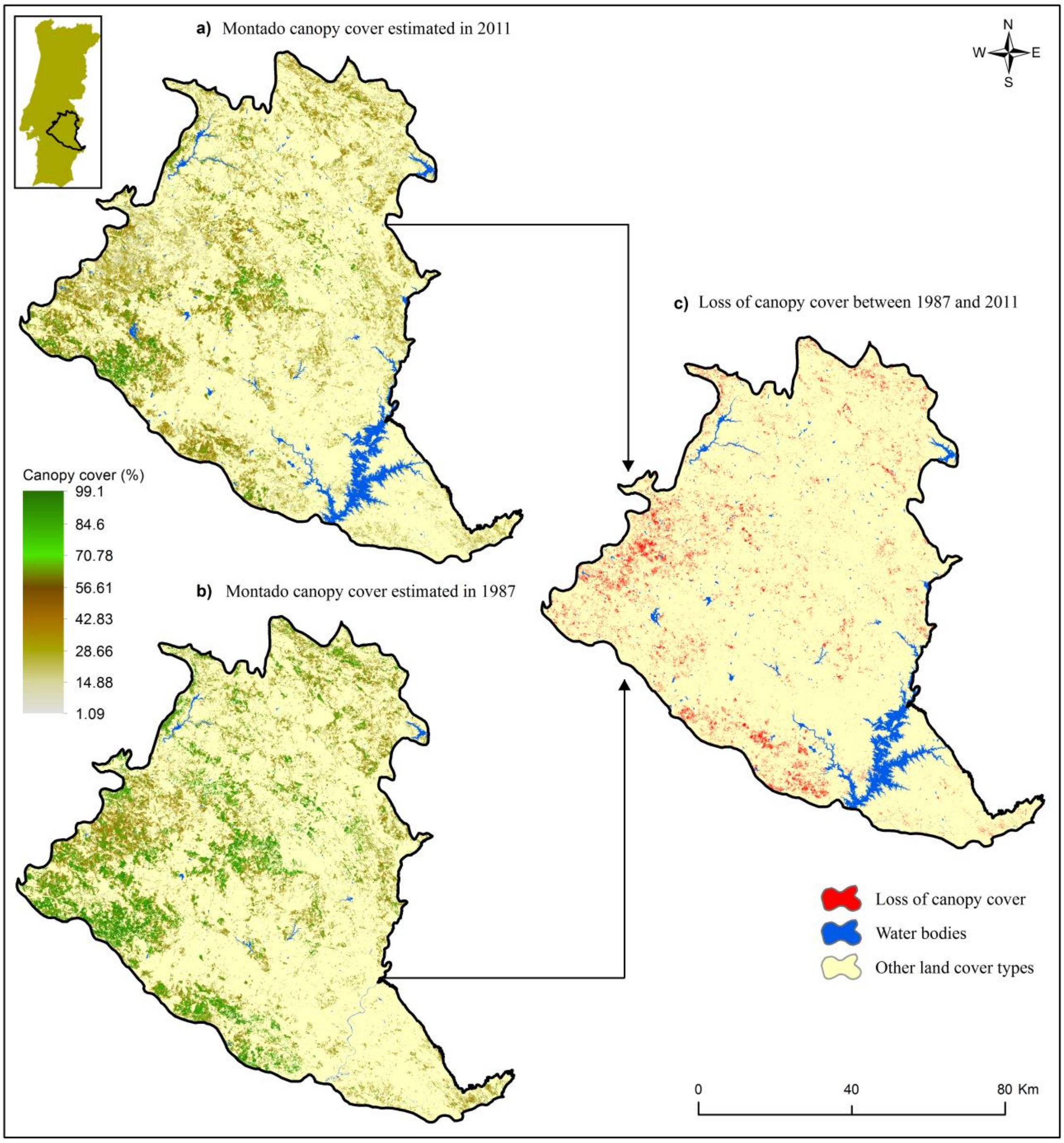


Figure 5 - Spatio-temporal patterns of montado canopy cover between 1987 and 2011. a) SGB model estimations for montado canopy cover in 2011; b) SGB model estimations for *montado* canopy cover in 1987; c) Landsat pixels that show *montado* canopy cover's decrease between 1987 and 2011.

5.4.2. Effects of montado canopy cover decrease on LSA and LST

In this study, the local effect of tree canopy cover decrease on LSA and LST was investigated. In order to assess solely the effects of canopy cover reduction on surface albedo and temperature, a prior evaluation of the LSA and LST average differences between 1987 and 2011, was carried out solely for the unchanged *montado* pixels (canopy cover changes ≈ ±0.001%). In these pixels, average differences of +0.004 for

LSA and +2.21º C for LST were found for the period studied. As these differences are not related to changes in canopy cover, in order to ensure a more accurate analysis of the effects of canopy cover decrease, the ΔLSA and ΔLST values presented below were determined by subtracting 0.004 and 2.21º C, respectively.

A spatial relationship between *montado* canopy cover decrease and changes in LSA is illustrated in Figures 6b and 6c. It was found that positive ΔLSA, which represents an increasing trend in LSA between 1987 and 2011, presents a strong spatial correspondence with pixels that represent the highest levels of *montado* canopy cover decrease. Results show that over the 24-year period, the average surface albedo increased from 0.174 to 0.186, therefore corresponding to a relative increase of 6.9%. Considering that the global average incident solar radiation reaching the Earth's surface stands at 188 W m^{-2} (Stephens et al., 2012), an increase in surface albedo of 0.012 may cause a reduction of 2.256 W m^{-2} in the surface shortwave absorption at the local scale being studied. As previously stated, changes in vegetation cover can modify LSA and hence affect the climate (e.g. Bonan, 2008; Davin et al., 2010). Therefore, as is reported in a number of studies, it may be expected that in the long term, an albedo increase may eventually lead to different local/regional meteorological conditions (e.g. Doughty, 2012; Ponce et al., 1997).

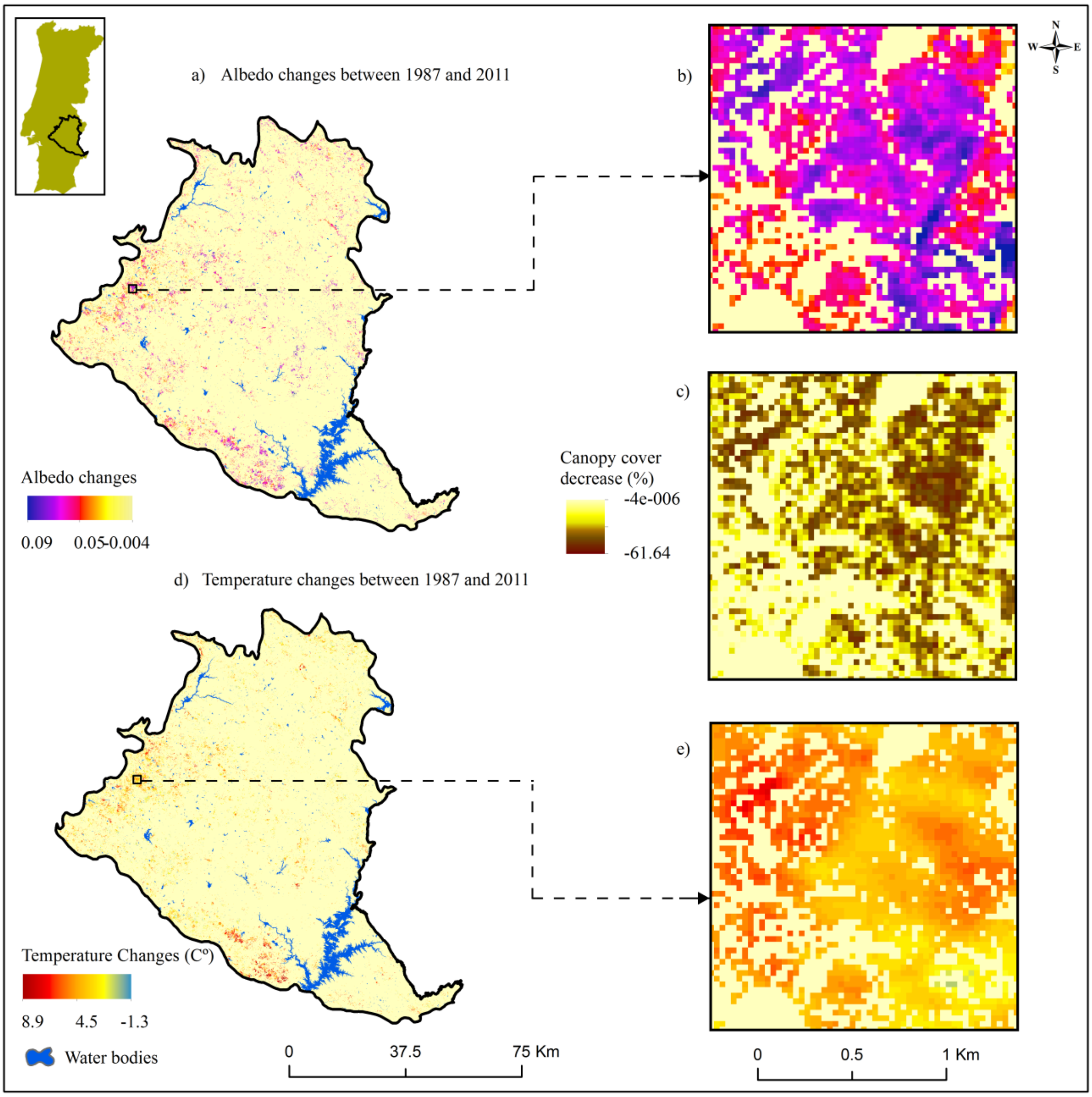


Figure 6 - Spatial relationship between *montado* canopy cover decrease (c), LSA changes (a and b), and LST changes (d and e).

Figure 7 (upper) illustrates the relationship between eleven classes (A to K) of canopy cover decrease and surface albedo change. From this graphic interpretation, it is possible to state that when *montado* canopy cover decrease is more intense, we may observe higher levels of surface albedo increase. For instance, a canopy cover decrease ranging from 1 to 5% (class A) leads to a small surface albedo increase of 0.002, while a canopy cover decrease ranging from 50 to 61.6% (class K, the maximum observed) means a huge surface albedo increase of 0.037. Tree canopies have lower albedo than shrubs, dry crops or pastures; and much lower albedo than bare soils (Bonan, 2008). In general, a decrease in *montado* canopy cover is associated with an increase in dry crops and pastures, shrubs and/or bare soil, which occupy a large proportion of the understory of *montado* ecosystems (e.g. Carreiras et al., 2006). This change in vegetation cover type (i.e *montado* trees to dry pastures) leads to higher albedo and consequently to a fall in absorbed solar radiation at the surface (Davin et al., 2010). This reduction in net radiation lowers both latent and sensible heat fluxes, which in turn reduce levels of heating in the atmospheric boundary layer as well as precipitable water vapour (Bonan, 2008). Reducing precipitable water vapour in the atmosphere leads to a decrease in cloud formation and consequently to a drop in rainfall (Pitman, 2003). Therefore, an increase in surface albedo will reduce energy fluxes (sensible and latent), convection, evapotranspiration; and rainfall processes will decline, leading to a drier atmospheric boundary layer (Charney et al., 1975, Charney, 1977; Dirmeyer and Shukla, 1994; Doughty, 2012; Davin et al., 2010).

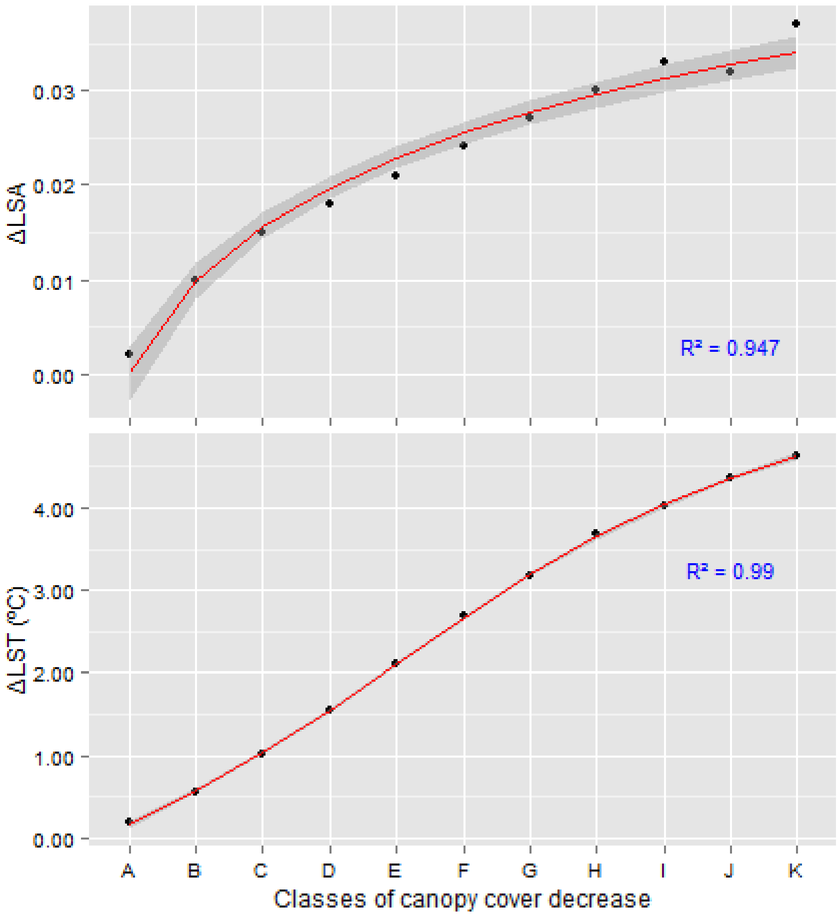


Figure 7 - Relationships between montado canopy cover decrease and changes in land surface albedo (ΔLSA) and temperature (ΔLST). Classes of canopy cover decrease: 1-5% (A); 5-10% (B); 10-15% (C); 15-20% (D); 20-25% (E); 25-30% (F); 30-35% (G), 35-40% (H); 40-45% (I); 45-50% (J); 50-61% (K).

The analysis of the relationship between *montado* canopy cover decrease and land surface temperature change for the 1987-2011 period also presented strong spatial agreement (Figures 6c and 6e), revealing that a reduction in tree cover is often associated with an increase in LST. Indeed, a clear relationship (R^2 = 0.99) was observed between LST increase and the decrease of *montado* canopy cover percentage (Figure 7, lower). Even for low percentage values of canopy cover decrease, a relatively high increase in LST (class A) was observed, as a tree canopy decrease in the range of 1-5% led to an average increase of 0.18ºC in LST. Moreover, the ΔLST relationship shifts towards a much higher increase in land surface temperature when canopy cover decreases fall in the range of 50-61% (average of 4.64ºC). These results are in line with other studies that have found significant differences in LST between open fields and tree-covered areas (e.g. Arribas et al, 2003; Mildrexler et al., 2011; Roberts et al., 2015). As stated earlier, the greater the decreases in *montado* canopy cover, the more dry crops/pastures and/or bare soil become exposed. Consequently, lower surface roughness occurs when crops, pastures and open lands dominate the tree fraction in the landscape. Reducing surface roughness is often associated with a decreasing trend in the transference fluxes of sensible and latent heat from the surface to the atmosphere (Pitman, 2003). Therefore, since the energy available at the surface cannot be transferred to the atmosphere through turbulent energy fluxes, the surface tends to warm up (Bonan, 2008; Davin et al., 2010). In addition, a reduction in tree density in *montado* ecosystems, as seen in canopy cover decrease, will modify rooting profiles and affect the evapotranspiration rate (Bonan, 2008; Doughty, 2010). Decreasing evapotranspiration in the system may lead to warmer and drier conditions at local level because evapotranspiration favours cloud formation and rainfall, causing surface cooling (Bonan, 2008; Davin et al., 2010; Zhu and Zeng, 2015; Kvalevag et al., 2010).

In summary, as argued by other authors, the observed surface albedo and temperature increases caused by *montado* canopy cover decrease may lead to local/regional climatic changes resulting in greater aridity, in the long term (e.g. Charney et al. 1975, Ponce et al., 1997). Consequently, a feedback loop caused by the *montado* canopy cover decrease, leads to an increase in surface albedo, surface temperature, and a reduction in water vapour in the atmosphere, thereby contributing to the declining trend in the *montado* ecosystem (Charney, 1977).

Chapter

6

Synthesis

6.1. Summary of main results and conclusions

This doctoral thesis addresses the *montado* landscape dynamics based on geo-computational methodological approaches using cartographic information and remote sensing-derived data, as well as the understanding of the main causes of its changes and impacts on biogeophysical processes. The work carried out focused specifically on the study and assessment of the usefulness and effectiveness of Earth Observation Satellites (EOS) for producing accurate and up-to-date *montado* land cover information as a key data source to identify and measure the *montado* landscape changes, and the related local effects. As indicated previously in chapter 1, four specific research objectives were defined: (i) quantifying *montado* area changes from 1990 to 2006 and assessing the influence of environmental, land management, and spatial factors in these changes (chapter 2); (ii) exploring the capability of EOS and advanced image classification techniques for producing accurate *montado* land cover maps (chapter 3); (iii) testing an existing remote sensing-based approach for estimating the percentage of *montado* tree canopy cover at the pixel level (chapter 4); and (iv) developing an effective remote sensing-based approach to understand the effects of *montado* canopy cover decrease in local land surface biogeophysical process changes (Chapter 5).

Firstly, this chapter aims to highlight the main results and conclusions obtained in chapters 2 to 5 of this thesis and to stress the innovative character of the research developed and of the results obtained. Secondly, it points out some suggestions for future research in the field of applied remote sensing and geographic modelling on the assessment of *montado* change effects on local/regional climate changes.

The study of recent *montado* changes (1990 – 2006) and influence of environmental, land management and spatial factors was carried out in chapter 2 of this thesis. A set of geoprocessing operations were developed to extract *montado* areas for 1990 and 2006 from available cartographic data sources. This information was used to investigate the changes detected in the *montado* distribution pattern for the whole southern Portugal from 1990 to 2006 and consequently determine the relative effects of selected environmental, land management and spatial factors on *montado* land cover change. Based on this *montado* land cover information, a regression rate of 0.14% $years^{-1}$ was estimated between 1990 and 2006. The findings reported in this chapter strongly support the hypothesis that land management, rather than environmental factors, constitutes the main driver of change in the condition of the *montado*, and, consequently, of its spatial pattern dynamics. Management practices are mostly associated with the intensity and type of grazing (livestock type, breeds, density, length of grazing period in each year, etc.) and shrub control techniques (soil mobilisation and surface shrub cutting). Even if these relations have been found before by other authors on a case-study basis, the present work has for the first time gathered and analysed all valid information for the whole region of southern Portugal and produced therefore a much needed large scale analysis of these processes and cause-effect relations. On one hand, a relationship is demonstrated between loss of management and the consequent dramatic reduction in human intervention, shrub encroachment, and decay in the *montado* due to fire or the return to dense maquis-type land cover. On the other hand, it is shown how increased livestock grazing pressures also lead to *montado* decline through progressive soil compaction and prevention of natural regeneration, thus producing increasingly larger tree-free *montado* areas. Coupled payments for livestock are maintained in Portugal until the present Framework Programe, as part of the Pillar I payments of the Common Agricultural Policy (CAP). This has resulted in the progressive intensification of livestock production, with increased grazing intensity by a higher number of grazing animals per hectare, and a general change from sheep to cattle grazing, causing therefore much higher impact on *montado* balance, especially as rarely there is an investment in pastures improvement (Almeida et al. 2013; Pinto-Correia et al. 2014). During the period of 16 years going from 1990 to 2006, these trends have resulted in stronger pressures on *montado* balance, and they will be most likely maintained in the present framework program (2014-2020), as the same coupled payments are still present in the current Pillar I regulation for Portugal.

Although these results showed that most of the variation in *montado* loss values were explained by land management either alone or in combination with environmental and spatial factors, with evidence from the whole *montado* region, it only focused on data and respective results obtained for a short time period (1990-2006). The lack of accurate and comparable multi-temporal *montado* land cover information (topic to be addressed in chapter 3) limits the emergence of a broader long-term *montado* change analysis framework. Despite this short-term *montado* landscape change analysis, the findings of this chapter clearly show that a better balance in terms of management reduces the risk of *montado* decline. And it shows, how distortions in management strategies caused by public policies, can have severe impacts on the long term balance of a complex land use system as the *montado*, in order to ensure that there are no conflicts between the effects of the production support and the objectives of sustainability as formulated for the *montado* at the national level.

The availability of accurate and comparable spatial information of *montado* land cover is crucial for understanding their spatial patterns, trends, and main drivers of changes. The usefulness of EOS and advanced image classification techniques for producing accurate *montado* land cover maps was clearly demonstrated in chapter 3 through an effective methodological approach by using Landsat 8 multispectral data, vegetation indices, and the Stochastic Gradient Boosting (SGB) algorithm. The obtained results may constitute a pioneering and accurate remote sensing-based *montado* mapping approach developed with the use of Landsat 8 OLI (LS8) imagery and vegetation indices (VIs). In fact, the most suitable Landsat 8-based data combinations were identified in this chapter and constitute a straightforward approach towards a more cost-effective and accurate *montado* mapping and monitoring system in the Iberian Peninsula and further Mediterranean rural areas.

Classification of the Landsat 8 OLI imagery combined with vegetation indices as ancillary information was performed using a SGB machine learning algorithm. Good accuracies were obtained for both LS8 and LS8 + VIs products (80.16% and 85.71%, respectively) by using this methodological approach. It has been demonstrated that SGB has the capability to produce accurate models using remote sensing data covering a complex landscape such as the Mediterranean region. Moreover, the importance of the SGB tuning parameter procedure on the results obtained has confirmed the considerable relevance of selecting the best combination of parameters, as parameterisation process is imagery data-dependent. The classification accuracy of the thematic maps produced with the use of multi-seasonal Landsat 8 OLI spectral bands increased significantly with the integration of vegetation indices into the classification scheme. This methodological approach allowed the most suitable vegetation indices to be determined in order to map *montado* land cover more accurately. It was also verified that this multi-seasonal approach may significantly enhance existing phenological and spatial differences for better discriminating among different vegetation classes with similar spectral characteristics, in both spring and summer seasons.

The lack of accurate *montado* maps describing the system' spatial distribution over time has been conditioning the implementation of a comprehensive *montado* monitoring program. Such information is crucial for supporting land planning and management policies-related decision-making. In chapter 2, *montado* changes and their respective drivers were studied over a 16-year period using a spatial analysis-based approach aiming to extract *montado* areas from the available cartographic information for southern Portugal. Even if this analysis brings in considerable progress in relation to previous analysis, this time window does not allow to thoroughly and comprehensively understand the *montado* change process on the long term. Therefore, the findings of chapter 3 constitute a first relevant step towards the development of a broader long-term *montado* research line aiming to address the need of identifying and mapping the spatial patterns of this ecosystem in southern Portugal, in the last few decades, by using current (Landsat 8 OLI) and past Landsat mission's data (namely TM and ETM+ sensors).

Montado patches (area) and canopy cover (tree density) are the main attributes that must be considered for a thorough analysis of *montado* spatio-temporal dynamics. The first one was addressed in the chapter 3, where an effective remote sensing-based approach was developed to accurately map *montado* areas by using EOS data. However, based on the results of chapter 3, only information about *montado* patches spatial distribution may be derived. In chapter 4, information about *montado* canopy density was assumed as an important attribute towards a more accurate identification of *montado* areas as High Natural Value farmlands (HNV). The *montado* is recognized in all European classifications as a paradigmatic example of High Nature Value land use system, where high conservation values and specific landscape patterns are associated with existing land use system. Nevertheless, there is an acknowledged lack of accurate information as to the management thresholds that make a *montado* area, at the farm or plot scale, possible to classify as HNV or not. There is an urgent need for precise and easily available information on this detailed classification. Consequently, the research presented in chapter 4 was conducted with the aim of implementing and testing the effectiveness of the Forest Canopy Density (FCD) model for mapping *montado* canopy densities, thereby supporting the production of more detailed geographical information on *montado* areas, which in turn may be used to promote more accurate identification and assessment of *montado* areas as HNV farmlands. Having been assessed by using four accuracy measures, the findings reveal that the application of the FCD model is effective and can constitute an important milestone for producing more detailed and valuable information on *montado* canopy density at a local/regional scale. The results show that using and combining biophysical indices such as the advanced vegetation (AVI), bare soil (BI), shadow (SI) and thermal (TI) indices has led to more reliable results when estimating and mapping *montado* canopy density classes. Overall, the FCD model showed strong agreement and good accuracy (OA= 78.0%; K= 0.71), thereby resulting in good overall estimations of the density of *montado* canopy. The results obtained constitute the first remote sensing-based product for mapping *montado* canopy density using the FCD model, which was originally developed for tropical forests. However, the FCD model showed a slightly lower accuracy (68.5%) for low *montado* density class (11-40% of tree cover), which may reveal some limitations of the FCD model for estimating accurately the percentage of *montado* canopy cover in such class. This limitation may be potentially restrictive for developing studies focused on the biogeophysical effects of *montado* canopy cover changes, where high accuracy in *montado* canopy cover estimation is mandatory to better understand these processes (topic to be addressed in chapter 5).

Developing reliable methodological approaches for identifying and mapping HNV farmlands is currently an important issue in the scientific community. Several initiatives have focused on producing strategies for precise HNV identification in order to effectively contribute to more targeted and specific management options (Almeida et al, 2013; Hazeu et al, 2014; Lomba et al, 2015). Using detailed spatial information on *montado* canopy densities, such as the data obtained in this chapter by applying the FCD model, may constitute a relevant step towards setting up a main methodological framework able to be applied at several scales. This may allow achieving a more straightforward and thorough identification of HNV farmlands in *montado* systems, as well as setting up a more reliable monitoring framework of changes that may be occurring. In fact, this type of *montado* cover information is essential for providing better support to the implementation of the CAP and other public policies with a direct influence on the *montado* management, and particularly to support the application of payments related to the High Nature Value of production systems.

Finally, after having analysed the *montado* change, its related drivers and its consequences in terms of land cover and of nature value, a remaining novel contribution to the study of the *montado* dynamics is the assessment of the impacts of these changes on the natural resources. In chapter 5, an effective remote sensing-based methodological approach was developed in order to highlight and demonstrate the direct role of *montado* canopy cover decrease in local biogeophysical properties' modifications, namely land surface albedo (LSA) and land surface temperature (LST). This is a novel perspective, as the natural resources condition is often seen as a cause of the *montado* land cover change – but logically, management driven changes in the *montado* pattern, has an impact on the functioning of the natural components of the system. *Montado* tree canopy cover was estimated for 1987 and 2011 using a different remote sensing-based approach than the one tested in the chapter 4, in order to overcome the above mentioned limitations of the FCD model. The results of this research provide new insights into the impacts of Mediterranean forest canopy cover decrease on land surface albedo and temperature.

A modelling procedure applying a SGB machine learning algorithm to Landsat 5-TM spectral bands and derived vegetation indices as explanatory variables, has estimated *montado* canopy cover with good agreement (R^2 = 81.5%; RMSE = 12.4%). It has also been demonstrated that the integration of vegetation indices such as EVI and SWIR32 in this type of modelling procedure may result in the production of more accurate estimations of tree canopy cover in semi-arid environments. In fact, the results revealed that EVI and SWIR32 indices were the ones with higher predictive ability for *montado* canopy cover estimation, by presenting a relative importance of 34.9% and 30.6%, respectively. Overall, an average decrease of 6.9% of *montado* canopy cover per pixel was calculated during this 24-year period. This result confirms that the *montado* ecosystem was much denser in 1987 than in 2011, therefore revealing a decreasing trend in tree cover.

This research provides a comprehensive presentation of the effects of tree canopy cover decrease on both LSA and LST of a Mediterranean agroforestry system. A clear spatial relationship between *montado* canopy cover decrease and changes in LSA and LST was demonstrated in this chapter. The response of surface albedo and surface temperature to different ranges of *montado* canopy cover decrease showed a strong positive relationship. When tree canopy cover decrease was low (1-5%), the increase in surface albedo and surface temperature were not particularly prominent: 0.002 and 0.18ºC, respectively. Nevertheless, a decrease of *montado* canopy cover higher than 50% implied significant surface albedo and surface temperature increases: 0.037 for LSA and 4.64ºC for LST. These results clearly demonstrate that the observed tree canopy cover regression over a 24-year period (1987 – 2011) in a Mediterranean semi-arid ecosystem may produce significant changes in two of the most important biogeophysical parameters (LSA and LST), which from a long-term perspective may potentially alter the micrometeorological conditions. This remote sensing-based approach, using specific and detailed information, makes a relevant contribution for effectively illustrating the relationship between *montado* canopy cover decrease over time and changes in LSA and LST. And thus, the present research has opened up for new insights as to the effects of the *montado* change, further than the most commonly studied of biodiversity, nature conservation and landscape character.

6.2. Recommendations for future research

This Doctoral thesis contributions may induce relevant improvements in *montado* conservation, planning and management-related public policies, as better understanding the main patterns and trends of *montado* changes and their drivers may improve the whole decision-making process. Over this research, a decline trend of *montado* ecosystem was clearly identified through the estimated *montado* area (Chapter 2) and tree canopy cover regression (Chapter 4 and 5). Furthermore, the demonstrated usefulness and effectiveness of Earth Observation Satellites (Chapter 3) was one of the most important outputs of this thesis towards a broader long-term *montad*o change analysis which may also include the assessment of its effects on local biogeophysical processes (Chapter 5). Nevertheless, further research, directly linked to the one now presented, is needed and therefore recommended at local/regional scale in order to address the following issues:

i. Identifying the relationship among *montado* management practices (e.g. shrub control and tree pruning) and land surface albedo and temperature values;
ii. Assessing the magnitude of the effects on energy fluxes (sensible and latent heat) and evapotranspiration rates resulting from the increase of both land surface albedo and land surface temperature in *montado* ecosystem;
iii. Identifying and assessing the effects of decreases in surface roughness (due to canopy cover reduction) on land surface temperature and land surface albedo.

The above mentioned research lines are extremely important to better understand the relative importance of each one of these factors in determining and inducing the arid conditions of Mediterranean agroforestry systems.

List of publications included in the thesis

- **Godinho**, S., Guiomar, N., Machado, R., Santos, P., Sá-Sousa, P., Fernandes, J.P., Neves, N., Pinto-Correia, T., **2014**. Assessment of environment, land management, and spatial variables on recent changes in montado land cover in southern Portugal. Agroforestry System. doi:10.1007/s10457014-9757-7

- **Godinho**, S., Guiomar, N., Gil, A., (***Submitted***). Using a stochastic gradient boosting algorithm to analyse the effectiveness of Landsat 8 data for *montado* land cover mapping: application in southern Portugal.

- **Godinho**, S., Gil, A., Guiomar, N., Neves, N, Pinto-Correia, T., **2014**. A remote sensing-based approach to estimating montado canopy density using the FCD model: a contribution to identifying HNV farmlands in southern Portugal. Agroforestry System. DOI:10.1007/s10457-014-9769-3

- **Godinho**, S., Gil, A., Guiomar N., Costa, M. J., Neves, N., (***Submitted***). Detecting the effects of Mediterranean forest canopy cover decrease in land surface albedo and temperature using Landsat-5 TM data.

Other Publications (2012 – 2015)

- Silva C. C., Lourenço R., **Godinho** S., Gomes E., Sabino-Marques H., Medinas D., Neves V., Silva C., Rabaça J. E., Mira A. **2012**. Major roads have a negative impact on the Tawny Owl Strix aluco and the Little Owl *Athene noctua* populations. Acta Ornithologica. 47: 47–54. DOI 10.3161/000164512X653917

- **Godinho**, S., Mestre, F., Ferreira, J.P., Machado, R., Santos, P., **2013**. Effectiveness of habitat management in the recovery of low-density populations of wild rabbit. European Journal of Wildlife Research. 59:847–858 DOI 10.1007/s10344-013-0738-3

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