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PROGRAMA OFICIAL DE DOCTORAT EN GEOGRAFIA

Contributions to the knowledge of the multitemporal spatial patterns of the Iberian Peninsula droughts from a Geographic Information Science perspective

Contribucions al coneixement dels patrons espacials multitemporals de les sequeres a la Península Ibèrica des de la perspectiva de la Ciència de la Informació Geogràfica

PhD Thesis

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If there is magic on this planet,
it is contained in water
(Loren Eiseley)

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Index of Acronyms

AEMET	State Meteorological Agency of Spain (Agencia Estatal de Meteorologia)
AIC	Akaike Information Criterion
AMO	Atlantic multidecadal oscillation index
AMOC	Atlantic Meridional Overturning Circulation
AO	Arctic oscillation
AR	Autoregressive
AVHRR	Advanced Very High Resolution Radiometer
CRU	Climatic Research Unit – University of East Anglia
DCAIP	Digital Climatic Atlas of the Iberian Peninsula
DOY	Day of Year
DPC	Day of Pixel Composite
ECOSTRESS	ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station
GEOSS	Global Earth Observation System of Systems
GI	Geographic Information
GIS	Geographic Information Systems
LCMC	Land Cover Map of Catalonia
LPDAAC	NASA Land Processes Distributed Active Archive Center
LST	Land Surface Temperature
MEI	Multivariate ENSO (El Niño and the Southern Oscillation)
MODIS	MODerate-resolution Imaging Spectoradiometer
NAO	North Atlantic Oscillation
NDDI	Normalized Difference Drought Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration
QA	Quality Assessment
QC	Quality control
SBA	Societal Benefit Areas
SDS	Science Data Set
SEM	Structural Equation Modelling
SPEI	Standardized Evapotranspiration Precipitation Index
SPI	Standardized Precipitation Index
SWIR	Short wave infrared
VCI	Vegetation Condition Index
VI	Vegetation Index
TVDI	Temperature Vegetation Dryness Index
WeMOI	Western Mediterranean Oscillation Index

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Resum

La sequera, una amenaça natural i insidiosa, és un fenomen complex que involucra processos climàtics i genera grans impactes ambientals i socioeconòmics. En els últims anys l'interès en el seguiment i en els efectes de les sequeres ha incrementat a causa de les situacions climàtiques extremes esdevingudes. Aquests episodis de sequera tenen implicacions sobre moltes Societal Benefit Areas (SBAs) abordades pel GEOSS (Global Earth Observation Systems of Sytems) de manera que es genera una interconnexió entre les diferents disciplines, com per exemple la sostenibilitat agrícola, la seguretat alimentaria, les funcions i serveis dels ecosistemes, la biodiversitat, les reserves de carboni, els recursos hídrics i els incendis forestals, entre d'altres. Segons el cinquè i últim informe publicat pel Grup Intergovernamental d' Experts sobre el Canvi Climàtic (IPCC), les projeccions de futur indiquen una disminució de les precipitacions en la conca Mediterrània que, juntament amb temperatures més càlides, pot desencadenar més episodis de sequera i reduir la disponibilitat d'aigua tant per sistemes naturals com per recursos humans.

Tot i que la recerca en sequera progressa adequadament, el fenomen encara no està prou ben caracteritzat i per tant la gestió adequada d'aquest tipus d'esdeveniments i de les seves conseqüències encara es fa difícil. Per exemple, a l'Espanya Peninsular la sequera és un fenomen recurrent que en les últimes dècades ha causat importants impactes naturals i socioeconòmics. D'altra banda, la Península Ibèrica Espanyola és un cas d'estudi prou interessant atesa la seva situació a la conca Mediterrània i pel seu complex i heterogeni territori. Amb quasi el 90 % de la seva superfície (35 % dedicada al sector agrícola i un 55 % a boscos) amenaçada per la sequera, la caracterització espacio-temporal de la sequera en aquesta àrea és fonamental pel seguiment, previsió i gestió de les seves conseqüències.

Les dades climàtiques i la teledetecció són el nucli de la present tesi, la qual contribueix al coneixement dels patrons espacials multitemporals de les sequeres a la Península i els seus efectes, des de la perspectiva de la Ciència de la Informació Geogràfica. En aquesta tesi s'aborda la identificació i caracterització de la sequera a diferents escales espacio-temporals i es demostra la necessitat d'un nou marc conceptual on la sequera forestal tingui el seu reconeixement. També contribueix a un millor coneixement dels episodis passats de sequeres a la Península Ibèrica Espanyola i dels seus possibles desencadenants gràcies al desenvolupament d'una nova base cartogràfica climàtica (precipitació i temperatura) i de sequera (Standardized Precipitation Index- SPI and Standardized Precipitation Evapotranspiration Index- SPEI) per al període 1950-2012, a 8 escales temporals diferents, que inclou més de 14 000 mapes continus a una resolució espacial de 100 m.

Les anàlisis dels mapes de sequera continus a nivell espacial i temporal ofereixen una visió espacial innovadora de la sequera que permet identificar la distribució espacial de les zones més afectades i quantificar la intensitat i l'extensió temporal d'aquestes, sovint revelant com a àrees afectades aquelles que no s'esperava i per tant suggerint una revisió de les unitats climàtiques actualment definides per l'àrea. Aquest enfocament multidimensional permet seguir la dinàmica espacio-temporal de les sequeres, les anomenades sequeres en moviment, i facilita la identificació d'esdeveniments simultanis, la present en un moment donat i la resident d'un episodi anterior, en l'espai i el temps. Les tendències de les sèries temporals del SPEI a diferents escales temporals ha identificat un canvi de règim sobtat entre el 1979 i el 1981 que afecta la part central i de l'est de la Península Ibèrica, i que és anticipat per senyals d'alerta de forma consistent. L'Oscil·lació Multidecadal Atlàntica (AMO) n'ha resultat ser el predictor més significatiu. L'avaluació dels impactes d'aquest canvi abrupte en la fixació de carboni dels boscos mediterranis de *Pinus halepensis* identifiquen disminucions significatives en els guanys de les reserves de carboni en la majoria de parcel·les forestals avaluades.

Tanmateix, els patrons de sequera basats en clima no poden explicar l'estat real de la vegetació. En canvi, les observacions remotes de satèl·lit proporcionen una visió complementaria amb una gran cobertura espacial i temporal de les condicions de sequera en la vegetació. Així doncs, s'ha calculat i usat diversos índexs de vegetació derivats del sensor MODIS (MODerate-resolution Imaging Spectoradiometer) com a possibles indicadors de paràmetres de l'estat fisiològic de la vegetació dels boscos. L'anàlisi exploratòria basada en series temporals de dades de clima i índexs de vegetació de MODIS mostra les capacitats de la integració d'ambdós tipus de dades a l'hora d'identificar i caracteritzar els patrons de sequera en els boscos a diferents escales temporals. Per exemple, els índexs de vegetació que tenen en compte la temperatura presenten una correlació de R^2~0.56 amb SPEI en escales temporals més curtes, mentre que si s'examinen escales temporals més llargues (al voltant d'un any) les correlacions més altes es troben amb els índexs que tenen en compte verdor i contingut d'aigua de la vegetació. Aquesta resultats mostren la robustesa de la integració de les dades de teledetecció i del SPEI i el sentit d'usar aquest últim índex en estudis de detecció de sequeres previs als que contemplen dades de teledetecció.

Finalment, s'ha desenvolupat un nou algorisme per tal de generar compostos de reflectàncies de 8 dies a partir d'imatges diàries, basat en una correcció topogràfica i una aproximació geostadística, amb la finalitat de millorar l'heterogeneïtat espacial que presenta el producte de 8 dies actual de MODIS (MOD09A1). Els resultats mostren que aquest nou producte, no només millora en gran mesura el producte actual sinó que també presenta una alta correlació amb els productes obtinguts mitjançant compostos del producte diari (MOD09GA), esdevenint un possible substitut d'aquest en processaments que requereixin molt de temps de càlcul.

En resum, la investigació duta a terme en aquesta tesi avança en diversos aspectes de l'estudi de la sequera, tant a nivell climàtic com a nivell forestal, i consolida un avenç en la investigació d'aquests fenòmens.

Summary

Drought, an insidious natural hazard, is a complex phenomenon involving climate processes that has large environmental and socioeconomic impacts. In recent years there has been an increasing interest in droughts effects and monitoring due to the current situations of extreme climatic events. Such drought events have implications on many of the Societal Benefit Areas (SBAs) that GEOSS (Global Earth Observation System of Systems) addresses; and this phenomenon set up an interconnection between different fields, such as agriculture sustainability, food security, ecosystem functions and services, biodiversity, carbon stocks, water resources, and wildfires, among others. According to the recently published IPCC 5th Assessment Report, a decrease in precipitation coupled with warmer temperatures associated to drought events is projected especially in the Mediterranean Basin, which will result in reductions on water availability for natural and agricultural systems and human needs.

Although research on drought is progressing, the phenomenon is still not well understood, and this fact makes difficult to adequately manage this type of events and their derived consequences. For instance, in the Spanish Iberian Peninsula droughts are recurring phenomena which in recent decades have led to major natural and socioeconomic impacts. Moreover, the Spanish Iberian Peninsula is an interesting case study due to its situation in the Mediterranean Basin and its heterogeneous complex territory. With around 90 % of its land surface (35 % agriculture and 55 % forest areas) highly threatened by droughts, understanding the spatial and temporal characteristics of drought in this area is essential for monitoring, forecasting and managing of its consequences.

Both climate and remote-sensing data are the core of this thesis that wants to contribute to the knowledge of the multitemporal spatial patterns of droughts in the Iberian Peninsula and their effects, especially on forests, from a Geographic Information Science perspective. This thesis addresses drought identification and characterization at different spatiotemporal scales and demonstrates the need for a new conceptual framework where forest drought has its own recognition. A better understanding of past droughts events affecting the Spanish Iberian Peninsula and their possible drivers has been achieved through the development of a monthly climate (precipitation and temperature) and drought (Standardized Precipitation Index- SPI and Standardized Precipitation Evapotranspiration Index- SPEI) cartographic Big Data base for the period 1950-2012 at 8 different timescales, which includes more than 14 000 continuous maps at a detailed spatial resolution of 100 m.

The analyses of spatiotemporally continuous SPEI maps offers an innovative spatial vision of drought, identifies the spatial distribution of most affected areas, and quantifies the intensity

and time extent of drought events, often unveiling areas more affected than previously expected and suggesting new future climatic units for the area. This multidimensional approach has enabled monitoring the spatiotemporal dynamics evolution of droughts, the so-called drought moving waves, which facilitates the identification of several simultaneous present and long-term drought events. Trends of SPEI time-series at different timescales identifies an abrupt regime shift between 1979 and 1981 affecting the central-eastern part of the Iberian Peninsula, which was consistently anticipated by early warning signals. The analysis indicates that the Atlantic Multidecadal Oscillation (AMO) is the strongest predictor of the shift. The evaluation of potential impacts of drought regime shifts in forest carbon sequestration of Mediterranean *Pinus halepensis* forests has also resulted in reduction in carbon stock accumulation rates in most of the evaluated areas.

However, climate-based patterns do not entirely explain the real state of vegetation. Instead, satellite observations potentially provide a complementary view with greater spatial and temporal coverage of drought conditions. Therefore, vegetation indices derived from MODIS (MODerate-resolution Imaging Spectoradiometer) sensor has been calculated as possible indicators of physiological forest parameters. An exploratory analysis based on time-series of climate and MODIS data has been carried out showing the capabilities of integrated climate and remote-sensing data to identify and characterize drought patterns on forests at different timescales. For instance, remote-sensing temperature indices exhibit R^2~0.56 with SPEI at the shortest timescales, while when examining timescales of about 1 year, the higher correlations are found with water and vegetation indices (R^2~0.38). These results show both the robustness of SPEI and remote-sensing data working together, and the sense of using SPEI for pre-remote-sensing drought studies.

Finally, a new methodology for generating MODIS 8-day surface reflectance products based on a topographic correction and a geostatistical analysis approach has been developed in order to address several issues related to the spatial heterogeneity of current MODIS 8-day composites (MOD09A1). Results show that this new product not only greatly improves the current product, but also presents a high monthly correlation with products obtained by the compilation of the daily product (MOD09GA), being a possible substitute of high processing time analysis of daily products.

In summary, the research carried out in this thesis covers many aspects of drought studies, meteorological studies and forest studies, consolidating progress in the investigation of the drought phenomenon.

Chapter 1

THESIS FRAMEWORK

1 Thesis framework

1.1 General introduction

The research presented below entitled "**Contributions to the knowledge of the multitemporal spatial patterns of the Iberian Peninsula droughts from a Geographic Information Science perspective**" makes an intense, Big Data, usage of the resources of GI Science (remote-sensing, spatial analysis, geostatistics, etc) to better understand drought along the 1950-2012 period, and with special emphasis on forest drought.

Drought, understood as a prolonged water deficit affecting various Earth systems and social frameworks, is considered one of the most complex of all natural hazards (Wilhite 1985). For instance, drought events have implications on many of the Societal Benefit Areas (SBAs) that GEOSS (Global Earth Observation System of Systems) addresses; and this phenomenon sets up an interconnection between different fields, such as health, food security, agriculture sustainability, ecosystem functions, biodiversity, carbon stocks, water resources, and wildfires, among others. For this reason there is an increasing demand for drought related information, such as the spatiotemporal characterization of drought events that could be useful for drought policies, management and mitigation plans.

On the other hand, most of the currently available studies on the impacts of drought in developed countries focus on the United States of America and Australia (Markandya et al. 2009), and there is a need to get data specifically for the European context (Martin-Ortega and Markandya 2009). Concretely, the Iberian Peninsula, located in a prominent region of the Mediterranean basin, is considered a region highly vulnerable to drought (Olcina Cantos 2006) and a hotspot for future impacts of global warming (IPCC 2014). In this scenario, estimating the impact of drought for the purpose of determining its environmental consequences acquires major relevance.

The Iberian Peninsula presents an interesting high climatic variability due to its latitudinal position, in where general atmospheric circulation, far from being static, defines an interesting climatic transition zone between the limit of arid regions (less than 400 mm annual precipitation) and more temperate or humid areas. Due to these circumstances, the Spanish Iberian territory frequently undergoes droughts which consequences are invaluable in terms of agricultural losses, ecosystem services, etc. Considering that around the 55 % of the Spanish Iberian Peninsula surface corresponds to forest area (Ministerio de Agricultura, Alimentación y Medio Ambiente 2014), the importance of the impact of drought on forests acquires a great dimension. Forests are invaluable ecosystems providing uncountable services to society; from their role as carbon storage, to their biodiversity, improvement of water quality or the ecotourism opportunities they offer (Foley et al. 2005). Therefore, the analysis of drought in the Spanish Iberian Peninsula over time and the spatial characterization of such events are essential, not only to identify drought derived impacts in a broadest sense, but also to know their particularities on forests ecosystems.

Reliable observations of the terrestrial environment are crucial for identifying and understanding climate change impacts, for promoting conservation and, above all, for improving the scientific understanding of ecosystems services (Herold et al. 2006). Traditionally, methods used to quantify meteorological drought were based on field observations (Pool 1913; Shirley 1934)or rainfall represented as points or isohyets. Data had to be greatly reduced in volume or classified in order to make them understandable and representable; so many local details were often filtered away and lost (Burrough and McDonnell 1998). Nevertheless, combination of several meteorological variables defining drought indices also became available. Indeed, the Palmer Drought Severity Index (PDSI) developed in 1965 (Palmer 1965) was a turning point in the evolution of drought indices (Heim 2002). The PDSI was created with the intent of “measuring the cumulative departure of moisture supply” and following it, several other indices were developed (Palmer 1968). As the scientific study of drought advanced, different kind of information needed to be mapped and these type of data were more usefully represented by a continuous quantitative surface that may be modeled mathematically (Burrough and McDonnell 1998). However, this quantitative approach was hindered by the lack of continuous observations; this issue was solved thanks to the development of Geographic Information Systems (GIS) which turned the application of logical and numerical modeling, interpolation and statistical methods to spatial data into a great relevance routine, still essential, and nowadays encompassed, together with cartography, Geodesy, Photogrammetry, Remote-sensing, Geostatistics, etc in Geographical Information (GI) Science, as we will comment shortly. GI Science has also benefited from the advances in Computer Science to enter in the domain areas that are using Big Data approaches to process and analyze huge amounts of data.

Concurrently, vegetation monitoring relied on extensive inventories of ground samples or permanent plot locations which were periodically measured and further analyzed through models and simulations (Barker and Fethe 1975). Notwithstanding, in 1960 there was a turning point in research, when the first meteorological satellite, TIROS-1 (Television Infrared Observation Satellite) was launched, although it was not until a decade later, in 1972, that Earth Observation research programs took a step further with the first high-resolution Earth observation satellite Landsat 1. The availability of satellite-based Earth observation data opened a new age in research meeting the growing demands for more spatially continuous data, more frequently acquired. New tools were needed to turn this numerical information into pictures or to identify meaningful patterns and therefore, the symbiosis between remote-sensing and cartography emerged. From that moment on, mapping based on GIS, remote-sensing processing as well as interpretation of derived remote-sensing data such as of vegetation indices (VI) were widely used for monitoring vegetation. The first drought studies using Landsat were published by Heilman et al. (1977) and Kanemasu et al. (1977). Landsat data was used as an input for evapotranspiration models estimating surface water content. Also Thompson (1976) and Thompson and Wehmanen (1979) normalized the use of satellite-acquired data as a tool for monitoring vegetation water deficiencies and moisture stress. Thereafter, the relationship between climatological events and their consequences on vegetation reached great importance and there was also progress in understanding the impacts of drought, and in the formulation of the theoretical basis. In 1982, Landsberg (1982) wrote a report considering the climatic aspects of drought stating that drought episodes were mainly dominated by circulation anomalies. The lack of capacity for drought prediction, the mismanagement of land resources, and considerations that a system for drought monitoring should be necessary, turned into major topics of interest in the scientific community (J. Wang and Choudhury 1981; Wiegand, Nixon, and Jackson 1983; Hellden 1984; Tucker and Choudhury 1987; Rock, Vogelmann, and Williams 1985). For instance, several VI were used as indicators for various environmental monitoring applications such as drought monitoring (Hunt and Rock 1989; R. D. Jackson and Huete 1991; Kogan 1990; W. T. Liu and Kogan 1996; Nemani et al. 1993; Nemani and Running 1989). Remote-sensing was completely recognized as a potential drought assessment methodology and it was demonstrated that satellite-based information could enhance previous drought measurements based only on *in-situ* physical variables (Peters, Rundquist, and Wilhite 1991).

Since then, there have been several approaches for monitoring vegetation drought from Landsat instruments as well as from other satellite sensors, such as AVHRR (Advanced Very High Resolution Radiometer) or MODIS (Moderate Resolution Imaging Spectroradiometer), (Billingsley 1984; Fensholt and Sandholt 2005; Gu et al. 2008; T. J. Jackson et al. 2004; Jain et al. 2009; Kogan and Sullivan 1993; Stellmes et al. 2010) but also from *in-situ* sensors such as field radiometers (Buddenbaum et al. 2015; Schut and Ketelaars 2003), an interesting technique although beyond the scope of this thesis. New missions have also expanded the spatial resolution and spectral capabilities providing science with a myriad of new observations and environmental parameters relevant to drought monitoring. For instance, and after so many years, the first Earth observation system fully dedicated to monitor and quantify the impact of drought and its side-effects on natural ecosystems, the ECOSTRESS, has delivery date by 2018. The ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station will provide critical insight into plant-water dynamics and in how ecosystems change with climate.

Given all these capacities, using GIS-based spatial interpolations from *in-situ* climatological data and remotely sensed data is a keystone in achieving a holistic view of drought, especially when accepting the challenge to combine them synergically, as in the present thesis, to demonstrate its invaluable utility.

1.2 Potentialities of Geographic Information Science in a context of drought studies

Earth observation-based approximations and mapping on the assessment and monitoring of land condition and land changes in the Iberian Peninsula as an example of dryland have been previously carried out (del Barrio et al. 2010; Stellmes et al. 2013) demonstrating the success of remote-sensing as a tool for vegetation monitoring at different scales, from local to regional. This is only achievable as long as a complete and regular coverage of Earth observations is available (Anderson et al. 2010) and by the use of the GIS as analysis tool. The possibilities offered by the GIS in the environmental sciences (Burrough and McDonnell 1998; Goodchild 2009; Senthil Kumar, Arivazhagan, and Rengarajan 2013) are widely recognized and this thesis is not going to delve into them. The complexity of drought hazards at both spatial and temporal levels requires of an advantageous scientific approach capable of considering continuous information in space and time. Furthermore, GIS provide a convenient approach for combining the handling of *in-situ* sensors, field data calibration and validation, and in particular, geospatial analysis and management of Big Data. This capability is two-fold: first, satellite data and their derived indices provide cumulative numerical approximations of drought and its impacts (Kogan and Guo 2014) easily managed through GIS tools, and second, remote-sensing data is, above all, an additional extraordinary tool to weather data (Kogan, Adamenko, and Guo 2012).

1.2.1 Vegetation indices (VI)

Knowledge and monitoring of biophysical and structural properties of vegetation are valuable for understanding the Earth as a system (Townshend and Justice 2002). Remote-sensing-derived vegetation indices, some of the oldest tools in remote-sensing, provide vegetation parameters for the accurate inventory of the global distribution of vegetation masses. Vegetation indices are indicators of relative growth and/or vigor of vegetation (Huete, Justice, and Liu 1994). They were developed in order to quantitatively and qualitatively evaluate the spectral response of vegetation over space and time, and are currently used in operational vegetation monitoring. These indicators are dimensionless and can be computed at satellite radiances or at radiometically corrected reflectances. Among the many variations that exist, there are several indices specifically suitable for drought monitoring. Drought indices derived from satellite data take into consideration different vegetation types and environmental conditions (Vicente-Serrano 2007).

Vegetation indices are mainly sensitive to three properties: canopy greenness, canopy water content and canopy temperature. The first of these properties is based on the observation that chlorophylls *a* and *b* in green leaves strongly absorb light in the red spectral region, while presenting high reflectance behavior in the Near Infrared (NIR) region. This results in strong reflectance contrast across these two spectral regions captured by the VI. The second property, canopy water, rely on the relationship between Short Wave Infrared (SWIR) which responds to changes in vegetation water content and the NIR, that is much less affected by water content (Ceccato et al. 2001). Finally, the third property, the canopy temperature, is based on changes on surface temperature due to absorbed incoming radiation and plant transpiration. All these properties, greenness, water content and temperature, are severely affected under drought conditions; therefore, the use of VI is a very apt tool for monitoring natural vegetation droughts.

In this thesis, several VI are used to demonstrate the suitability of MODIS data for drought monitoring. All they are detailed and discussed in Section 5.5.

1.2.2 Suitability of spatiotemporal resolution and long term availability

The most common classification of different satellite sensors results from the diverse spatial, temporal and spectral resolutions. For instance, most Landsat sensors provide most data at a spatial resolution of 30 m, while MODIS provides data at 250 m, 500 m and 1 km of nominal pixel size, and AVHRR at 1.1 km of nominal pixel size. Similarly, the revisiting frequency also depends on satellite and sensor specifications and is usually inversely proportional to spatial resolution. Therefore, AVHRR has a temporal resolution of hours (also improved by its constellation nature along time), while MODIS-Terra revisits the same area daily and Landsat every 16 days (at Equator). Similarly, the lower the spatial resolution, the largest the viewing swath; from around 180 km in Landsat to 2330 km in MODIS. Regarding spectral specifications, the multispectral mode, having several bands in the solar spectrum domain and one or more in the thermal domain, is the common spectral configuration on these types of missions.

In the context of the present research, it is necessary to take into account the optimal requirements for a fruitful and continuous drought monitoring approach over regional forested areas. Indeed, in a high spatial resolution image, a pixel covers several trees, which is suitable for monitoring forests at stand level. However, if the objective is to monitor a regional extension, pixels sizing between 100 m and 500 m are the most appropriate given that they cover several hectares but still contain relevant information on forest canopy properties (Deshayes et al.

2006). Also at this spatial resolution, the swath is larger, providing regional coverage area in fewer images. Nevertheless, the main requisite for long-term monitoring is the temporal resolution. Long-term and often acquired data records are fundamental for operational drought monitoring in order to provide a significant historical context of drought intensities and impacts (Wardlow et al. 2012). This requirement is coupled with the need for temporal regularity of data if it is to be analyzed with time series methodologies like the analysis carried out by (Eklundh, Johansson, and Solberg 2009; Udelhoven and Stellmes 2007). Certainly, Landsat sustained observational data record coves the longest available period accounting for more than 30 years of data available, and since 2008 this has also been available to users free of charge (Gutman and Masek 2012). Unfortunately, Landsat data is difficult to use for regular monitoring due to its infrequent temporal coverage with inevitable cloud contamination (Carrão, Gonçalves, and Caetano 2008). In fact, Ju and Roy (2008) found that monitoring applications requiring more than one cloud-free Landsat image per year would be harshly limited due to cloud cover. Additionally, only a limited number of studies used dense Landsat time series (Kennedy, Yang, and Cohen 2010; Masek et al. 2008) given that the large data volume involved is still not operational at certain geographical scales (Defries and Belward 2000). On the other hand, MODIS acquisitions provide users with daily free data which, although it is also affected by cloud cover contamination, meet the 70 – 100 % cloud-free requirements in a given-8 day period for almost all the global territory (Whitcraft et al. 2015). However, a major limitation of MODIS is its relatively short period of record (15 years) compared to Landsat. A decade may not be sufficient to study drought from a climate perspective, but alternatively may provide invaluable information about the ecological processes linked to the natural hazard (AghaKouchak et al. 2015). The good compromised achieved between MODIS temporal and spectral resolution together with the 500 m spatial resolution of some spectral bands, make MODIS data an attractive candidate for drought forest monitoring.

1.2.3 Drought monitoring and mapping

A good way of representing quantification of drought hazard is through mapping. The marriage between GIS, a powerful set of tools for collecting, storing, processing, analyzing and displaying spatial data, and remote-sensing allows drought spatial information handling and mapping. In fact, the presentation of drought information in a single map with a simple classification system is preferred by decision makers and the general public (Hayes et al. 2012). Following this simple premise, several drought monitoring indicator programs based on climate data and sometimes incorporated with *in-situ* or remote-sensing data have emerged. For instance, the Historical Palmer Drought Indices Monthly Maps (http://www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers/psi/190011-200310) distributed by NOAA, provide drought conditions in the contiguous U.S. as measured by several variations of the PDSI, at coarse levels.

Also, the weekly United States Drought Monitor (USDM) (Svoboda et al. 2002) (http://droughtmonitor.unl.edu/) assess current drought conditions in the United States. The weekly map is based on measurements of climatic, hydrologic and soil conditions as well as reported impacts and observations from more than 350 contributors around the country. Instead, the Global Integrated Drought Monitoring and Prediction System (GIDMaPS) (AghaKouchak, Hao, and Nakhjiri) (http://drought.eng.uci.edu/) is a drought monitoring and prediction system that provides near real-time drought information based on multiple drought indicators and input datasets. On the other hand, the North American Drought Atlas explains the history of Meteorological Drought Reconstructed from 835 tree-ring chronologies distributed over much of North America for the past 2005 years (http://iridl.ldeo.columbia.edu/SOURCES/.LDEO/.TRL/.NADA2004/.pdsi-atlas.html). This Atlas significantly adds to the historical picture of long-term climate variability over the Northern Hemisphere. Other initiatives such as the Global SPEI database (SPEIbase) (http://sac.csic.es/spei/database.html) which offers long-time, robust information about drought conditions at the global scale with a 0.5 degrees spatial resolution and a monthly time resolution will be discussed in Section 3.1.

Finally, several efforts have been made to built a global drought early warning system, setting up a series of continental-based virtual regional networks and integrating various regional and continental drought monitors, remote-sensing datasets and other data resources from around the world. This is the case of the initiative leaded by the Group on Earth Observations and the World Meteorological Organization, which want to establish a Global Integrated Drought Information System (GIDIS) (http://www.drought.gov). The United States National Integrated Drought Information System (NIDIS) has already implemented such structure, but the global approach still presents several challenges to overcome.

1.3 Objectives

Together, the drought monitoring challenge previously exposed and the availability of the powerful tools of GI Science so far described, provide an interesting framework in which to develop this thesis. This interdisciplinary context, defines the motivations of this thesis that can be summarized in four pillars:

a. The need for a contextualization and definition of drought from a forest perspective and its scientific recognition as such.
b. The persisting evolution in the use and management of *in-situ* and remote data and its modeling in a Big Data context.
c. The potentiality of remote-sensing data as a tool for spatiotemporal continuous monitoring.

d. The questioning about the existence of global factors that influence the spatiotemporal patterns of drought which are essential to understand the present and to predict future events.
e. The need to contribute in methods for better treatment of GI information.

According to the above-mentioned premises, the following research issues have been defined:

- To propose of a new theoretical framework for drought including context-based forest drought.
- To improve spatiotemporal modeling of *in-situ* meteorological data and improve its massive management (Big Data approach).
- To characterize past meteorological drought events (1950-2012) affecting the Spanish Iberian Peninsula through climatic and spatial patterns and identification of their possible causes.
- To use GI Science potential tools for detecting phenological changes in forests due to drought events. To evaluate potential and limitations of MODIS data and its derived VI in forest drought studies.
- To evaluate the integration of climate time series and MODIS data as an analytical tool for the detection of forest drought. Is only MODIS data suitable for monitoring forest drought or are both necessary?
- To explore the possibility to improve current 8-day MODIS surface reflectance composites.

1.4 Manuscript organization

The thesis presented in here is divided into six chapters.

In **Chapter 1**, introduced so far, the objectives and motivations of the thesis are contextualized. The general introduction reviews the concerns about the consequences of drought events in the Spanish Iberian Peninsula, emphasizing the drought impact of forests given the major role of this ecosystem in the study area. This chapter also provides a brief overview of the role of remote-sensing and GIS in the study of droughts which together with the drought concerns set out the framework where to define the objectives. Finally, it also explains how the following chapters are arranged.

Chapter 2 includes a critical reflection on the classification of types of drought and a new approach is proposed in order to highlight the singularity of the forests in a context of drought. A review of the major socioeconomic drought events from 1950 to 2012 affecting the Spanish Iberian Peninsula according to social perception in press media is also included.

Chapter 3 considers the need for a new climate database in the context of the present thesis and also explains the full process of its elaboration: how to move from *in-situ* data to spatiotemporal continuous maps.

In **Chapter 4** drought indices suitable for the characterization of meteorological drought patterns are introduced. A new computational methodology that allows spatiotemporal continuity is presented and a full drought database for the Spanish Iberian Peninsula is developed. This chapter also includes several analyses which demonstrate the potential of such data.

Chapter 5 evaluates the suitability of integration of climate data and MODIS data as an analysis tool for forest drought detection and describes a new methodology for improving MODIS 8-day products useful for drought studies.

Finally, **Chapter 6** gathers final considerations and also introduces futures possible lines of research.

The bibliographic references consulted during the process of investigation and preparation of this thesis and an appendix consisting of two annex are also included in the last section of this manuscript. **Annex A** contains a collection of news published in national newspapers considered supporting information for **Chapter 2**. **Annex B** includes a snapshot of each of the 5804 SPEI maps generated.

All figures included in this thesis are own preparation except those in which the source is specified.

Chapter 2

DROUGHT DEFINITIONS AND TYPES

A new proposal

2 DROUGHT DEFINITION AND TYPES. A new proposal

2.1 Drought definition and types

Defining drought is quite a challenge, an issue taken up by several authors over the along the last few decades. Some first evidence of this challenge is the lecture “Objective definition of hydrologic droughts” delivered at the conference of Recent Drought in the Northeastern United States, organized by the Department of Meteorology and Oceanography of New York University in 1967 (Yevjevich 1967), where a call for systematic research on large continental droughts was made. Digressions and discussions surrounded a topic that is still a controversial issue given the different perspectives from which drought can be investigated (Mishra and Singh 2010; Namias 1955; Yevjevich 1967). Drought may be investigated from a scientific point of view, analyzed from the perspective of a water manager and quantified from the standpoint of an affected society; all those approximations demonstrate the impracticality of a universal definition of the term (Lloyd-Hughes 2013). Even so, this type of event is widely understood as an extreme persistence of precipitation deficit over a specific region for a prolonged period (Zargar et al. 2011) which is generally reflected as an important disturbance on human activity (Namias 1955), developing significant socioeconomic and environmental damages (Xu et al. 2015). This general understanding of drought may become more accurate depending on the context of the application (Andreadis et al. 2005). Indeed, in 1985 Wilhite and Glantz (Wilhite and Glantz 1985) grouped drought into four types. Three of them were physically based perspectives and the fourth was centered on its impacts on society: meteorological, agricultural, hydrological and socioeconomic. These four types present different timings, impacts and recovery rates, and they occur in a particular order establishing a relationship among them (Figure 2.1) (American Meteorological Society 2013; Wilhite and Glantz 1985). A description of them follows:

The **meteorological** (also known as climatological) (Wilhite 2000) definition of drought is the most widespread and it essentially results from a meteorologist’s point of view. There is a large volume of published studies analyzing droughts through the evaluation of precipitation data (Altava-Ortiz et al. 2011; Gibbs and Maher 1967; Lana et al. 2006; Lana, Serra, and Burgueño 2001; Marshall 1976; Martin-Vide and Gómez 1999). According to them, this type of drought is directly related to precipitation and it is understood as a threshold of short-term precipitation deficit over a region. Meteorological drought is usually the consequence of the development of constant large-scale disturbances in atmospheric circulation patterns and given its nature it is difficult to reduce its frequency or severity. Meteorological drought should be considered region-specific given that the atmospheric conditions leading to precipitation shortages are dependent on climate regime (Wilhite 2000).

A meteorological drought turns into an **agricultural drought** when negative effects on crop development become a direct consequence of water deficit. This second type of drought is based on the availability of soil water content related to the water needs of crops, and it implies the inadequacy of soil moisture to meet evapotranspirative demands so as to initiate and sustain crop growth (Changnon 1987). The concept of agricultural drought should account for the variability of different crop types (i.e. biological characteristics), different stages of crop development (Wilhite 2000) and the physical and biological properties of the soil (e.g. infiltration rates, slope, water holding capacity). A considerable amount of literature has been published on this issue (Van Bavel and Verlinden 1956; Easterling et al. 1988; Kumar 1998; Patel et al. 2011).

The third type of drought, the **hydrological drought**, a long-term dryness, is defined as the departure of surface and subsurface water resources (e.g. stream flow, groundwater and reservoir levels) from some average condition during certain periods. It is usually defined at the river basin scale and it is often out of phase with both meteorological and agricultural droughts. It examines the lagged effects of precipitation shortages on subsurface water resources. Hydrological drought develops more slowly because it involves stored water that is depleted but not replenished (Dai 2011). Recovery of the hydrologic system is slow and the impacts of hydrological drought on the top part of the system (e.g. upstream of a river basin) may extend throughout the river course. Much of the literature on hydrological drought pays particular attention to catchment properties or geology as the main factors influencing these types of events (Clausen and Pearson 1995; Leng, Tang, and Rayburg 2015; Pfister, Weingartner, and Luterbacher 2006; X. Wang et al. 2015). Van Loon et al. (2014 and 2015) also described in detail several hydrological drought subtypes, which are beyond the scope of this thesis.

When any of the above-mentioned droughts types have a direct impact on the economy of a society, an indirect fourth type of drought is produced: the **socioeconomic drought**. This is associated with temporary or abnormal failures of water supply to meet demands of society and economic sectors. In a sense, all types of drought have an impact on some social function or human activity. Droughts may impact crop or forest productivity, increase fires, livestock and wildlife mortality rates. Therefore, all droughts that society is concerned about are socioeconomic (Kallis 2008) and the approach for evaluating this types of drought is clearly monetary (Keyantash and Dracup 2002). In contrast to the other drought types, a reduction of its risk is feasible and drought policies, management and mitigation plans for reducing socioeconomic drought are being developed (Wilhite, Sivakumar, and Pulwarty 2014).

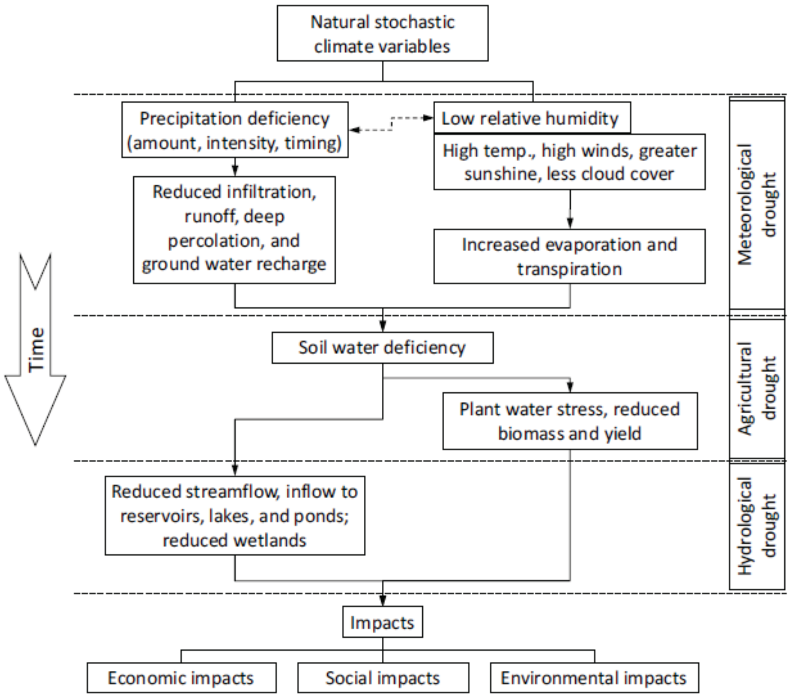


Figure 2.1. Relationship between meteorological, agricultural and hydrological droughts, their general sequence of occurrence and their duration. Source: Zargar et al. (2011) modified from Wilhite (2000).

2.2 The relevance of agricultural drought

As previously introduced in this chapter, research to date has tended to focus on drought in agricultural systems rather than in natural ecosystems such as forests (Blauhut, Gudmundsson, and Stahl 2015), mainly for two reasons.

The first one is because agriculture is generally the first economic sector to be affected by drought (Maybank et al. 1995; Wilhite, Hayes, and Svoboda 2000), especially if the precipitation deficit occurs during the growing season. In Europe, the 2003 drought event produced losses in the agricultural sector estimated at $13{\cdot}10^9$ Euro (Dinar and Mendelsohn 2011). Agricultural economic loss during the 2010-2013 drought event in southwestern China's Yunnan province was estimated at more than $2{\cdot}10^9$ Yuan (€278 million) (FAO 2013). In 2012, 80 % of the agricultural land of the United States experienced drought, with an estimated cost of US\$$31{\cdot}10^9$(€$27.5{\cdot}10^9$) (NOAA 2015). Between 1989 and 2008, more than US\$$17{\cdot}10^9$ of indemnities were paid out for drought–related losses to agricultural services in the United States (Dinar and Mendelsohn 2011). In Spain, drought indemnities in the last decade reached a record of more than €$30{\cdot}10^9$. With special relevance to the context of the present thesis, it is interesting to note the 2007-2008 drought episode which occurred in Catalonia (Northeastern Iberian Peninsula). This event was considered the most severe of the last century in the region and triggered agricultural losses estimated at €$116.84{\cdot}10^6$ (Martin-Ortega and Markandya 2009).

The second one is due to convoluted understanding of natural vegetation. Natural ecosystems include countless formations, from apparently simple meadows with life cycle akin to some crops, to natural mature forests characterized by their multiyear life cycles. To characterize drought on natural vegetation is a challenge given the complexity of the term. We understand that sensitivity to drought is species-dependent, and obviously, the growth cycles of certain natural ecosystems, for instance prairies versus forests, are not comparable. Therefore, drought on prairies or on forests (as examples of natural ecosystems but much different) will present different characteristics. For this reason, in the framework of this thesis the term natural vegetation will be used mainly to refer to natural forests and shrublands formations.

In the Spanish Iberian Peninsula the agriculture sector is one of the most important occupying around the 35 % of the landscape (*Encuesta Sobre Superfícies Y Rendimientos de Cultivos. Resultados Nacionales Y Autonómicos.* 2015) and until the middle 60s it was the main national economic sector. Besides, drought is not a new phenomenon in the Iberian Peninsula, but an old and recurrent one (Font Tullot, 1988). This area frequently undergoes precipitation deficits which have effects on the agriculture sector and its surrounding economy, and which can, as last, turn out as a socioeconomic drought.

To illustrate and understand the relevance of such events, an overview of agricultural and socioeconomic droughts in the Spanish Iberian Peninsula from 1950 to 2012 is carried out and presented in the next Section.

2.2.1 Drought events in the Spanish Iberian Peninsula and its socioeconomic perception in the national press

Over the past 60 years, much more information has become available on drought occurrences in the Iberian Peninsula. Many historians have described drought episodes through the analysis of precipitation series and the consequences of precipitation deficit on society (Pita López 1989; Gil Olcina and Morales Gil 2001; Olcina Cantos 2006; Sacasas 2010). However, the media, and concretely the national press, is one of the best sources for monitoring the social perception of meteorological drought and its impacts on society, especially during the period 50s to 80s, a time when publishing scientific literature was limited. Before going deeper on the review of the news published by the national media, and in order to conceive the magnitude of each of the episodes described, it is necessary to understand the climate that characterizes the Iberian Peninsula.

Meteorological droughts affecting the area are somehow singular given the distinct type of climates present at the Iberian Peninsula. Precipitation regimes and air temperature, characterized by influence of the Mediterranean sea and the Atlantic ocean, define some of the

Köppen-Geiger climate categories (Köppen 1936; Peel, Finlayson, and McMahon 2007). These include, among others, temperate climate without dry season (with dry or hot summer)(*Csa/Csb*), temperate climate with dry season and hot or temperate summer (*Cfa/Cfb*), and dry climate such as hot desert and steppe (*BWh/BSh*) (Figure 2.2) (AEMET 2011). Indeed, any lack of precipitation in regions characterized by mean annual rainfall below 600 mm or in those identified as unusually degraded areas (del Barrio et al. 2010), will exacerbate a situation of drought. Simultaneously, these areas have a considerable adaptation to drought while regions with higher rainfall patterns are more sensitive to water scarcity. Droughts in the Iberian Peninsula have variable starting and ending periods, and these events are usually interrupted by exceptional torrential rains.

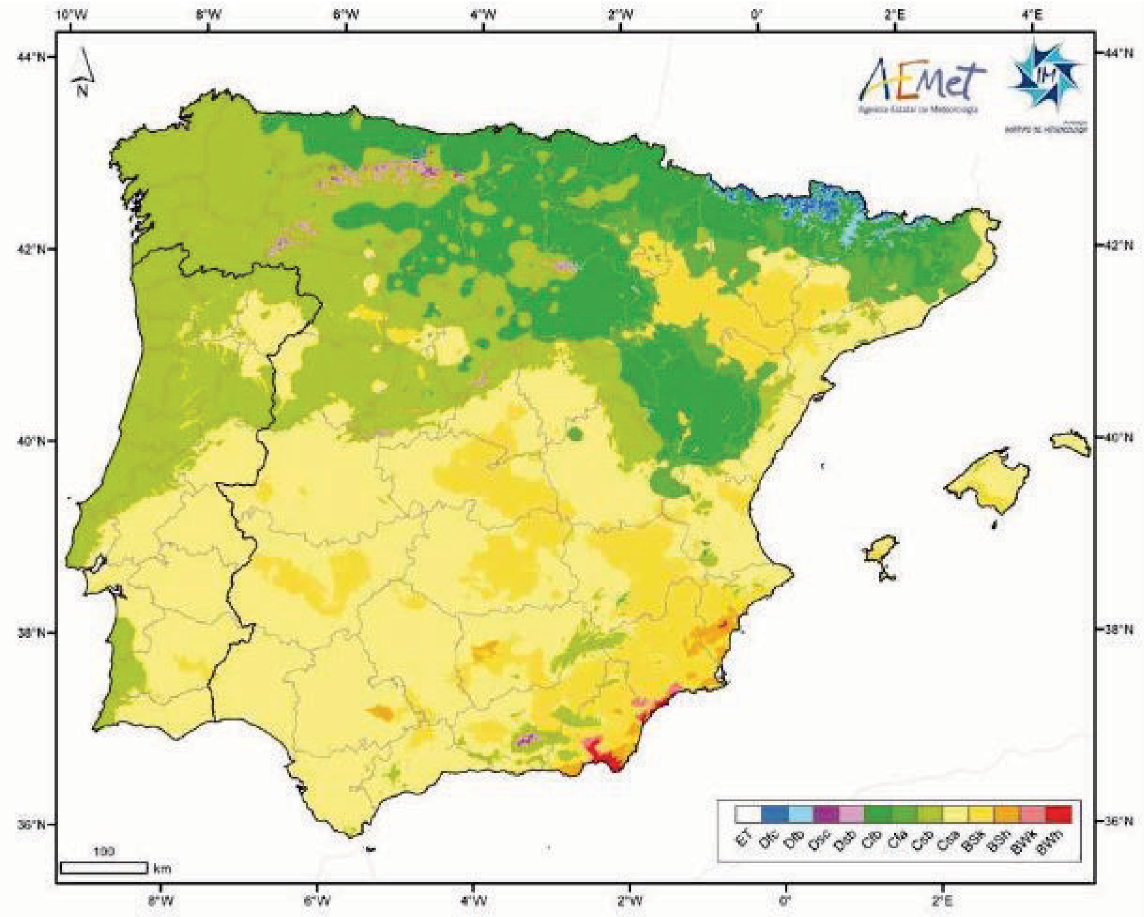


Figure 2.2. Köppen-Geiger climatic classification for the Iberian Peninsula and the Balearic Islands. Source: AEMET (AEMET 2011).

According to several authors there are 3 types of drought events affecting the Iberian Peninsula. Those events having a wide-spread effect on the Iberian Peninsula, are defined as "Iberian droughts" while events having local impact either in the North or Southeast regions are reported as "Cantabric droughts" and "Southern droughts" respectively (Gil Olcina and Morales Gil 2001; Olcina Cantos 2006).

The next review of descriptions of drought events published by the national media as well as scientific contributions during the last 63 years follows this classification.

For example, in 1954-1955 a moderate reduction in precipitation was recorded in Basque Country, Cantabria and Galicia, the most humid regions of Spain. The newspapers echoed the exceptional (and surprising) situation experienced in the North, which included energy shortages (reliant on hydroelectricity) and damages to crop yields so anticipating the harvesting (see Annex A1).

In contrast, the episodes affecting Andalucía (Southern area of the Iberian Peninsula) during the 60s were brief and less intense than the 50s drought in the North, with average annual precipitation deficits of 23% (Pita López 1987).

The next chronological Spanish meteorological drought wave began in the northeastern part of the peninsula, in Catalonia, in 1973 and quickly spread throughout the country. The year 1973 is remembered for its unusually low temperatures, some late spring snowfalls and scarce precipitations (Figure 2.3).

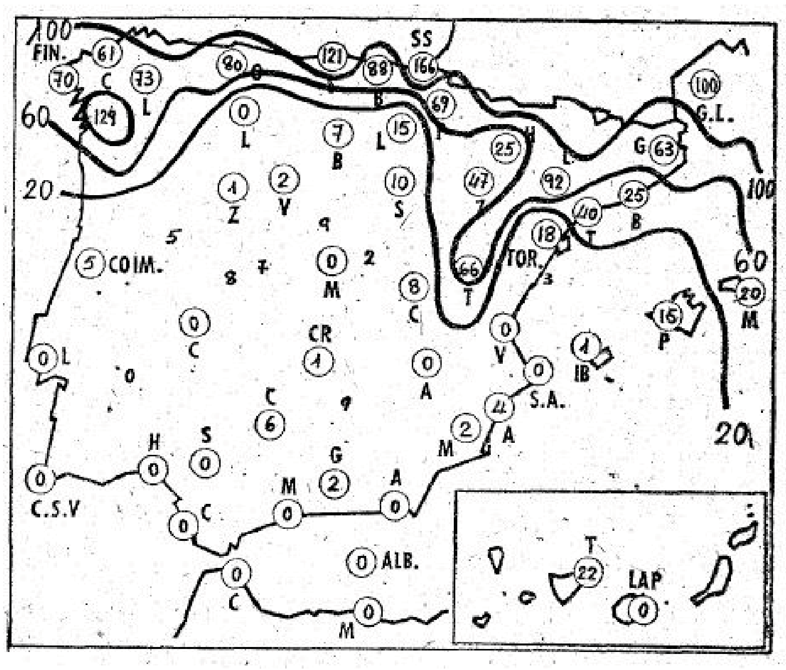


Figure 2.3. September 1974 isohyets map from *La Vanguardia* newspaper. Numbers in circles denote September total precipitation, in mm. The central-southern part of Spain suffered an exceptional dry autumn.

The situation quickly turned into a hydrological and socioeconomic drought in the region, with wildfires affecting large extensions of natural forests like, for instance, the 28 episodes in only one weekend (more than 1,300 ha burned) affecting a local area in Catalonia, and leading to restrictions in water use (see Annex A2). Fears that the drought would spread throughout the

Peninsula became a reality by the end of the year. This new Iberian drought, which lasted for 3 years, had its greatest impacts in Galicia and Andalucía; and other moderate consequences in the Iberian Central Plateau and the Cantabric Ledge (see Annex A2). Wetlands ecosystems were seriously damaged and natural springs, rivers and reservoirs dried up. The agricultural sector was affected and also logging actions on dry forests were carried out. Agricultural economic losses alone were estimated at more than $200{\cdot}10^6$ Euro.

Following 1977, which had a cold winter and plenty of spring rainfall, a new drought episode began which affected the whole country. According to most observatories, this drought began in spring / late summer 1979 (Pérez Cueva and Balada Ortega 1983) and presented its worst effects between 1980 and 1985, the years 1981, 1983 and 1985 being the driest in precipitation records (Lana, Serra, and Burgueño 2001; Altava-Ortiz et al. 2011). The records indicate a Peninsula-wide reduction in precipitation of 40 %. Other, more localized episodes were also recorded along the Mediterranean coast and later at the North ledge, resulting in a Cantabric drought (see Annex A3).

The most severe episode affecting the northern region of Spain was documented in 1989-1990, with a reduction of normal precipitation of approximately 35 %. The drought sequence ended with a social drought leading to restrictions in industrial and human water use.

Shortly after, in 1991-1995 another Iberian drought episode was recorded. It was especially pronounced in the southern and southeastern parts of the Peninsula, where rainfall was reduced up to 60 %. Agricultural and hydrological drought rapidly overtook the country. Reservoir levels fell to historical minimums of 9% in some cases (Sacasas 2010) (see Annex A4). During this event, 12 million people suffered from domestic supply restrictions. Economic losses in the agricultural sector were estimated at approximately $1\,800{\cdot}10^9$ Euro, and the implementation of the National Hydrological Plan outlined during the previous drought episode, was accelerated, with new hydrologic transfers and reservoir plans. However, the plan was not passed until some years later, in 2001. The woody flora of central and southern Spain was described as severely damaged in 1994 and two years later was still affected (Peñuelas, Lloret, and Montoya 2001).

The most recent Iberian noticeable event of note within the period 1950-2012 started in 2003, when a heat wave affected Spain and most of Europe (Ciais et al. 2005). The European economy was significantly impacted, especially the agricultural and forestry sectors (Jolly et al. 2005). In this case, the most affected period was between 2004 and 2007 (García-Haro et al. 2014; Altava-Ortiz et al. 2011). During 2004-2005 rainfall was, for the entire territory, 40 % less than the normal average (Sánchez, Hidalgo, and Bruna 2006). However, the domestic water supply was guaranteed, while irrigation rates had to be reduced in several areas (Urquijo, Stefano, and Calle 2015). Specifically in Catalonia, the lack of rain and falling levels of reservoirs to 35 % of capacity prompted adaptation of the Drought Decree (Sacasas 2010) Unfortunately, drought in the Catalan region continued until 2008 which had an extraordinary winter drought (Figure 2.4), at which point an exceptional decree for water conservation was established (Llasat et al. 2009).

Figure 2.4. La Llosa del Cavall water reservoir in Catalonia. Left, 21/02/2008 photograph vs. right, 30/09/2008. Source: Agència Catalana de l'Aigua (http://aca-web.gencat.cat/aca/sequera/es/evolucio-llosa-3.jsp).

Although descriptive literature allows the identification of meteorological drought episodes in the Iberian Peninsula, quantification of their real intensity requires of numerical methods since meteorological drought and socioeconomic droughts intensities are not always correlated. The level of impact described in each episode is subjective to social perception and it depends on the direct impact to society rather than on a real decrease in precipitation. For instance, low decreases in precipitation may result in socioeconomic drought if the consumption of water is excessive. Moreover, natural ecosystems are also affected by meteorological droughts, though in terms of social perception this is sometimes unimportant. Drought indices are useful indicators for overcoming this social subjectivity, and these together with geospatial analysis enable quantifying the intensity of drought episodes and determining objective levels of impact on natural ecosystems and derived consequences on society.

2.3 A critical view of drought types

Although extensive discussion and examples of the agricultural and socioeconomic droughts has been carried out, not many references in the literature were found that discuss the role of natural vegetation (e.g. forests) in the commonly-accepted drought scheme (Figure 2.1).

It is possible that forest drought does not have as large an economic impact as agricultural drought, especially in countries where there is no real economic return from forestry. However, under the current framework of climate change and ecosystem services, where the carbon cycle, carbon stocks and mitigation of climate change are issues of great concern and are research keystones, forests are crucial. Furthermore, forests are also meaningful because of the direct invaluable ecosystems services that they provide to society, including biodiversity, opportunities for recreation, and ecotourism in general (Birch et al. 2014; Daily et al. 2009; Ferraz et al. 2014; Jacob, Wilson, and Lewis 2014; Running et al. 2004; Wu et al. 2002), but are also implicated in water quality and reduction of flash floods or in nitrate contamination of waterways. Forests are one of the most important storage systems for carbon, containing 77% of the global vegetation biomass carbon pool (Lavalle et al. 2009), but at the same time they are one of the most vulnerable ecosystems to climate change (changes in temperature, precipitation and extreme weather events) (Lutz, Washington-Allen, and Shugart 2008; Lavalle et al. 2009). Despite the recognized importance of forest ecosystem services, quantification of forest changes and affectation due to drought has been lacking (Hansen et al. 2013). For all these reasons, we believe that forest drought it is an important research topic and its characterization and management are crucial.

Despite characterization of drought effects on forest species at a detailed physiological level on the local scale has been a focus of the scientific community (Cáceres et al. 2015; Galiano et al. 2012; Pool 1913; Poyatos et al. 2013; Shirley 1934; W. Wang, Vinocur, and Altman 2003; Zavitkowski and Ferrell 1968), conducting global studies over wide areas is complex given limited economic and time resources as well as constrictions leading from limited accessibility (Anderson et al. 2010). In 2010, Allen et al. (2010) analyzed literature on forest mortality driven by climatic water or heat stress and identified about 150 studies world-wide conducted over 40 years. Although Allen et al. recognized that research has increased in recent decades (as did Wulder (1998)), the authors highlighted the need for a coordinated global observation system in order to overcome information gaps and scientific incertitude, and to improve knowledge on the prediction and consequences of climate change on forest ecosystems. Drought can have important and often harmful effects on forests, related to fire, hydrology ecosystem function and services, or timber production, among others. Forest management and forest decision support services are based on several key inputs, usually related to spatiotemporal patterns of drought and to the identification of areas vulnerable to potential drought impacts. Therefore, forest drought present new challenges regarding vulnerability research.

Even though the trigger factor of drought stress in either agriculture or natural vegetation (and especially forests) is meteorological drought, it is evident that agricultural drought, although akin to the natural vegetation one, is not the appropriate model to follow. The characteristics shown by natural and agricultural ecosystems in terms of structure, function and phenology (aforementioned) are extremely different. Obviously, forest structure, which comprises undergrowth, differing tree density and variability in leaf area index (LAI), ought to have its own drought response. As a simplified case in point, it is clear that when the soil moisture is largely exhausted under conditions of drought, the deep-rooted forests are able to outlast the crops, since they can draft deeper layers of the soil, supplying their own leaf zone demands. Besides, the timing of the agricultural crop cycle (agrophenology) which determines the productive success of the crop, is distinct from the cycle of natural vegetation such as forests since they differ in length (shorter-lived annual or biennials plants vs. perennial), sensitivity to weather conditions, and water and soil requirements. Also, the impact of drought on forests and recovery rates are distinct from agricultural systems. Agricultural drought might be meaningful in terms of economic losses which may be normalized in the following annual yield while forest economy recovery rates may take several decades. Moreover, forest drought might lead to losses of biodiversity and biomass which could result in an environmental disaster. In summary, the characteristics of forest drought are different from those of agricultural drought in terms of duration, intensity and spatial area affected.

2.4 A new proposal

These dissimilarities require that the analysis of drought affecting natural vegetation and particularly forests, be carried out from a different perspective. This view is supported by Collier and Webb (2002) whom made an attempt to introduce the term ecologic drought. They described ecologic drought as detrimental to native plants that do not have the benefit of irrigation, without considering the type of vegetation (annual plants vs. perennial vegetation). Unfortunately this perspective was not widely used.

For the reasons discussed above, and in the framework of the present thesis, we believe that drought affecting natural vegetation needs to be categorized as a new type of drought and we propose a modified scheme based on the original one proposed by (Wilhite 2000)(Figure 2.5).

An adequate approach for understanding natural vegetation drought requires new methodologies given the complexity of this type of ecosystem. Shrublands and forests in Mediterranean areas, for instance, are usually located in mountain areas with rugged, steep and irregular topography that hinder accessibility for performing *in-situ* measurements. Also, the lag time between the precipitation deficit and the expression of first symptoms of drought on vegetation is determined by several variables, causing difficulties in research. Therefore, a lot of uncertainty still exists about the global effects of droughts on natural forests and there is a need to understand the negative impacts of such events.

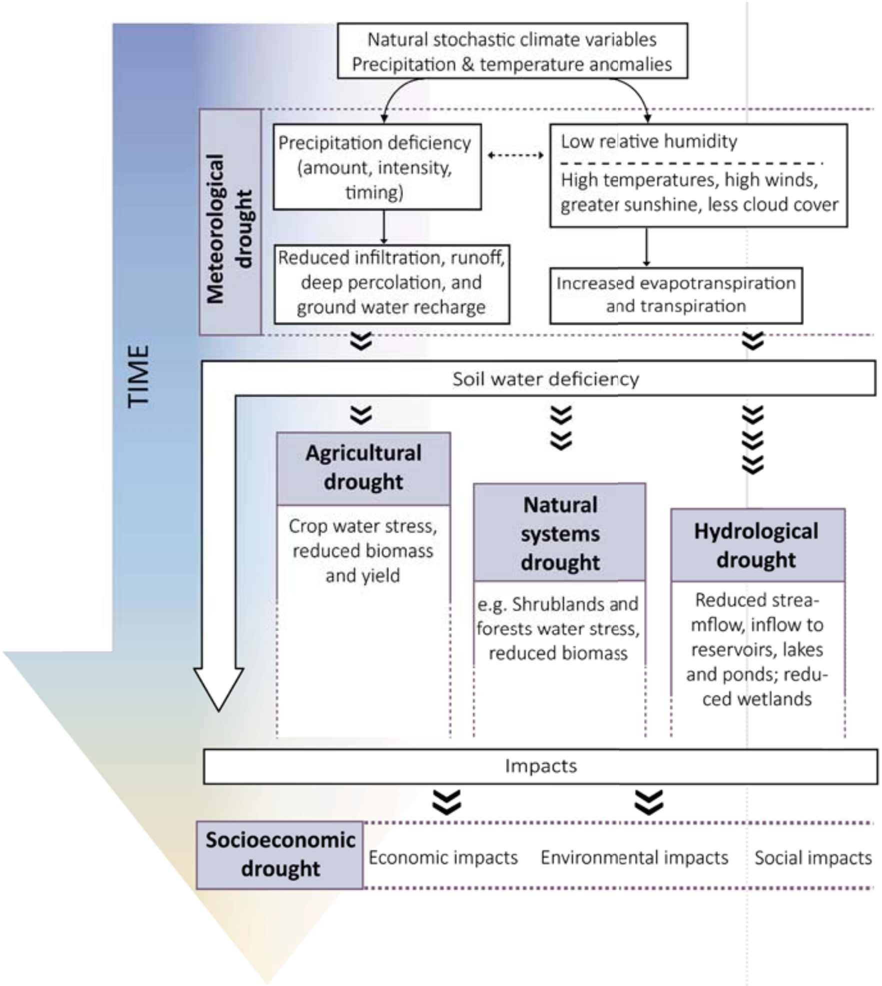


Figure 2.5. New proposed scheme of drought types based on the original scheme in Wilhite (2000).

Moreover, in the 21st century, the changing climate is increasing drought risk in the Iberian Peninsula, especially in forests (Hlásny et al. 2014). It will also be essential to have an adequate description of the spatiotemporal characteristics defining forest drought and a better understanding of its spatiotemporal evolution given its dynamic nature; this knowledge will be critical for managing future drought risk as well as planning reasonable forest management, allowing improved preparation and contingency planning (Zargar et al. 2011).

Chapter 3

CLIMATE DATABASE

From meteorological stations to time-series of spatially continuous maps

3 CLIMATE DATABASE. From meteorological stations to time-series of spatially continuous maps

3.1 Why is there a need for a climate database?

In order to carry out an accurate analysis and to monitor trends and threats in forests related to drought events, quantifications of meteorological drought are essential. Traditionally, droughts have been monitored through the analysis of *in-situ* data, i.e. ground-based observations (meteorological stations or flux towers) (Casas et al. 2007; Hayes et al. 1999). However, meteorological stations are mostly located in urban areas or in agricultural regions and frequently have different record lengths and variable data quality. Instead, flux towers mainly located in natural areas have a poor spatial distribution. Therefore, natural areas are not well outfitted with scientific instruments mainly due to the absence of economic activity linked to data collection and, in the case of rugged terrain, difficult accessibility and other problems such as snow avalanches. These facts make it necessary to use interpolated grids to map corresponding meteorological variables (Thornton, Running, and White 1997). Whatever data's origin, its good availability and quality are essential (Lavalle et al. 2009).

Characterization of meteorological drought patterns on the Spanish Iberian Peninsula is necessary in the context of the present thesis. There are currently several climate databases providing long-term climate observations and derived anomalies for the Iberian Peninsula. For instance, the Global Climate Monitor (http://www.globalclimatemonitor.org/) is a global climate web viewer containing downloadable climatic information (monthly and annual mean temperature and precipitation) published by the Climatic Research Unit (CRU) (University of East Anglia). It provides data since 1901 presented as grids with a spatial resolution of 0.5° (approximately 55 km). Likewise, the European Climate Assessment and Dataset (ECA&D) of the Royal Netherlands Meteorological Institute (KNMI) (Haylock et al. 2008; Spinoni et al. 2015) provides E-OBS daily gridded observational dataset for precipitation and temperature at a spatial resolution of 0.25°. Further, the Global Standardized Precipitation Evaporation Index (SPEI) database, developed by Vicente-Serrano, Beguería, & López-Moreno, (2010) and calculated using the CRU dataset, offers long-term information about drought conditions at global scale, with a monthly resolution from 1901 to 2013 (frequently updated) and with a 0.5° spatial resolution. Also, NOAA's National Center for Environmental Information (NCEI) provides public access to global meteorological variables from Global Historical Climatology Network station data since 1880, but those are not freely available. Despite the above, none of the available databases allow studying drought event at the local scale (Spinoni et al. 2015): what is needed is spatiotemporal continuous data at high (detailed) spatial resolution, being a compendious dataset of Spanish monthly observations and its anomalies.

This chapter gives an overview of the climate dataset generated and used in further analysis. The presented methodology transforms raw *in-situ* data into accurate informative data resulting in a high-quality climate database available for the whole Iberian Peninsula.

3.2 The Digital Climatic Atlas of the Iberian Peninsula: an inspiring model

In 2000, Ninyerola, Pons, and Roure, (2000, 2005, 2007a) published the first Digital Climatic Atlas of the Iberian Peninsula (DCAIP). It was designed as a set of digital climatic maps of mean air temperature (minimum, mean and maximum), precipitation and solar radiation (Pons and Ninyerola 2008). At the time, this innovative approach involved research into statistical techniques, spatial interpolation of discrete climatological data spread over the territory, and corresponding ancillary variables, such as altitude or continentality. As a result, a complete interoperable set of monthly and annual digital climatic maps at detailed spatial resolution of 200 m for the period 1951-1999 were released.

So far, data from the DCAIP has been used in several studies such as the analysis of NDVI time series (B. Martínez and Amparo Gilabert 2009), quantification of the geographical variation of tree recruitment, growth and mortality of Iberian forests (Coll et al. 2013), forest drought mortality (Carnicer et al. 2011), trends in surface vegetation dynamics (Alcaraz-Segura et al. 2008), or modeling invasive alien species (Marcer et al. 2012), among others.

The wide use of the Atlas demonstrates its robustness and its success. Therefore, an improved version of this existent methodology has been adopted as the basis of the new climatic database developed in this research.

3.3 Methodology

3.3.1 Precipitation and temperature records

The absence of reliable, continuous and high-density of weather observations is still, nowadays, one of the majors concerns in climate research. In Spain, the State Meteorological Agency (AEMET) and also other regional institutions such as the Meteorological Service of Catalonia, or the Institute of Studies of Andorra (IEA-CENMA) have made a major effort towards maintaining and updating meteorological data. As a result, an effective and dense network of ground meteorological stations measuring a wide range of climatic variables is available for research. In this study, climatic data were derived from 3646 (temperature) and 6871 (precipitation) climatic series complied by the AEMET during the period 1950-2012 (Figure 3.1). This thesis will not include data from Portugal because the ground meteorological stations considered reliable by the Instituto Português do Mar e da Atmosfera (IMPA) configure a low density network. However, the dense Spanish network can provide an approximate vision of Portugal trends, thus this area was also included in the computations.

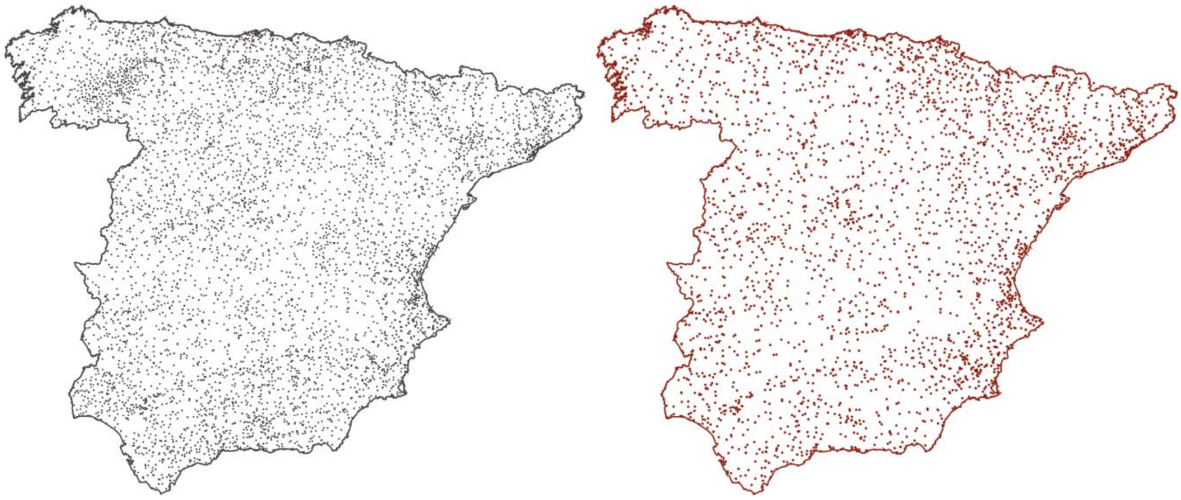


Figure 3.1. Location of national and Andorran meteorological stations. A total of 6871 gauges recording precipitation (left) and 3636 recording temperature (right) have been used.

The distribution of thousands of meteorological stations captures a vast variety of temperatures and rainfall Köppen regimes (from arid to temperate without dry season) present in the Iberian Peninsula. The length of the series has been determined following the existent recommendations stating that a minimum length of 30 years of observational data is required to obtain representative samples of the distributional characteristics of principal drought variables like, for example, precipitation (Guttman 1994; Hayes et al. 1999; Spinoni et al. 2014). Consequently, the longer the record used, the more reliable the results are. The daily precipitation and temperature data has been aggregated into monthly scale observations for the analysis.

A quasi-automatic quality control (QC) processing has been applied to deal with this massive dataset, removing the effects of non-climatic factors on the basis of methods that also include quality indicators based on expert knowledge (Lawrimore et al. 2011). Although completeness and homogeneity of the records are guaranteed by the AEMET (Botey, Guijarro, and Jiménez 2013) an extra filtering has been carried out. Indeed, when dealing with monthly series, homogenization and outlier detection is the main quality control procedure for the data and can be considered as an essential part of the detection of break points (Szentimrey 2006; Venema et al. 2012).

Current expert-based homogenization techniques are focused on direct methods with multi-break detection, metadata completeness and multi-test comparison (Mestre et al. 2013; Toreti et al. 2011). Nevertheless, in order to cope with huge databases, a compromise between automatic and expert-based QC methods is needed. In this regard, a quasi-automated QC system based on three criteria has been implemented. The first criterion analyses the length of the data provided in order to remove short-length series, this way avoiding non-stable or poorly accurate data. To this end, only gauges installed before the year 2000 with 5 or more years of data and gauges installed after the year 2000 with 1 or more years of data have been considered. Newer stations, although offering shorter time series, usually have better quality and more accurate data. The second criterion deals with relocation of meteorological stations. Since most of the heterogeneities detected in the variables are caused by site relocation (Begert, Schlegel, and Kirchhofer 2005), a process with geolocation and refinements (common spatial reference system and datum) was performed. The third criterion involves a spatiotemporal analysis of the station data. Each monthly record has been spatiotemporally compared to the nearest meteorological stations with similar topoclimatic conditions through automated comparisons of mean monthly temperature series as detailed in Menne, Williams, and Vose (2009) and those data with differences of at least three standard deviations have been removed. These records are used as dependent variables.

3.3.2 Independent variables, modeling and testing

Gridded data is a potential improvement over the use of isolated data (Robeson 2008). Following the methodology cited in Section 3.2, several widely identified factors that contribute to climate have been selected as independent spatial variables in the model. Precipitation has been modeled according to 4 parameters: altitude, latitude and continentality, being the latest considered through the logarithmic distance to the Atlantic Ocean and the logarithmic distance to the Mediterranean Sea. Distance to the Cantabric Sea is highly correlated with latitude (R^2=0.951) and thus is not used. Temperature has been modeled using an extra variable: potential solar radiation (Pons and Ninyerola 2008). Among several available digital elevation models, the model used for altitude is a resampled version of the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) Global Digital Elevation Model at 100 m spatial resolution.

For an assessment of model accuracy, a multiple regression fitting method incorporating residual interpolation for inverse distance weighted (IDW) was built on a set of 70 % of the total number of meteorological stations as fitting points. The model was independently cross-validated through the remaining 30 % of stations. Afterwards, the model was applied to all meteorological stations. The independent test result Root Mean Square Error (RMSE) had a median of 23.5 l/m^2 (min: 4.1 l/m^2; max: 66 l/m^2) for precipitation and 1.2°C (min: 0.7°C; max: 2.1°C) for mean temperature. The final climate database was composed of a total of 3024 monthly maps at 100 m spatial resolution. A pair of examples illustrating of the final results is shown in Figure 3.2. The whole database will be published in the Internet and will be freely available for users.

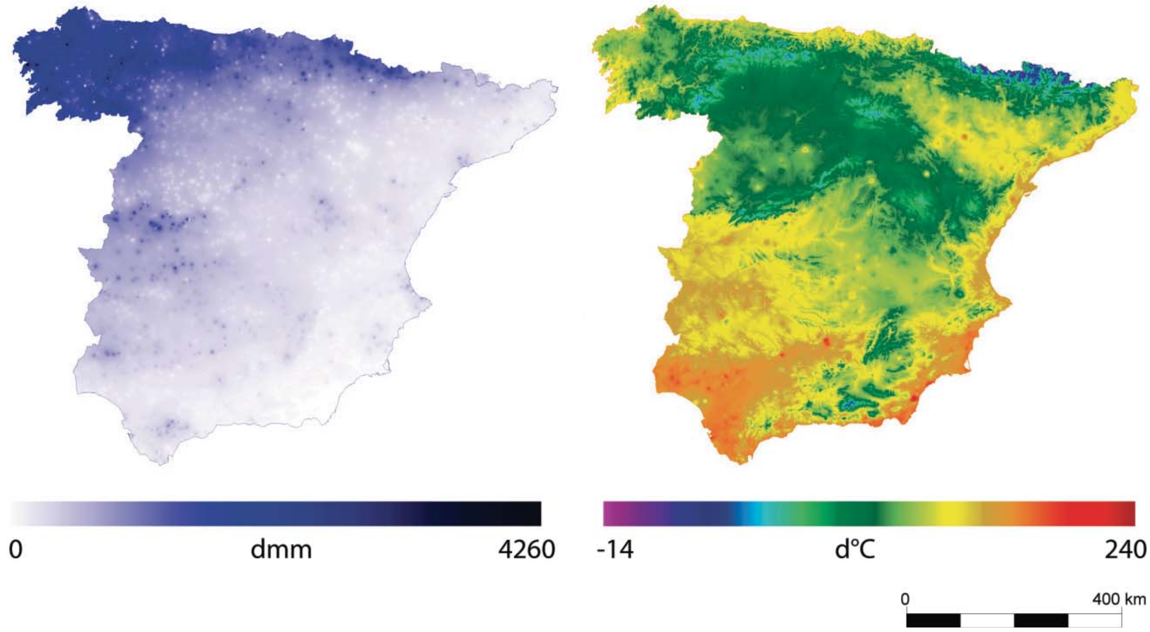


Figure 3.2. General view of the digital map of total precipitation (left) and mean temperature (right) of October 1984.

Chapter 4

DROUGHT DATABASE

Transformation of a climate database to spatiotemporal drought maps and their analysis

4 DROUGHT DATABASE. Transformation of a climate database to spatiotemporal drought maps and their analysis

From the point of view of climatology and statistics, several tools can be used to analyze drought, but the most used indicators are drought indices. This chapter explains which indices have been used in the present research and how the drought database has been developed. Finally, an analysis which demonstrating the potential of the data is presented.

4.1 Drought indices

An important feature of drought monitoring is its quantitative interpretation. Drought identification and proceedings for evaluation have slowly evolved during the last decades to finally settle on drought indices as indicators. Drought indices aid in monitoring the spatial patterns of drought, which include intensity, duration, spatial extent and severity and other climate-related anomalies from the past. This characterization is needed for drought forecasting, development of water management plans and decision-making in the current context of climate change.

Drought indices are quantitative measures which characterize drought levels by assimilating drought indicators, such as precipitation and evapotranspiration, into a single numerical value which is more readily usable than raw data (Deshayes et al. 2006; Zargar et al. 2011). There are various requirements which should be met by any drought index. First, it must be useful for real-time monitoring (Niemeyer 2008). Second, it must detect the beginning or end of a drought period. Third, it must indicate a drought level (Zargar et al. 2011). Fourth, it should be able to quantify the drought for different time-scales to understand which type of drought is developing (McKee, Doesken, and Kleist 1993). Accumulated water deficits functionally separate drought type as discussed in Section 2. And finally, the main requirement is that it must facilitate communication of drought conditions among different stakeholders. Most of the indices are based on meteorological data such as precipitation, but an increasing specialization of indices based on specific types of drought is evident. Specialized indices integrate other variables such as soil moisture, streamflow or remote-sensing data.

More than one hundred indices have been defined by various authors (Heim 2002; Mishra and Singh 2010; Niemeyer 2008) over the last decade. Indices have been compared and their advantages and drawbacks (Heim 2002; Zargar et al. 2011) and some others have been recommended as preferential by scientists (Keyantash and Dracup 2002; Paulo and Pereira 2006) and organizations such as the World Meteorological Organization (Hayes et al. 2010).

Among all the recommended indices, a couple of them, the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) stand out for their excellent quantifications of the severity of droughts in a spatiotemporal context (Keyantash and Dracup 2002; Vicente-Serrano, Beguería, and López-Moreno 2011).

The following section gives an overview of the advantages and potential of the SPI and the SPEI which set them apart as perfect candidates for use in this thesis.

4.1.1 Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI)

Standardized Precipitation Index (SPI)

The SPI was presented at the American Meteorological Society meeting in 1993 (McKee, Doesken, and Kleist 1993). This relatively simple index, designed to quantify the precipitation deficit for multiple timescales, is based only on precipitation.

Calculation of SPI for a specific time period at any location requires a long-term monthly precipitation database with at least 30 year record, but 50 years has been recommended (Guttman 1994; Guttman 1999; Hayes et al. 1999). The monthly precipitation time series can be modeled using different statistical distributions, such as the Gaussian, Pearson III, log-normal or gamma. Existing literature has identified the gamma distribution as the one which best fits climatological precipitation time series at regional scales (Lloyd-Hughes and Saunders 2002; Thom 1958) although some exceptions are found in some regions, for example in Turkey. The computing methodology involves fitting a Pearson III or Gamma probability density function to a given frequency distribution of precipitation totals for each station and each time scale of interest (Edwards and McKee 1997). The corresponding cumulative probability is then transformed using an equal probability to a normal distribution with a mean of zero and a standard deviation of one for a given time unit (i.e. monthly), time scale and location, which is, itself, the value of the SPI. Therefore, the SPI values are in fact standard deviations. An exhaustive overview of the calculation procedure for calculation of SPI is given in Edwards and McKee (1997) and Lloyd-Hughes and Saunders (2002). The level of the anomaly is usually classified into several categories, like the ones described in Table 4.1.

Index Value	Drought Class	Probability (%)
≥ 2.0	Extreme wet	2.3
1.5~2.0	Very wet	4.4
1.0~1.5	Moderate wet	9.2
-1.0~1.0	Near normal	68.2
-1.5~-1.0	Moderate dry	9.2
-2.0~-1.5	Severe dry	4.4
≤ -2.0	Extreme dry	2.3

Table 4.1. SPI and SPEI-based thresholds for classifying drought condition and probability of occurrence.

Negative SPI values indicate less than average precipitation, i.e. dry event, while positive values indicate greater than average precipitation, thus wet events. A threshold of -1 or lower is selected to identify the drought condition, which ends as soon as the SPI becomes positive again. The scale of the departure from the mean is therefore a probabilistic indicator of intensity for each event, either dry or wet.

As pointed out in the introduction of this section, the main advantage of this index is that it can be calculated for several timescales. The most commonly-used timescales are monthly and yearly, being the first the most appropriate for monitoring effects of drought conditions on vegetation (Mishra and Singh 2010). Usually the timescales range from 1 month to 72, but the most frequently used timescales are 3, 12, 24 and 48 months timescales. Each of the timescales responds to specific conditions and has its own interpretation. Consequently, a 1-month SPI is very similar to the percentage of normal precipitation. Its main application is monitoring agricultural drought which manifests as crop stress, primarily during the growing season. A 3-month SPI indicates short-and medium-term moisture conditions providing a seasonal estimation of the precipitation. The 6-month SPI reflects medium-term trends in precipitation and may indicate first anomalies in streamflows and reservoir levels. And, the 9-month SPI inter-seasonal patterns act as a bridge between short-term and long-term droughts indicators. SPI timescales of 12 month or longer characterize long-term precipitation patterns linked to streamflows, reservoir levels and groundwater levels anomalies (Figure 4.1). Figure 4.1 also illustrates the fact that longer-term droughts are essentially made up of multiple shorter-term droughts (Edwards and McKee 1997).

Nevertheless, the SPI procedure also has a weakness: it is only based on precipitation information without considering other meteorological variables that play important roles during the development of a drought event. Precipitation is the main factor controlling the formation and persistence of drought conditions, but evapotranspiration is also an important variable

(Heim 2002; Lloyd-Hughes and Saunders 2002). In the current context of global change, where global warming is predicted by several models (Allen et al. 2010; Asadi Zarch, Sivakumar, and Sharma 2015) the inclusion of temperature, as a variable addressing potential evapotranspiration (PET), should not be ignored in drought modeling. This is the principal reason why the Standardized Precipitation Evapotranspiration Index (SPEI) was later developed.

Standardized Precipitation Evapotranspiration Index (SPEI)

As an evolution of the SPI, the SPEI was developed by Vicente-Serrano, Beguería, and López-Moreno (2010) with the objective of including changes in evaporation demand as a variable. Therefore, the SPI only considers climatic water supply while SPEI addresses both climatic water supply and demand. The SPEI uses precipitation, mean temperature and latitude as inputs and is based upon the original SPI computing procedure. The mean temperature is used to estimate PET with the Thornthwaite method (Thornthwaite 1948) although other variables that may affect PET, such as wind, are not taken into account. The difference between precipitation and PET is modeled using a three-parameter log-logistic distribution instead of a gamma distribution, and its cumulative distribution function is finally transformed into a standardized variable. As a result, SPEI has an average value of 0 and a standard deviation of 1.

The suitability of the PET as a climatic parameter and the standardized probability distribution makes this index useful for comparing drought or wetness across different locations and seasons. Details of the calculation process for SPEI are found in Vicente-Serrano, Beguería, and López-Moreno (2010). The thresholds and categories used to interpret SPI are equally useful (Table 4.1). The SPEI presents advantages over its predecessor, including better applicability for arid regions (Beguería, Vicente-Serrano, and Angulo-Martínez 2010), and the SPEI authors also identify better results in assessing droughts in summer compared to other indices (Vicente-Serrano et al. 2012).

4.1.2 Computational approach

Several programs for calculating SPI and SPEI are available through several web portals. For instance, the National Drought Mitigation Center distributes a program for calculating SPI (NDMC 2015) with up to 6 SPI time windows simultaneously for a given point location. There is also a SPEI calculator distributed as individual software or as a R package (Beguería and Vicente-Serrano 2013). Nevertheless, given the climatic database developed in the context of this thesis, a spatiotemporal continuous calculation approach has been implemented. Moreover, this approach has advantages in terms of time and computational effort in the processing of big data.

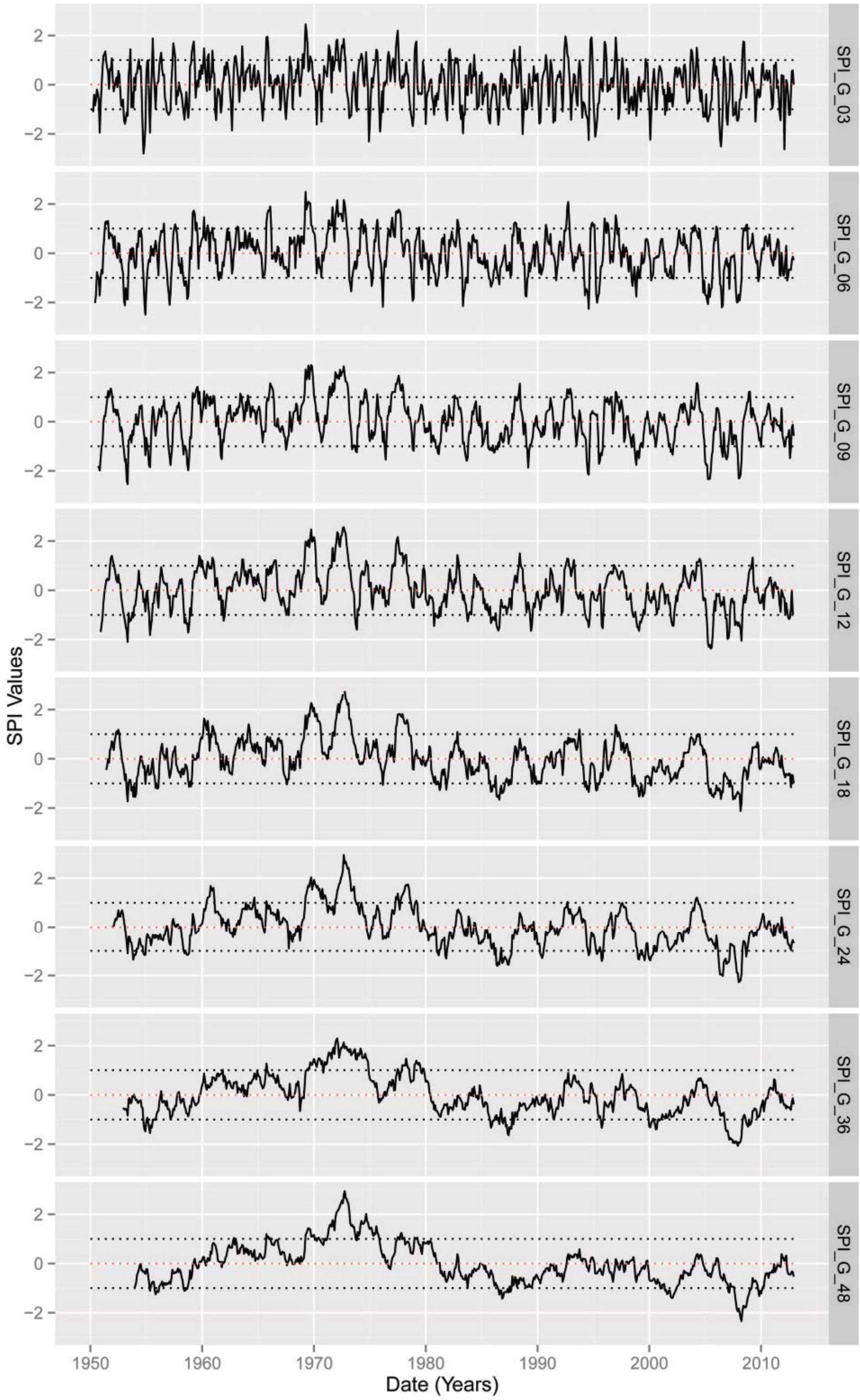


Figure 4.1. Example of an SPI 63-year time series at different time scales in Catalonia. Note that the smaller the timescale, the greater the number of events, whereas with a longer the timescale there are fewer events but duration is longer.

According to Lloyd-Hughes and Saunders (2002) indices computed from the gridded data are representative of those obtained from station data. Therefore, drought index maps necessary for analyses in this thesis are calculated from data obtained in Chapter 3.

The implementation of the continuous approach has been developed as a module of the MiraMon Remote-sensing and Geographic Information System software (Pons 2015). The program, which can be compiled in 32-bit and 64-bit mode, computes either SPI or SPEI allowing inputs of single point data, typically from weather stations (Station Mode), or continuous data from a geographic area, which is defined by a set of rasters (Raster Mode). According to the methodologies described in section 4.1.1, SPI can be calculated adjusted to a gamma or Pearson III function while SPEI is fitted to a log-logistic distribution. In raster mode, the number of files comprising the series is not a limiting factor and can handle very long series (the current limitation is a series of 365 000 data). In this mode, the latitude value required for the computation of SPEI, is geodetically computed at the beginning and end of each raster line and is lineally interpolated between these values. It is considered that this procedure is sufficiently accurate in most map projections and cases. Raster mode also supports missing data. A drawback which deserves to be mentioned is the fact that sometimes the numerical fitting is not possible, indicating singular areas. This problem is minor and already known for these kinds of calculations (Lloyd-Hughes and Saunders 2002). It is also worth noticing that this module runs quite slow. This is a consequence of a large number of operations including: managing (open/close) a large amount of files (duplicated in the case of SPEI); performing unit conversions (if needed) and missing data supported; the computation of latitude at the beginning and ending of each raster line; and, of course, the function fitting of the time series for each of the millions of raster pixels, which numerical results of the statistical process. For instance, calculation of SPEI at the 18-month timescale for the whole Iberian Peninsula at spatial resolution of 100 m (11082 columns by 8852 rows) and for a time series of 63 years has a calculation cost of approximately 12 hours. The raster mode output is a multiband raster, so that clicking any pixel of the map and querying by location it returns a whole time series of the index for the selected coordinate (Figure 4.2).

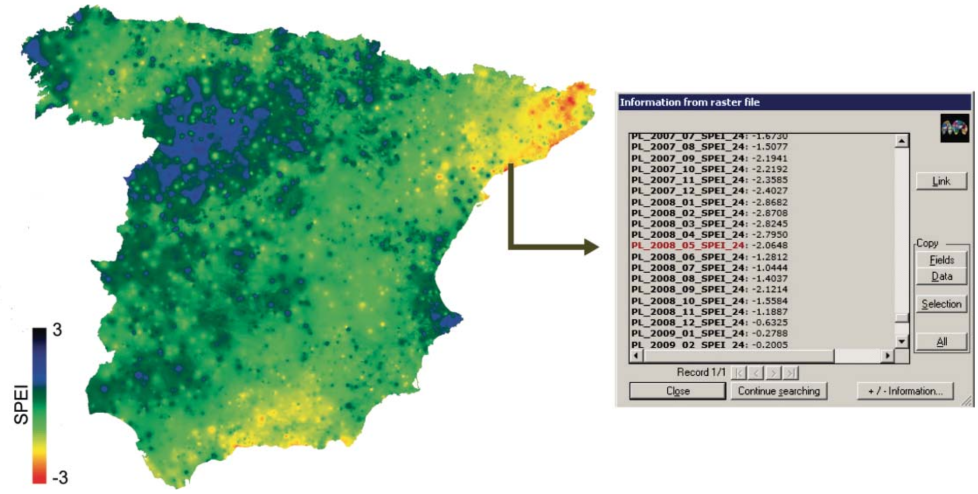


Figure 4.2. Example of a SPEI map computed at a 24 month timescale (May 2008) and its corresponding output with the whole SPEI series for a given location query.

Using the above procedure, a drought map database has been created using the MiraMon software. SPI and SPEI indices for the Spanish Iberian Peninsula at 100 m spatial resolution have been computed at 8 different timescales: 3, 6, 9, 12, 18, 24, 36 and 48-month based on the climatic time series (Chapter 3) (Figure 4.3) ranging from 1950 to 2012. Altogether this results in a drought dataset of approximately 12 000 maps which along with the climate database, results in a big climate and drought data cube comprising more than 14 000 grids. Indeed, the final database, with more than 600 000·10^6 points of information, is part of the Big Data context of the research.

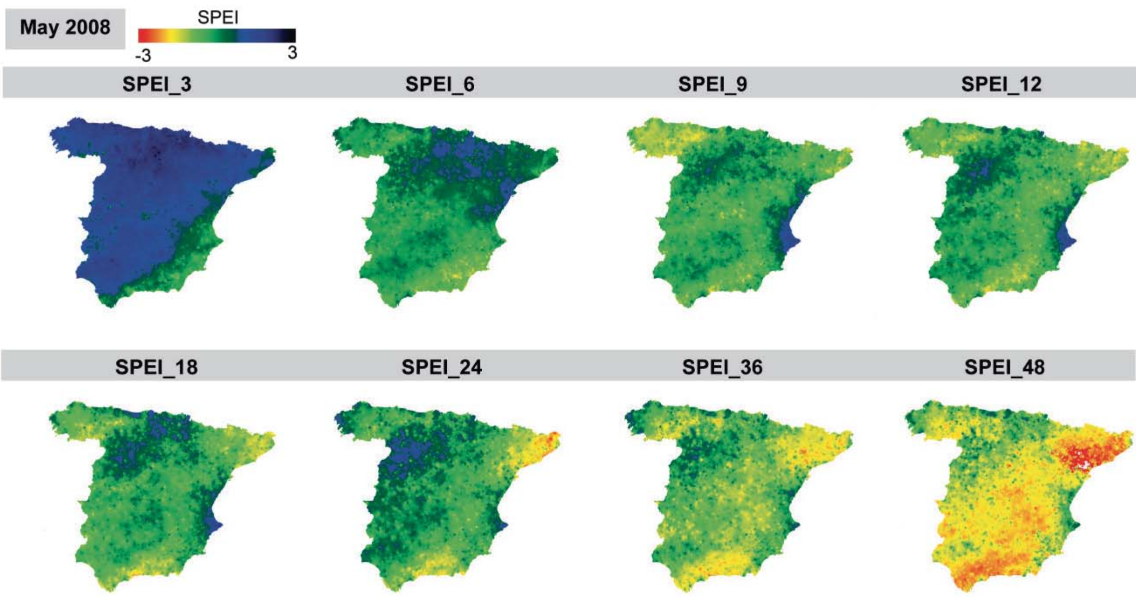


Figure 4.3. Series of timescales computed for a given month (May 2008) showing the spatial distribution of drought. SPEI 3-month indicates a wet episode but long-term maps (SEPI_24-48) indicate a strong drought event at the NE of the Iberian Peninsula. This example highlights the importance of temporality and illustrates how drought dynamics change with timescale.

4.2 Characterization of meteorological droughts

According to Andreadis et al. (2005) characteristics of drought are expressed in four dynamic dimensions which are defined by the following essential features: intensity, severity and temporal and spatial extent. These factors determine the overall impact of a drought. A complex approach such as this is possible through the use of geospatial science, which allows the analysis of the temporal evolution of a given spatial behavior of interest. Remote-sensing and GIS are excellent data and tools for successfully implementing this approach, as has been shown in Section 4.1.2.

As happens with the definition of drought it is challenging to find a unique term for characterizing drought which is accepted by the scientific community. Instead, several term definitions exist and its usage sometimes is switched (Andreadis et al. 2005; Dracup, Lee, and Paulson 1980; Olcina Cantos 2006; Wilhite 2000; Xu et al. 2015; Zargar et al. 2011). In the context of the present thesis drought characterization will be based on meteorological drought indices and the following descriptions will be adopted (Figure 4.4).

Time extent represents the temporal length of a drought event (Xu et al. 2015). It is quantified by the number of consecutive time units that are below a specified threshold specifically established for the study region. Duration is partitioned into two phases (Parry et al. 2015). The first is defined as the time span between the initiation time of initiation of the event (drought starts below threshold anomalies) and the start of the period of recovery from maximum drought. The second phase is defined as the termination period which begins after the drought has ended and lasts until normal conditions are reached (Figure 4.4).

Droughts also differ in their **frequency or return period**, defined as the average time between drought events having a severity which is equal to or greater than the threshold specifically established for the study region.

Intensity refers to degree of the given anomaly. It is measured by the departure from normal conditions in consideration of the drought threshold specifically established for the study region, and the measured parameter is an indicator such as the Standardized Precipitation Evapotranspiration Index (Figure 4.4).

The feature **severity or magnitude** is defined as the positive sum of the index values for all the months within a drought event (WMO 2012) (Figure 4.4).

The last essential characteristic of drought is the **spatial extent**. It is described as the affected area over the longitude-latitude surface and may be variable during the event (Wilhite 2000).

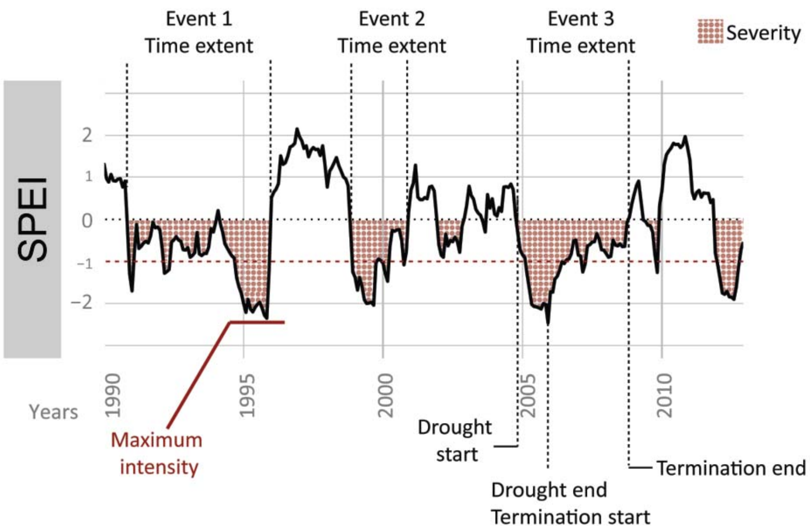


Figure 4.4. Schematic of features characterizing meteorological drought. Example for the SPEI (simulated example).

4.3 SPEI spatial and temporal preliminary analysis of meteorological droughts in the Spanish Iberian Peninsula

A tentative analysis of the spatial and temporal characteristics of meteorological major droughts in the Spanish Iberian Peninsula from 1950 to 2012 was performed. Previous studies have already attempted to describe meteorological drought patterns on the Iberian Peninsula or even at the global scale (García-Haro et al. 2014; Paulo and Pereira 2006; Vicente-Serrano 2006a; Q. Wang et al. 2014). However, none of those studies described the patterns at high spatial resolution over as many decades. The following investigations stand out for its detailed spatiotemporality.

4.3.1 Areas affected by recurrent long time extent episodes of drought

In order to contribute with another view to identify the most affected areas by meteorological droughts, an analysis counting the number of episodes with a time extent of a minimum of 4 or 7 months (as representative lengths causing harmful effects) occurred along the whole time series (63 years) was carried out for SPEI at 3, 12 and 24-month timescales (Figure 4.5). Results identify persistently affected areas, which are represented as high values in Figure 4.5. Those areas are frequently hit by drought episodes lasting more than 4 or 7 months.

Short-term drought (3-month timescale) consecutive episodes of more than 4 or 7 months are less frequent given that the high variability of the 3-month series (above and below zero pattern, see Figure 4.1). Indeed, this high variability hinders consecutive sequences of negative SPEI for droughts of more than 4 months (more frequent in the center and Southeastern part of the Iberian Peninsula), and especially those regarding more than 7 months (more frequent in the center part of the Iberian Peninsula). The average number of long drought episodes (more than 7 months) is 1 (Figure 4.5 left bottom map).

Moreover, long-term drought (24-month timescale) consecutive periods of more than 4 or 7 months indicates areas where at least 4 month drought episodes are present (maximum of 19 episodes at least 4-month long and 13 episodes at least 7-month long in 63 years). Contrary to the high variability of SPEI 3-month series, long-term series presents smoothed long-term patterns (see Figure 4.1) which can easily include episodes of 4 or more consecutive months of drought. For instance, the central part of the Spanish Iberian Peninsula presents areas affected by 14 to 19 drought episodes of at least 4 consecutive months (Figure 4.5 right top map). Instead, episodes of more persistent drought (at least 7 month) yield, as expected, less frequent number of episodes (6 to 9 episodes in general) (Figure 4.5 right bottom map). These less frequent long-term drought episodes are located at the western part of the Spanish Iberian Peninsula. This area is the most frequently affected by serious long-term droughts although perhaps is not one of the classically considered hot spots for drought, for instance the vision offered in del Barrio et al. (2010).

Intermediate-term droughts describes through SPEI 12-month timescale and at least 4 consecutive months are located at the north and east regions of the Spanish Iberian Peninsula (Figure 4.5 middle top map) as well as in the central-western part, giving an interesting picture that geographically contrasted with the SPEI 24-month map. These type of episodes are repeated several times (maximum of 21) during 63 years. When analyzing the spatial pattern for at least 7 months (Figure 4.5, middle top map) is relatively similar (except for a lower affectation in the NE part of Catalonia) but, logically, with lower values due to the longer time extent required to count more frequent affectations.

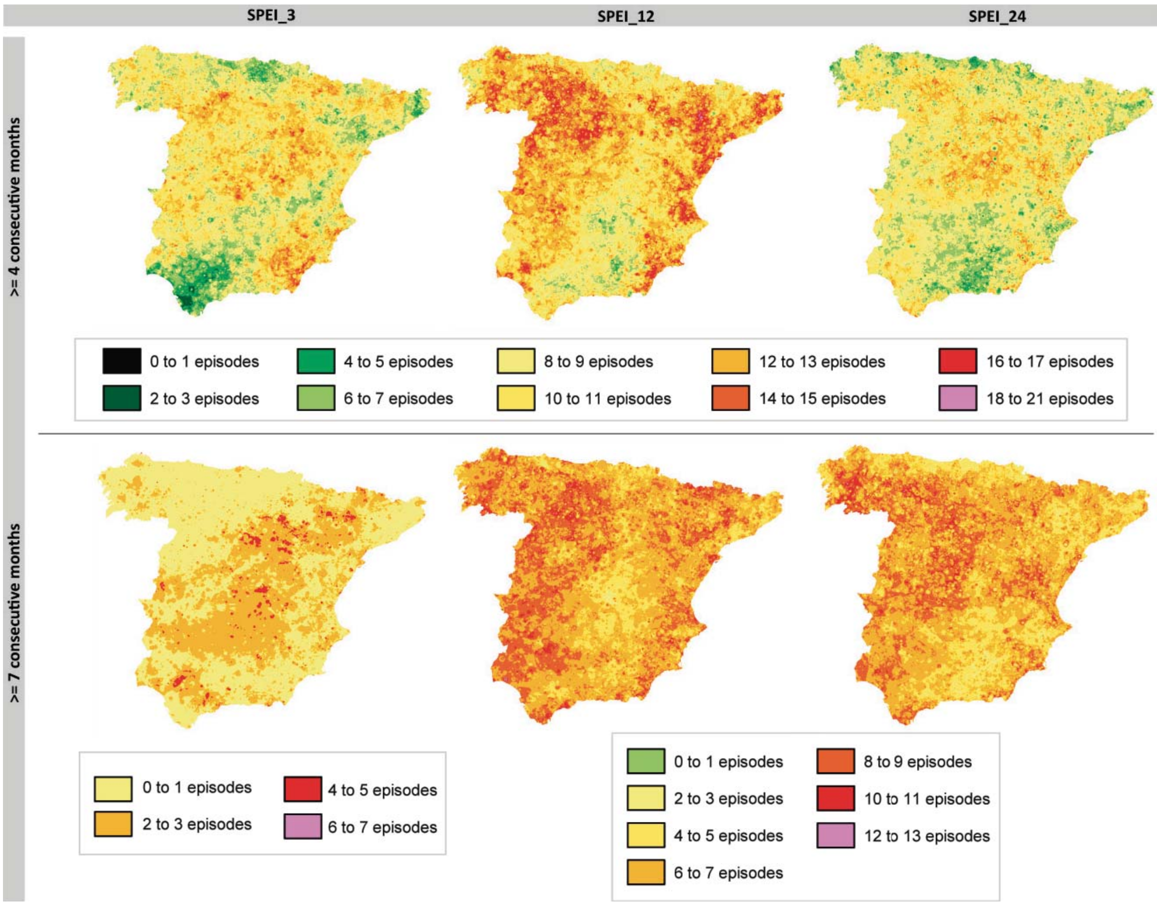


Figure 4.5. Frequency of drought episodes presenting at least 4 months of continuous time extent (top) and at least 7 months of continuous time extent (bottom) for SPEI 3, 12 and 24-months timescales. Note the different type of legends.

In summary, these drought patterns allow identifying areas affected by recurrent drought episodes at different timescales for the period 1950-2012, being the most frequent long-term droughts probably the most harmful. This analysis offers a new perspective where some areas of the Spanish Iberian Peninsula considered as extremely wet are revealed as the most affected by drought events, and it leads to reconsider the climatic unit models of the Iberian Peninsula. Also, these maps can be really useful for researchers looking for areas to perform field work monitoring in complementary close-up and functional drought studies over areas frequently affected.

4.3.2 Maximum meteorological drought intensities and their spatial distribution

The distribution of minimum and maximum values for the whole period 1950-2012 has been plotted for the two time-scales of 3 and 24-month (Figure 4.6).

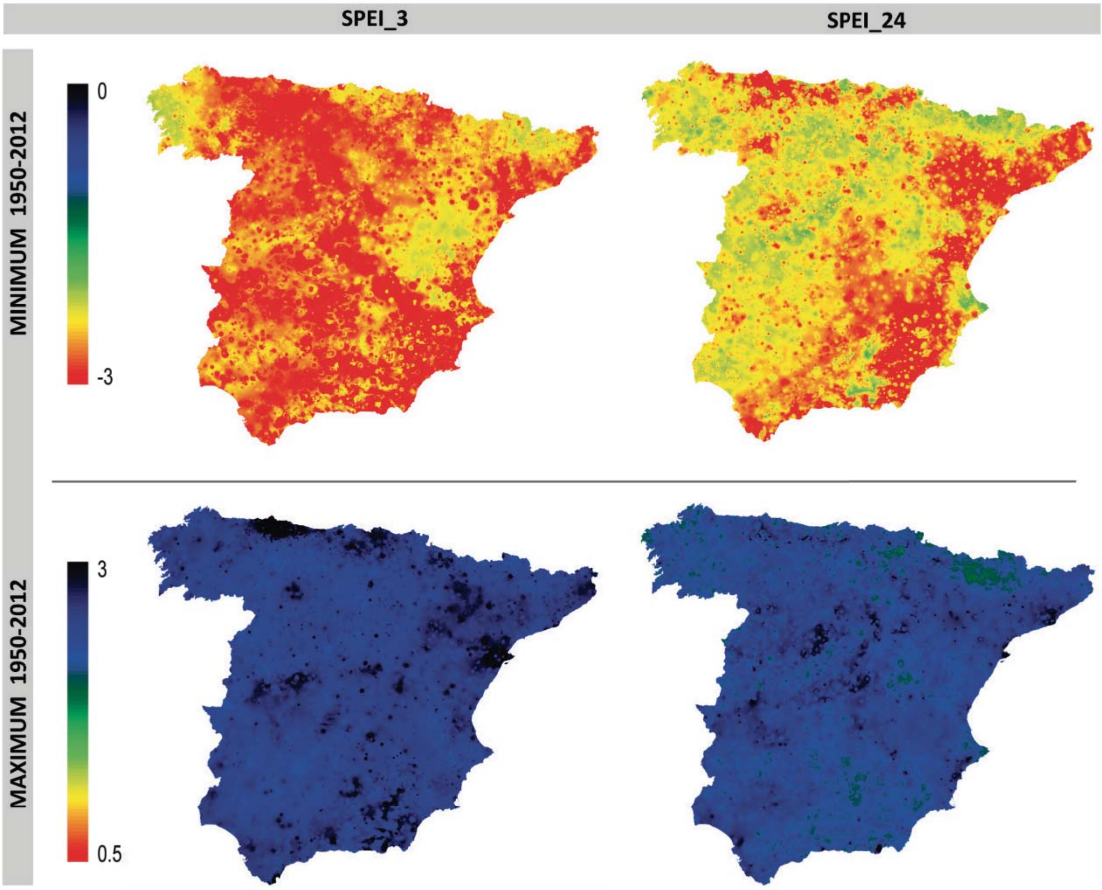


Figure 4.6. Distribution of minimum and maximum SPEI values for the whole period.

At short-term scales (SPEI 3-month) distribution of the areas affected by meteorological anomalies is almost homogeneous, excluding the most occidental part of Spain, Galicia, the Pyrenees and the eastern-central area corresponding to the Iberian system mountain range. On the other hand, the SPEI 24-month minimum distribution indicates the areas worst affected by long-term droughts. As shown in Section 2.2.1, these are classified as areas presenting a temperate climate with or without dry or hot summer. Therefore, these regions are the most vulnerable given that any lack of precipitation together with a long-term residual drought will exacerbate the drought situation. The case of the north coast corresponding to Asturias is also noteworthy since it presents both significant minimum and maximum SPEI values making this region more sensitive to water scarcity.

4.3.3 Evolution of the spatial extent of drought

The interannual variability of severe drought areas was analyzed through SPEI at two different time-scales: 3-month and 24-month (short-term and long-term droughts, respectively). The percentage of drought (SPEI ≤ -1) area for each year during 1952-2012 was calculated. The analysis was restricted to drought episodes affecting at least one third of year (4 months) (Figure 4.7).

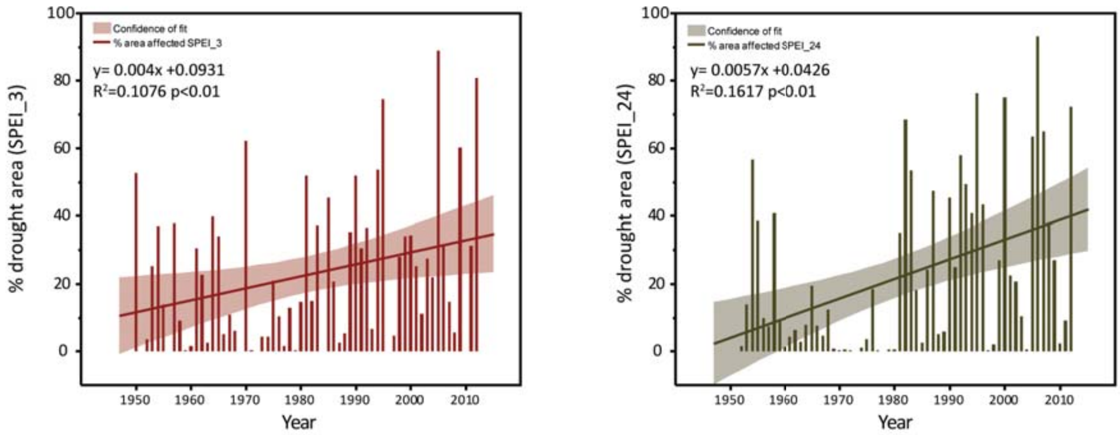


Figure 4.7. Spanish Peninsula Iberia area affected by severe drought for 3 and 24-month SPEI during the period 1950-2012. Computation of the area affected has been restricted to drought episodes affecting at least 4 months. The tendency line indicates a worst case scenario with time, especially for long-term droughts.

The evolution of the area affected by droughts for the period 1952-2012 rose significantly overall, especially when considering long-term drought episodes. The results indicate that each decade there has been drought episodes affecting at least 4 months of the year. Interestingly, both indices explain different events. For instance, the short-term drought index shows that in 1970 and 2009 more than 60 % of the surface area of the Spanish Iberian Peninsula was affected by a meteorological drought. On the other hand, 1982 stands out for its widespread long-term drought event, affecting more than 60 % of the surface area of the Spanish Iberian Peninsula. The high frequency short-term dry events of the late 70s and early 80s, absent in the long-term series, led to a long-term drought period for much of the region during the following decades. Droughts at the beginning of 21st century are evident in both time series. The most widespread event for the studied period was in 2005 and affected almost 89 % of the surface area of the Spanish Iberian Peninsula. This illustrates the fact that major drought events begin as short-term droughts, later become intermediate-term events, and finally, end up being long-term droughts, which may be more hazardous. These results agree with previous studies providing evidence that the longer the time-scale, the longer the events last, but that these are less frequent are (Hayes et al. 1999; Vicente-Serrano 2006b).

4.3.4 Characterization of spatiotemporal drought moving waves

This Section contains part of the Conference Communication published in: Domingo-Marimon, C., Ninyerola, M., Pons, X., & Cristóbal, J. (2015). A love story about forest drought

detection: the relationship between MODIS data and climate time series. (Vol. 17, p. 13193). Presented at the EGU General Assembly Conference.

Several studies have analyzed the spatial and temporal variation of droughts through the study of local data, frequently using meteorological gauges data (Buttafuoco and Caloiero 2014; Vicente-Serrano 2006a; Vicente-Serrano 2006b), yielding the analysis to a small dimension. As a result, most of the time the analyses were performed separately in space and time, identifying either the time evolution of drought over a fixed area or the spatial patterns of drought at a certain time (Xu et al. 2015). However, a better understanding of spatiotemporal variation of drought is necessary.

One of the main advantages of working with data which is spatiotemporally continuous is the multidimensionality achieved by the analysis. The spatiotemporal continuous drought maps generated in this thesis allow the characterization of the spatiotemporal evolution of a given drought event demonstrating that integration of spatially continuous information derived at several time-scales is the best tool for monitoring drought conditions (Svoboda et al. 2002; Vicente-Serrano 2006b). These maps enable an innovative and integrative visual approach ideal for complementing the traditional information and for characterizing the phenomenon of drought moving waves.

For example, Figure 4.8 shows the spatiotemporal characterization of the 2003 drought event. Thermal and pluviometric anomalies started in May 2003 and lasted until September. This event was temporally located during summer and did not have long-term effects in terms of meteorological anomalies.

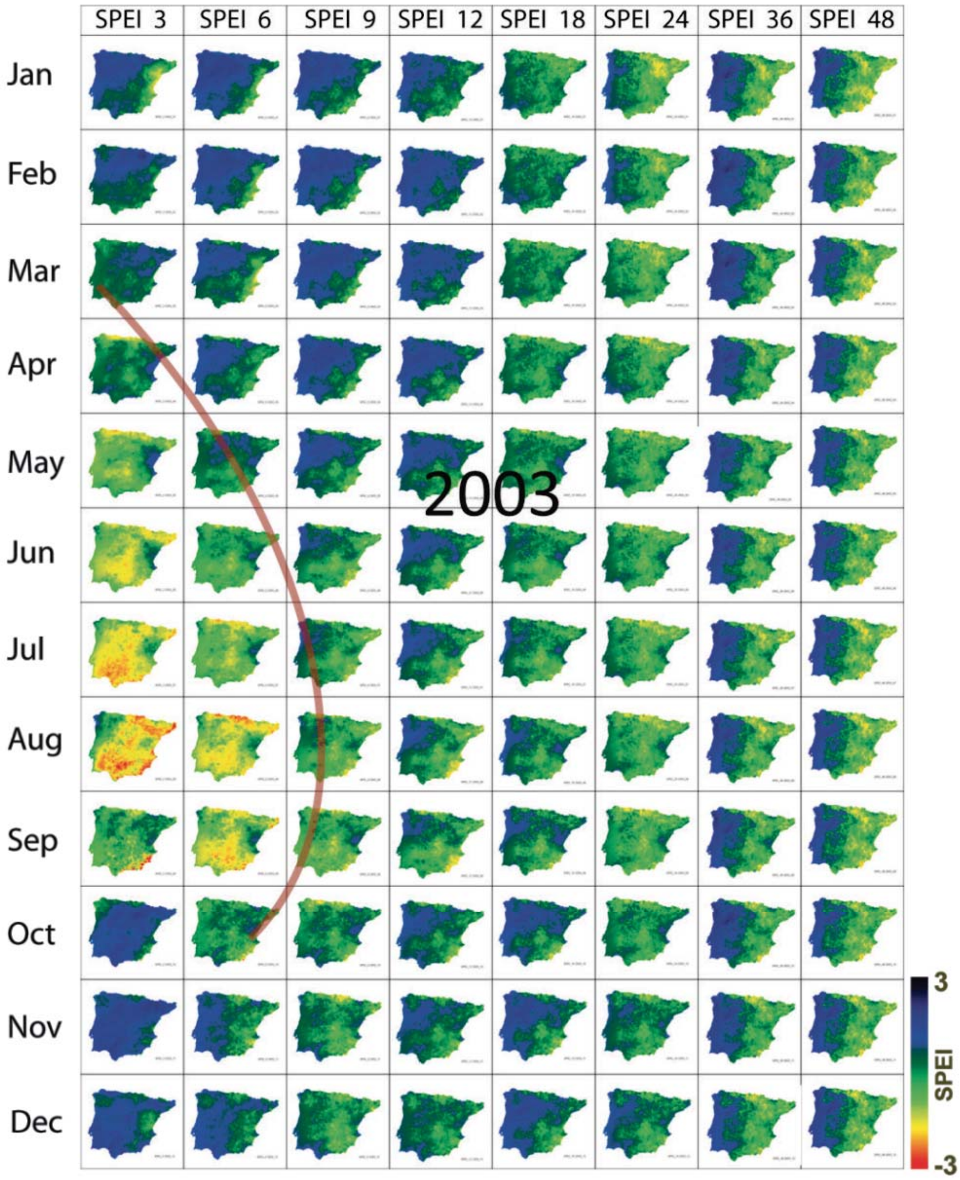


Figure 4.8. Evolution of the 2003 drought event. According to the spatiotemporal analysis, this event was temporally located during summer and did not spread in time.

In contrast, Figure 4.9 demonstrates how the summer 2005 drought behaved as a moving wave spreading its effects in time, until the end of 2008. In this case, the initial short-term drought did translate into a long-term drought. This together with the emerging anomalies during winter 2007-2008, led to the exceptional drought situation which affected the Northeast part of Spain, Catalonia, already explained in Section 2.2.1 (see also Figure 2.4). This example also illustrates two additional arguments. The first is related to arguments expressed by M. D. Martínez, Lana, and Burgueño (2010), who considered that a drought period may be worsened by the continuation of a dry summer, but it is likely that the main cause of a drought be a relevant precipitation shortage episode in a wet season.

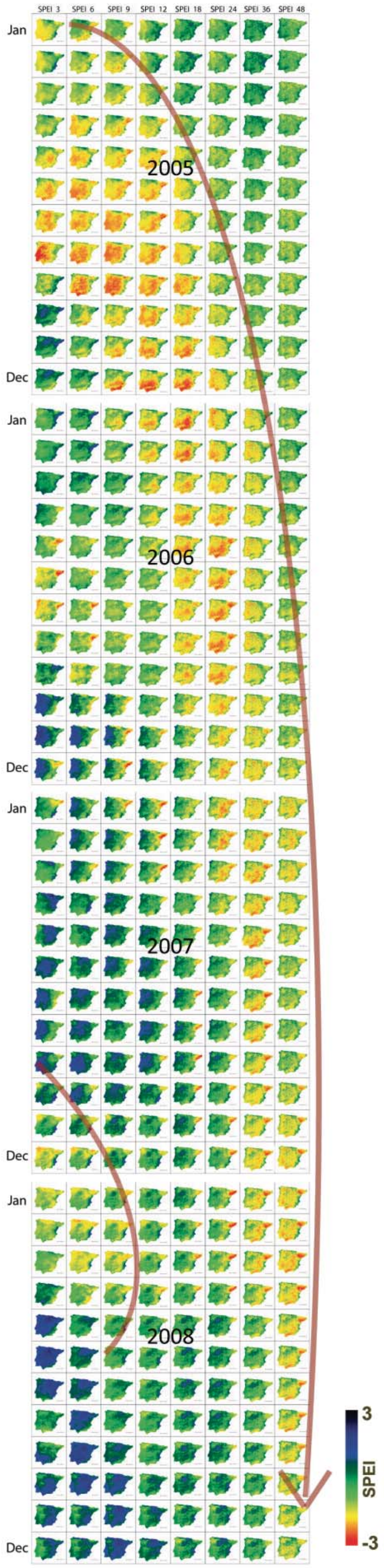


Figure 4.9. Evolution of the 2005 drought event. According to the spatiotemporal analysis, this event spread in time extending its effects until end of 2008.

The second line of reasoning is that a region may experience wet and dry spells simultaneously when considering various timescales (Zargar et al. 2011).

Additional drought moving waves can be appreciated in Annex B, which includes thumbnails of each SPEI map from 1950 to 2012 for each timescale (3, 6, 9, 12, 18, 24, 36 and 48-month).

This characterization of moving waves provides information which is invaluable for the development of drought monitoring systems and emergency and mitigation plans implemented by policy makers (Wilhite, Sivakumar, and Pulwarty 2014). Moreover, these moving waves allow spatiotemporal delimitation of areas suffering meteorological anomalies (Buttafuoco and Caloiero 2014), since these may seriously affects the state of natural ecosystems, such as forests. A noteworthy aspect is the easy identification of several simultaneous drought events: i.e. the drought episode of the period considered and the resident drought of a previous episode, which together can trigger even greater consequences.

4.4 Prospects for causes, effects and early prediction of meteorological drought: an interdisciplinary approach

A modified version of this Section has been submitted to Proceeding of the Natural Academy of Sciences; Jofre Carnicer[1], Cristina Domingo[1], Miquel Ninyerola, J. Julio Camarero, Timothy M. Lenton, Vasilis Dakos, Montserrat Ribas, Emilia Gutiérrez, Jordi Almiñana, Josep Peñuelas, Xavier Pons.

Understanding the causes of meteorological droughts as well as their possible impacts on forests is a challenge which must be addressed by science. If additionally the aim is also the pursuit of prediction indicators, only an interdisciplinary approach linking different perspectives may lead to success.

4.4.1 Abstract

‘Regime shifts’ within modes of natural climate variability have been linked to impacts on marine and terrestrial ecosystems (Carpenter et al. 2011; Lenton et al. 2008; Scheffer et al. 2009). However, the relationships linking oceanic multidecadal variability (Chen and Tung 2014; Kerr 2000; Rahmstorf et al. 2015; Tung and Zhou 2013), the dynamics of abrupt shifts in drought regimes, and carbon sequestration by forests remain poorly assessed. Here we document abrupt shifts in drought regimes in the Spanish Iberian Peninsula, a hotspot for future impacts of global warming. The strength of the shifts was significantly associated with the relative influence of the Atlantic multidecadal oscillation index (AMO), and the shifts were consistently anticipated by early warning signals. Our results indicate that Atlantic variability is a key regulator of abrupt

[1] JC and CD conceived and designed the study and analyzed the data and contributed equally to the work and therefore share first authorship.

shifts in local drought regimes in the Mediterranean Basin, in turn producing significant shifts in the decadal trends of forest carbon sequestration. These results suggest that the projected weakening of the Atlantic Meridional Overturning Circulation (AMOC) during this century could reduce the carbon sink activity of semi-arid forests, and create a positive feedback on atmospheric CO_2 concentrations.

4.4.2 Introduction and objectives

The quest to identify the diverse mechanisms driving abrupt shifts in the dynamics of climate and ecosystems has gained considerable scientific attention in recent decades (Carpenter et al. 2011; Chen and Tung 2014; Lenton et al. 2008; Rahmstorf et al. 2015; Scheffer et al. 2009; Tung and Zhou 2013). Numerous empirical studies have reported abrupt regime shifts between contrasting persistent states of ecosystems (Carpenter et al. 2011; Lenton et al. 2008; Scheffer et al. 2009) and have also identified a variety of early warning signals for anticipating critical transitions in the face of ongoing global change (Carpenter et al. 2011; Lenton et al. 2008; Scheffer et al. 2009).

Fluctuations in the surface temperature of the North Atlantic Ocean, quantified by the Atlantic multidecadal oscillation (AMO) index (Enfield, Mestas-Nuñez, and Trimble 2001; Kerr 2000), are important drivers of long-term changes in the trends of drought and rainfall in North and South America, western Europe, the African Sahel, and other areas of the globe (Enfield, Mestas-Nuñez, and Trimble 2001; McCabe, Palecki, and Betancourt 2004; Sutton and Hodson 2005). Fluctuations in the AMO index are in turn thought to be driven by fluctuations in the underlying strength of the Atlantic Meridional Overturning Circulation (AMOC), which transports heat northwards across the equator in the Atlantic basin. However, it remains uncertain whether transitions between the warm and cold phases of AMO result in abrupt or gradual shifts in local drought regimes and how these shifts vary geographically. Furthermore, the responses of key ecosystem services, such as the carbon sequestration in forests, to multidecadal shifts in drought conditions are poorly understood. Improved analyses are needed to fill this knowledge gap, coupling the study of drought indices, early warning indicators, and teleconnection indices. The Spanish Iberian Peninsula is an excellent representative region for exploring these links because of its marked climatic gradient, the significant influence of the AMO on regional climate (Guemas et al. 2015; Mariotti and Dell'Aquila 2012) and the severe impacts of drought on forest ecosystems in the region (Carnicer et al. 2011).

Our main aims were first to assess the existence of abrupt shifts in drought regimes in this area, to test the relationships of the shifts to the Atlantic multidecadal variability, and to examine whether these shifts were preceded by early warning signals. We also quantified the impacts of the Atlantic multidecadal variability on the dynamics of forest carbon storage in selected areas affected by abrupt shifts in their drought regimes.

4.4.3 Detailed methods

The SPEI database configured in Chapter 4 was used as the data source for the study. We used the SPEI covering different time scales (3, 6, 9, 12, 18, 24, and 36-month) to identify and quantify droughts. The study area was subdivided into grids of 280 × 280, 140 × 140, and 70 × 70 km^2 (Figure 4.10). A spatially averaged value of monthly SPEI was calculated for each grid cell for the period 1950-2012. Big data GIS analyses were performed using MiraMon (Pons 2015).

The Atlantic multidecadal variability was quantified using the AMO index (Enfield, Mestas-Nuñez, and Trimble 2001). We also gathered data for four additional teleconnection indices that have been significantly associated with drought dynamics in the Iberian Peninsula: the North Atlantic Oscillation (NAO) Index (Jones, Jonsson, and Wheeler 1997), the Western Mediterranean Oscillation Index (WeMOI) (Martin-Vide and Lopez-Bustins 2006), the Multivariate ENSO Index (MEI) (Wolter and Timlin 1993), and the Arctic Oscillation (AO) Index (Thompson and Wallace 1998).

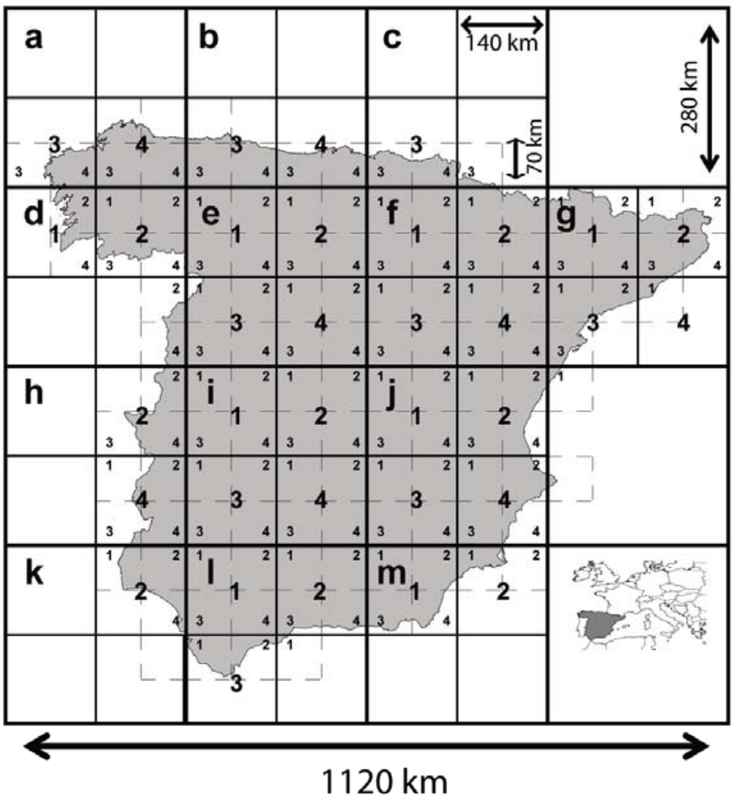


Figure 4.10. Map of the grid system used to study drought responses in the Spanish Iberian Peninsula. Three different grid scales were examined: 280 x 280 km^2 (12 grid cells; a-m); 140 x 140 km^2 (35 grid cells; a3-m2) and 70 x 70 km^2 (130 grid cells; a33 – m22).

SPEI time series were visually inspected and trends were analyzed applying spline fits. To detect abrupt shifts between multiannual periods characterized by significantly different SPEI values, we applied regression tree analyses using the JMP 10 package (SAS Institute Inc 2012). We identified an optimal splitting point (i.e. time of shift) in the time series separating multiannual periods characterized by contrasting SPEI values (De'ath and Fabricius 2000). The magnitude of the shift between two periods was quantified by the amount of variance explained by the model and was therefore inversely proportional to the model-corrected Akaike Information Criterion (1/AICc). The splitting criterion was based on the LogWorth statistic. When a significant shift was detected in the regression tree and spline analyses, we applied a Tukey-Kramer analysis to test for significant differences in SPEI values between the two multiannual periods before and after the splitting point.

We applied structural equation models to assess the relative influence of the AMO and the other teleconnection indices (NAO, MEI, WeMOI, and AO) on SPEI variability. The basic model scheme analyzed is based on Figure 4.14a.

Early warning signals were quantified using the earlywarnings R package (Dakos et al. 2012). The analyses were restricted to the time period before the splitting point previously identified by the regression tree models. The function generic early warning signals (generic_ews) and the function qda_ews were used to estimate the following eight statistical moments within rolling windows along the time series: the autoregressive (AR) coefficient ar(1) of a first-order AR model fitted to the data, the standard deviation, skewness, kurtosis, the coefficient of variation, the return rate of the data estimated as the 1-ar(1) coefficient, the density ratio of the power spectrum of the data estimated as the ratio of low to high frequencies, and the autocorrelation at the first lag of the data. The trends of these eight statistical moments were estimated by using the nonparametric Kendall tau correlation coefficient. The function sensitivity_ews was applied to plot the Kendall tau estimates and their *p*-values for the range of rolling-window sizes used, together with a histogram of the distributions of the statistic and its significance. The analyses were computed for a large range of window sizes (winsize parameter: 10, 20,…50 years). We computed and plotted the power spectrum estimated by the spec.ar function for all frequencies within each rolling window.

To assess the impacts of shifts in the drought regime on forest carbon sequestration, we selected a Mediterranean conifer, *Pinus halepensis* Mill., and quantified the yearly variation in gain of carbon stocks in 20 stands (Figure 4.11 and Table 4.2). This species was selected because it is the dominant native conifer in the eastern region of the Iberian Peninsula and in the Mediterranean Basin.

Code	Site	County	Lat (º)	Long (º)	Altitude (m)
1. AL	Alcubierre	Zaragoza	41,82	0,51	278
2. ARC	Archivel	Murcia	38,09	-2,033	1086
3. AYN	La Dehesa. Ayna los Luisos	Albacete	38,59	-2,08	1000
4. BAN	Banyoles. Porqueres.	Girona	42,11	2,74	260
5. CS	Castejón de Valdejasa-Zuera	Zaragoza	41,89	-0,91	500
6. ENG	Serra d'Enguera. Navalón.	Valencia	38,86	-0,90	800
7. FUE	Fuentespalda	Teruel	40,83	0,08	850
8. GAR	Garraf. Olesa de Bonesvalls	Barcelona	41,34	1,84	300
9. GDM	Guardamar del Segura	Alacant	38,09	-0,65	10
10. ISI	Los Isidros. Venta del Moro	Valencia	39,45	-1,28	635
11. LLA	La Llacuna. Serra d'Ancosa	Barcelona	41,45	1,53	730
12. MAI	Serra de Maigmó. Tibi.	Alacant	38,53	-0,64	900
13. MCL	El Mencal. Pedro Martínez	Granada	37,51	-3,17	1150
14. MIR	Miramón. Monegrillo	Zaragoza	41,62	-0,33	500
15. MTS	Montsant. Margalef	Tarragona	41,33	0,82	775
16. PNF	Peñaflor de Gallego	Zaragoza	41,78	-0,73	375
17. PU	Puerto de Alcubierre	Zaragoza	41,82	0,50	520
18. QRL	Puig de les Marietes. Querol	Tarragona	41,39	1,43	770
19. RET	La Retuerta de Pina. Pina de Ebro	Zaragoza	41,48	-0,24	386
20. VA	Valareña. Ejea de los Caballeros	Zaragoza	42,09	-1,35	520

Table 4.2. List of the examined stands of Pinus halepensis. Coordinates are specified using datum WGS84.

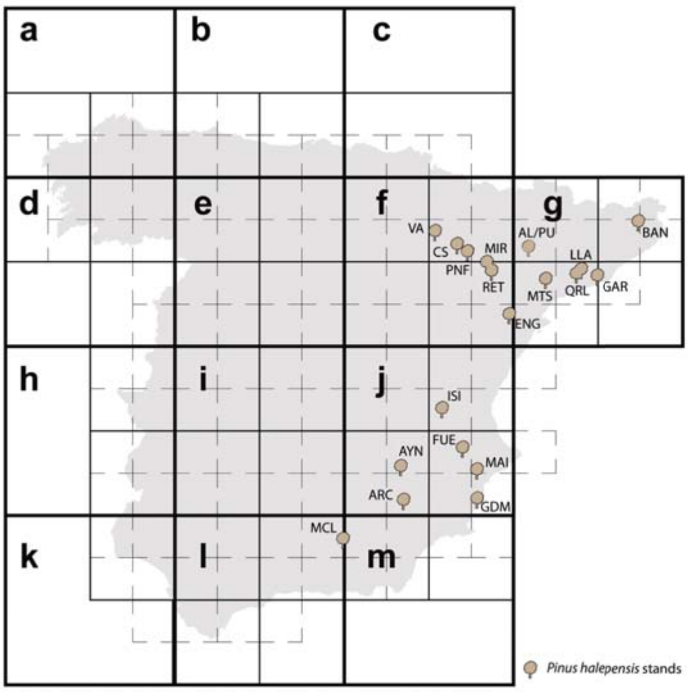


Figure 4.11. Detailed map of the distribution of the examined *Pinus halepensis* stands.

The selected stands represented the native geographical distribution of this taxon across the Iberian Peninsula, providing a regional assessment for this species (Camarero et al. 2015; Ribas

2006). Tree density and stand basal area were estimated in each stand. A variable number of trees (8-38) were also randomly sampled for dendrochronological analyses in an area of 2 ha (Ribas, 2006). The selected trees were at least 5 m apart. We extracted 2-4 radial cores per tree at 1.3 m using a Pressler increment borer. Wood samples were sanded and visually cross-dated. Tree-ring widths were measured to the nearest 0.01 mm using a LINTAB measuring device (F. Rinntech, Germany), a binocular scope, and the programmes CATRAS and TSAP. COFECHA assessed the accuracy of the visually cross-dated samples (Camarero et al. 2015). For each tree, we also measured the diameter at breast height (1.3 m), height, the length of sapwood in the extracted cores, and the annual increase in basal area (Camarero et al. 2015). Finally, we applied species-specific allometric equations (Montero, Ruiz-Peinado, and Muñoz 2005) to calculate annual increases in biomass and total carbon (kg ha^{-1} y^{-1}). We applied regression tree analyses to detect shifts in the annual rates of carbon sequestration in the derived time series (De'ath and Fabricius 2000).

4.4.4 Results and discussion

We started by analyzing the time series of drought trends in the Iberian Peninsula using the SPEI (Vicente-Serrano, Beguería, and López-Moreno 2010). This index allowed us to explore shifts in drought regimes at temporal scales ranging from 3 to 36 months during 1950-2012. Regression tree analyses identified a consistent shift in SPEI trends affecting the entire central-eastern Iberian Peninsula over the period 1979-1981 (Figure 4.12). This abrupt shift was consistently detected in regression tree models across a wide range of SPEI temporal scales (3-36 months) and across different scales of spatial grids (Section 4.4.6: Supplementary Figure 4.4.6.1/Supplementary Figure 4.4.6.2/Supplementary Figure 4.4.6.3).

Average SPEI values consistently differed before (1950-1979) and after the abrupt shift (Figure 4.13a, Tukey-Kramer test $p<0.0001$). A different pattern of longitudinal variation of average SPEI values was also consistently observed before and after the 1979-1981 shift – with the SPEI switching from increasing with longitude to decreasing with longitude (Figure 4.13b). These results indicate an abrupt large-scale shift in drought trends in this area and justify testing for alternative large-scale drivers of these trends (i. e. teleconnections).

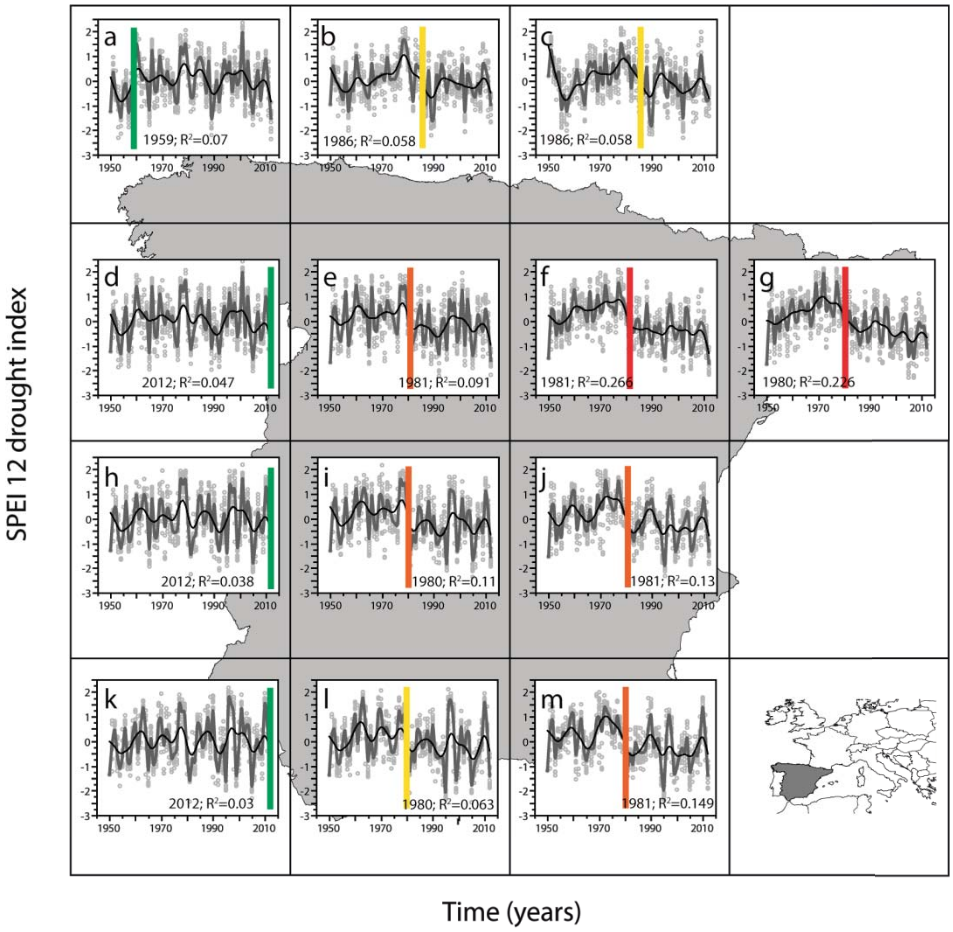


Figure 4.12. Drought-regime shifts. Observed shifts in monthly SPEI series (12-month window) at a grid resolution of 280 x 280 km^2 in the Spanish Iberian Peninsula. The year of a shift and the variance explained by the regression tree model are indicated. The splitting points obtained by the regression tree analyses for 1950-2012 are indicated by colored vertical bars. Red bars indicate shifts characterized by R^2 >0.20. Orange bars indicate significant shifts with regression tree 0.10<R^2<0.20. Yellow bars indicate 0.01<R^2<0.10. Green bars indicate a splitting point departing from the studied 1979-1981 time period. Negative SPEI values indicate dry periods.

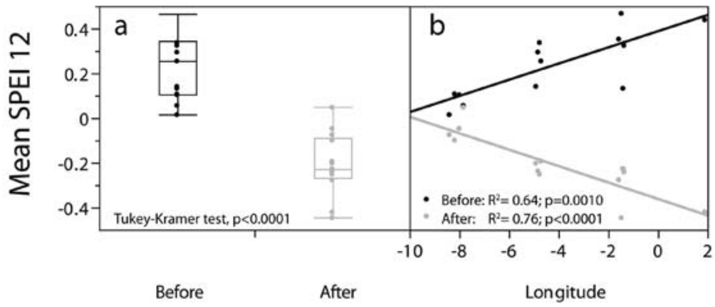


Figure 4.13. Drought-regime shifts. Observed variation in mean SPEI (12-month window) values between the 1950-1979 and 1987-2012 time periods at a grid scale of 280 × 280 km^2. These two time periods illustrate the contrasting values before and after the splitting point detected by the regression tree analyses. **a,** Tukey-Kramer test identifying significant differences between time periods. **b,** Longitudinal variation of mean SPEI 12-month values in 280 × 280 km^2 grid cells. Contrasting trends were observed before and after the shift.

To identify the teleconnections associated with the abrupt shift in SPEI values, we applied structural equation models to contrast the relative influences of five indices on SPEI: the AMO, the NAO, the WeMOI, the MEI, and the AO indices. The models identified AMO as the strongest predictor of the variability in SPEI values (Figure 4.14a, Supplementary Figure 4.4.6.4/Supplementary Figure 4.4.6.5). The standardized coefficients of AMO on SPEI were robust predictors of the magnitude of the regime shift detected by the regression tree models in each grid cell (Figure 4.14b). These results identified the AMO index as a significant predictor of the abrupt shifts in the drought regime in the study area (Supplementary Figure 4.4.6.5).

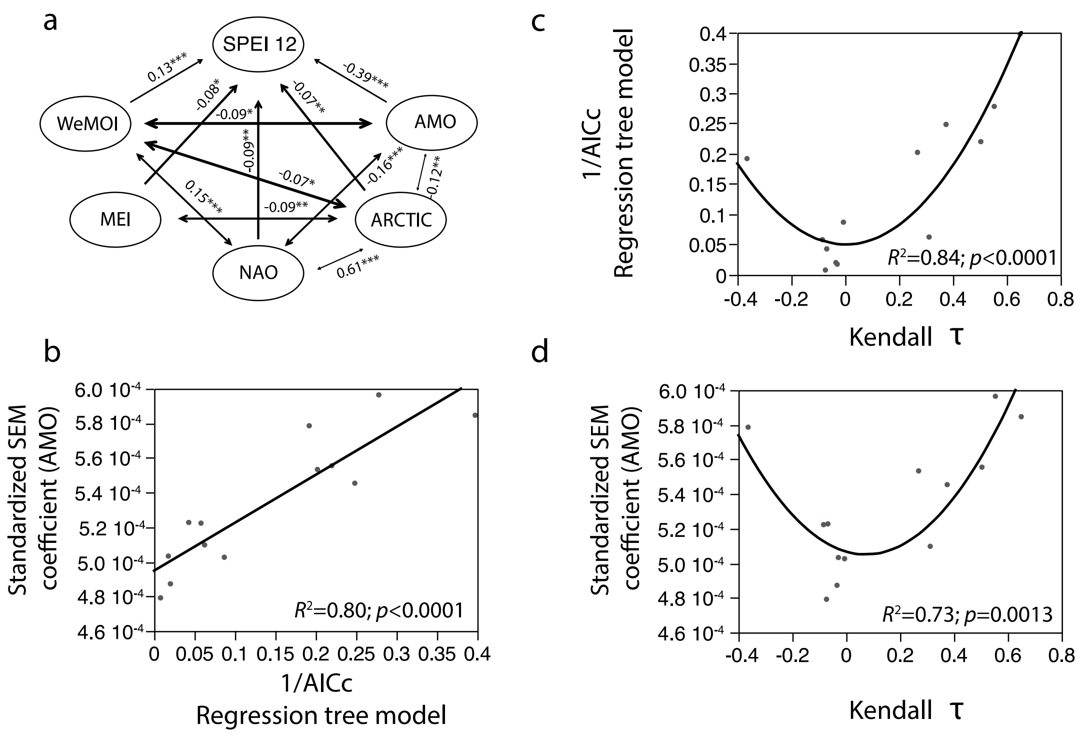


Figure 4.14. Structural equation modeling (SEM) and analyses of early warning signals. **a,** Standardized coefficients in the SEM model for grid cell **g** (280 × 280 km^2 scale, Figure 4.10). Model-fitting parameters: χ^2=3.036, p=0.36; BIC=-16.81. **b,** Relationship between the standardized coefficients in the SEM models linking AMO and SPEI and the variation explained by the regression tree analyses (1/AICc). **c,** Relationship between the nonparametric Kendall tau correlation coefficient for the AR(1) moment (based on the SPEI 12-month time series during the 1950-1979 period) and the variance explained by the regression tree models (1/AICc). **d,** Relationship between the nonparametric Kendall tau correlation coefficient and the standardized coefficients of the SEM connecting AMO and SPEI 12-month.

Having identified abrupt shifts in drought regime linked to the AMO, we examined whether they carried any early warning signals. We assess this by estimating changes in lag-1 autocorrelation in the SPEI time series (Dakos et al. 2012) based on a sliding window of SPEI monthly data before the abrupt shifts. Changing autocorrelation can reflect changes in the balance of negative and positive feedback governing the dynamics of the SPEI index. Abrupt shifts in drought regime in the eastern Iberian Peninsula were preceded by an increase in autocorrelation (Figure 4.15). The values of the Kendall tau statistic quantifying autocorrelation trends were positively associated with the magnitude of the observed shift in the local SPEI time series (Figure 4.14c) and with the effect of the AMO on the drought indices (Figure 4.14d).

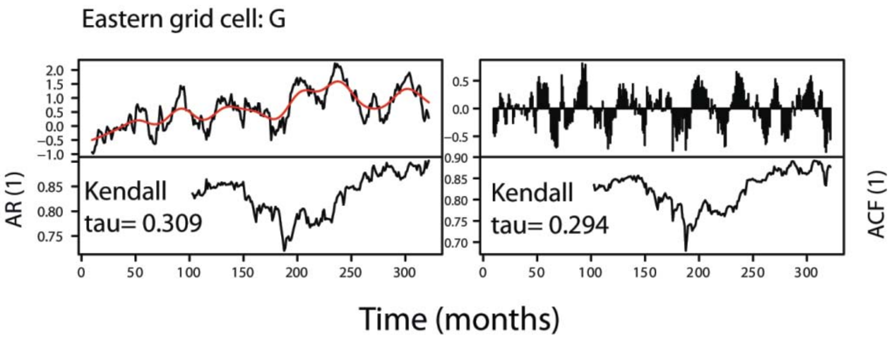


Figure 4.15. Early warning signal analyses for the 1950-1979 time period for Easter grid cell **g**. The autoregressive coefficient AR-1 (early warning signal) for the time series of the multi-scalar drought index SPEI 24-month is shown. This cell shows a continuous increase in AR-1 values in 1970-1979 and positive Kendall tau values. A peak (maximum value of AR-1) is achieved just before the shift (1980).

To assess the effects of abrupt shifts in the drought regime on forest carbon storage, we examined the yearly increase in carbon stock in 20 forest stands of *Pinus halepensis* Mill. during 1950-2012 (Figure 4.11). We combined dendrochronological analyses and allometric equations to calculate the variation in carbon stocks in each of the forest stands for 1950-2012 (Montero, Ruiz-Peinado, and Muñoz 2005). The trends of the gains in carbon stocks clearly shifted in 18 of the 20 stands, changing from sustained positive gains to stable, non-significant trends (Figure 4.16). The trends in two cases reversed from positive to significantly negative (Figure 4.16a-c). In contrast, the dynamics of carbon gain did not qualitatively shift in two stands at the southern edge of the study area (Figure 4.16o-p). Regression tree models based on tree-ring width data identified significant shifts in 16 of 18 stands during 1978-1981, in line with the shift in drought dynamics (Figure 4.12, Figure 4.13, Supplementary Figure 4.4.6.1/Supplementary Figure 4.4.6.2/Supplementary Figure 4.4.6.3).

We combined a variety of models (ordinary least squares and structural equation models) and identified AMO as the best teleconnection index for predicting changes in carbon stocks in the Aleppo pine stands. The models revealed a significantly stronger AMO signal for carbon-stock gains in northern stands (p values < 0.0001 in 5 stands; p values < 0.001 in 2 stands; p values < 0.01 in 3 stands; p values < 0.05 in 1 stands). These results suggest that multi-decadal shifts in local drought regimes under the influence of the AMO have considerable impacts on local carbon sequestration by a dominant Mediterranean tree (*P. halepensis*).

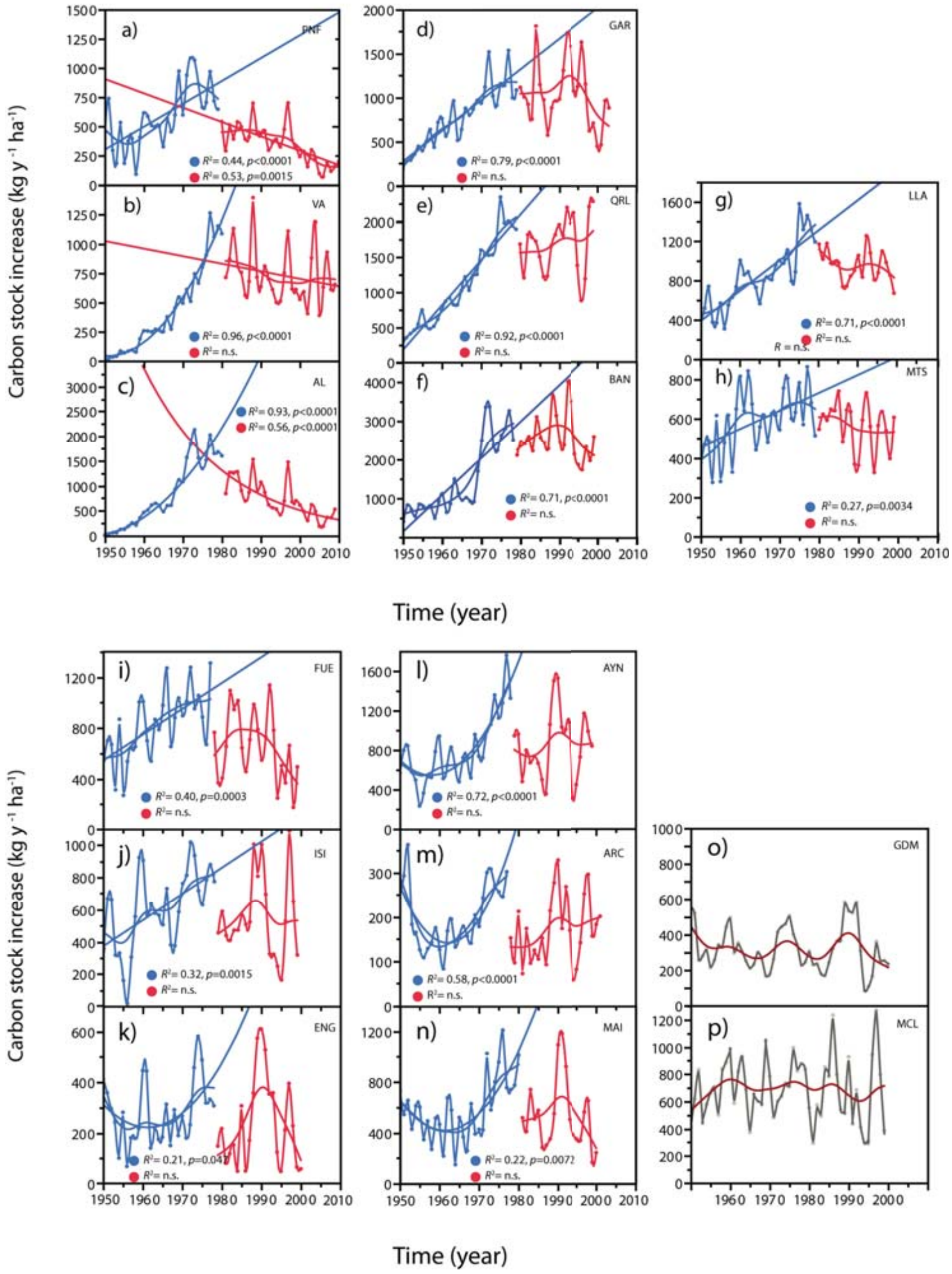


Figure 4.16. Observed changes in carbon-stock dynamics in 16 stands of *Pinus halepensis.* **(a-h)** Stands located in the northeastern Iberian Peninsula and **(i-p)** stands located in the southeastern Iberian Peninsula. Blue dots and lines represent the observed trends in carbon gain during the first three decades. Red dots and lines illustrate the observed dynamics during 1980-2010. Significant linear and non-linear trends are shown (ordinary least squares regression and polynomial fits). Smoothed trends fitted by the cubic spline method are represented (λ values = 0.01 and 100). No significant shifts were observed in stands GDM and MCL **(o-p).**

In summary, our results show that abrupt shifts in multiannual drought regimes affect extensive areas, roughly 350 000 km^2, of the Iberian Peninsula. These trends towards drier conditions were significantly associated with the AMO index and with increasing temporal autocorrelation in the SPEI time series (Figure 4.14). Furthermore, shifts in drought regime impacted the dynamics of carbon sequestration in Mediterranean Aleppo pine stands.

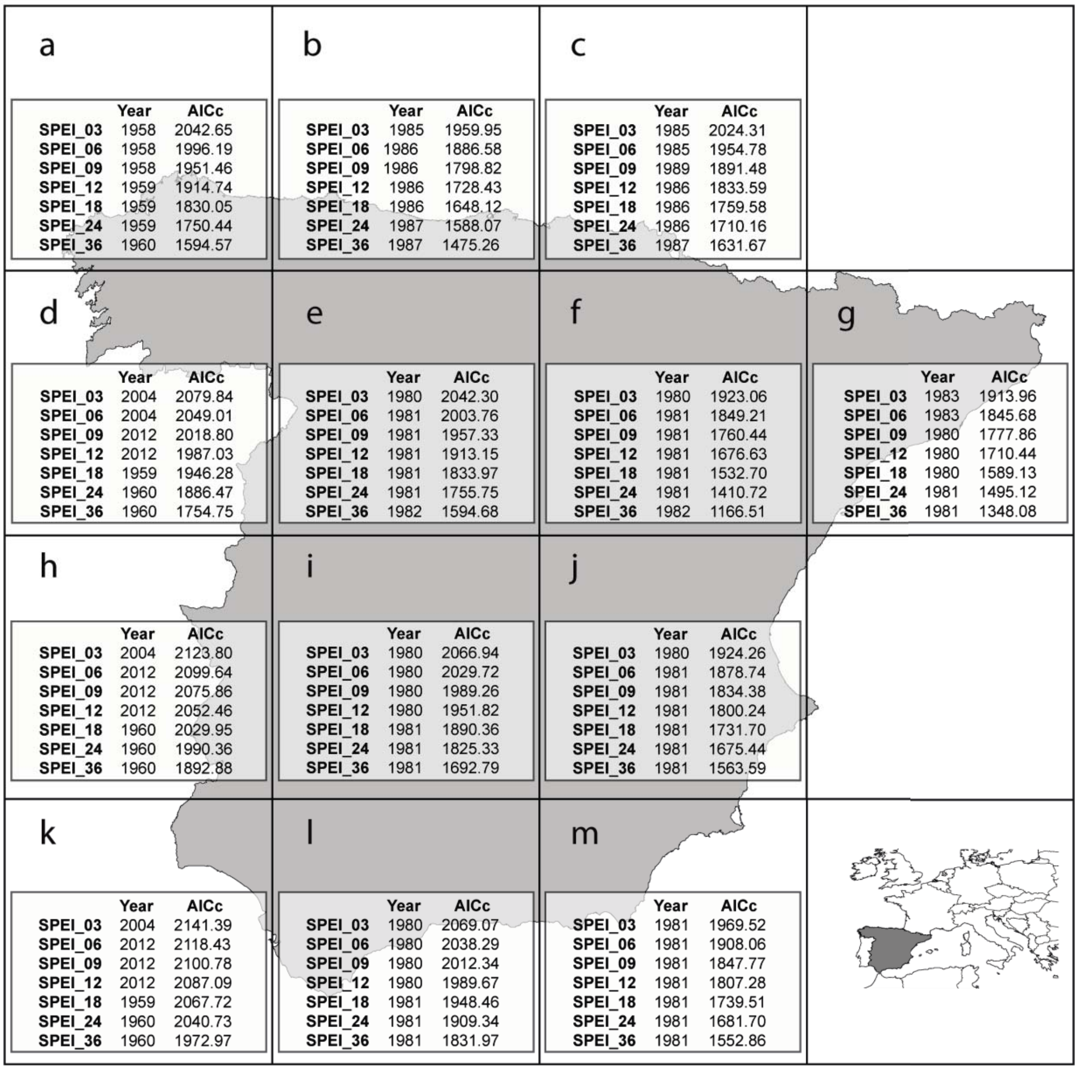
These results add to previous studies reporting significant associations between the Atlantic multi-decadal variability, quantified by the AMO index, and large-scale patterns of drought (Enfield, Mestas-Nuñez, and Trimble 2001; Sutton and Hodson 2005). The AMO variability has long been hypothesized as ultimately linked to the Atlantic Meridional Overturning Circulation (AMOC) (Kushnir 1994), with warm phases of the AMO corresponding to a faster AMOC and increased transport of saltier water to sinking areas of the North Atlantic subpolar region. A transition from warm to cool phases may imply increased melting rates of Arctic ice during the warm phase, producing less dense surface water in the subpolar regions, reduced sinking activity, and a subsequent general slowdown of the AMOC (Chen and Tung 2014). A strong AMOC slowdown after 1975 has been described as an unprecedented event in the past millennium (Rahmstorf et al. 2015). The AMO is also significantly associated with sea-level air pressure and anomalies in wind circulation (Alexander, Halimeda Kilbourne, and Nye 2014; Kushnir 1994). During the 1970s and 1980s the AMO shifted from a warm to a cold phase (Enfield, Mestas-Nuñez, and Trimble 2001). Prior to the reported shift in 1980 and during the warm phase of the AMO (i. e. 1940-1970), sea-level pressure was lower than normal over the Central Atlantic Ocean (40-50ºN, 20-40ºW) (Kushnir 1994). In contrast, sea-level pressure increased during the transition to the subsequent cold phase (1970-1980), paralleled by reduced cyclonic circulation and weaker westerly winds in the Central Atlantic Ocean (Kushnir 1994).

These changes may have contributed to an abrupt decrease in the transport of atmospheric moisture from the ocean to the Iberian Peninsula and to the differences in SPEI values observed in this area (Vicente-Serrano et al. 2013; C. Wang, Lee, and Enfield 2008). A recent study highlights that enhanced warming of terrestrial surfaces relative to oceans (Sherwood and Fu 2014) may account for recent drought dynamics in the Iberian Peninsula. The combination of a low supply of water vapor from oceanic sources and increased land temperatures in this area has tended to increase reference evapotranspiration and decrease relative air humidity (Azorin-Molina et al. 2015; Vicente-Serrano et al. 2013). For example, the increase in the surface temperature since the late 1970s was much smaller in areas of the Atlantic that supply moisture than for the land (Vicente-Serrano et al. 2013). In addition, surface temperatures did not increase after 1995 in the areas of the two main sources of oceanic moisture (Atlantic and Mediterranean) (Vicente-Serrano et al. 2013), and a progressive shift to a warm phase of the AMO during this period was paralleled by increased heat transported to deeper layers in the Atlantic and Southern Oceans and a salinity anomaly in the subpolar North Atlantic (Chen and Tung 2014), which have slowed the warming trends of sea-surface temperatures since the beginning of the century (2000-2015).

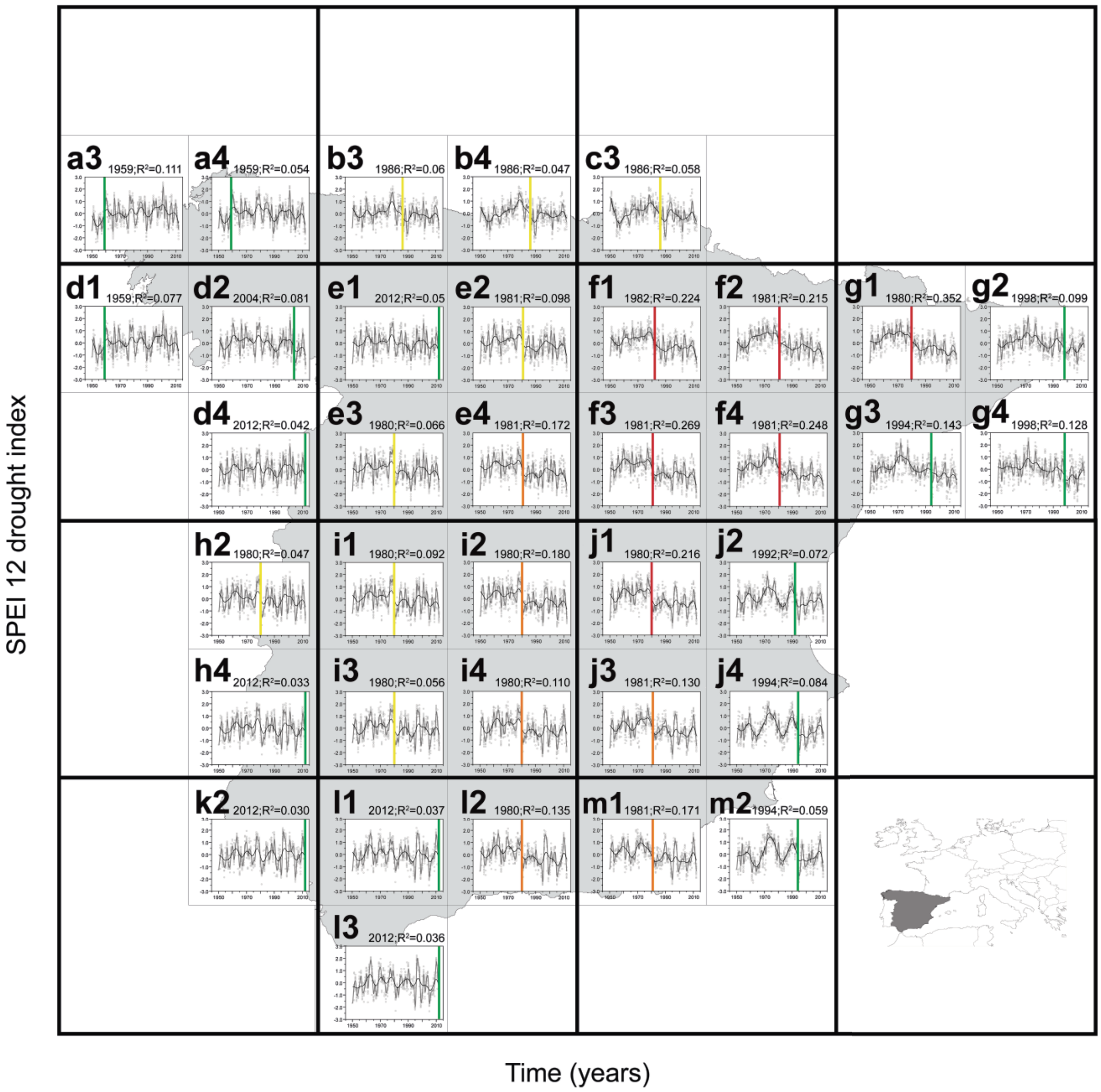
4.4.5 Conclusions

The emerging picture is a complex interplay of factors determining drought dynamics in the Iberian Peninsula, characterized by multi-decadal effects of the AMO on oceanic sources of humidity and the differential impact of warming trends in oceanic and terrestrial surfaces (Azorin-Molina et al. 2015; Sherwood and Fu 2014; Vicente-Serrano et al. 2013). Our results thus indicate that the AMO, beyond its key role in determining periods that slow the dynamics of global warming, is also significantly associated with multi-decadal changes in key ecosystem services such as carbon sequestration. The projected weakening of the Atlantic Meridional Overturning Circulation during the next decades (Robson et al. 2014) may substantially reduce the carbon sink activity of semi-arid forests across extensive areas in the Western Mediterranean basin, promoting in turn a positive feedback response on atmospheric CO_2 concentrations. Our study thus suggests that a new avenue of research is warranted, combining the coupled feedbacks between carbon sequestration by forests, multi-decadal climatic dynamics, and global warming.

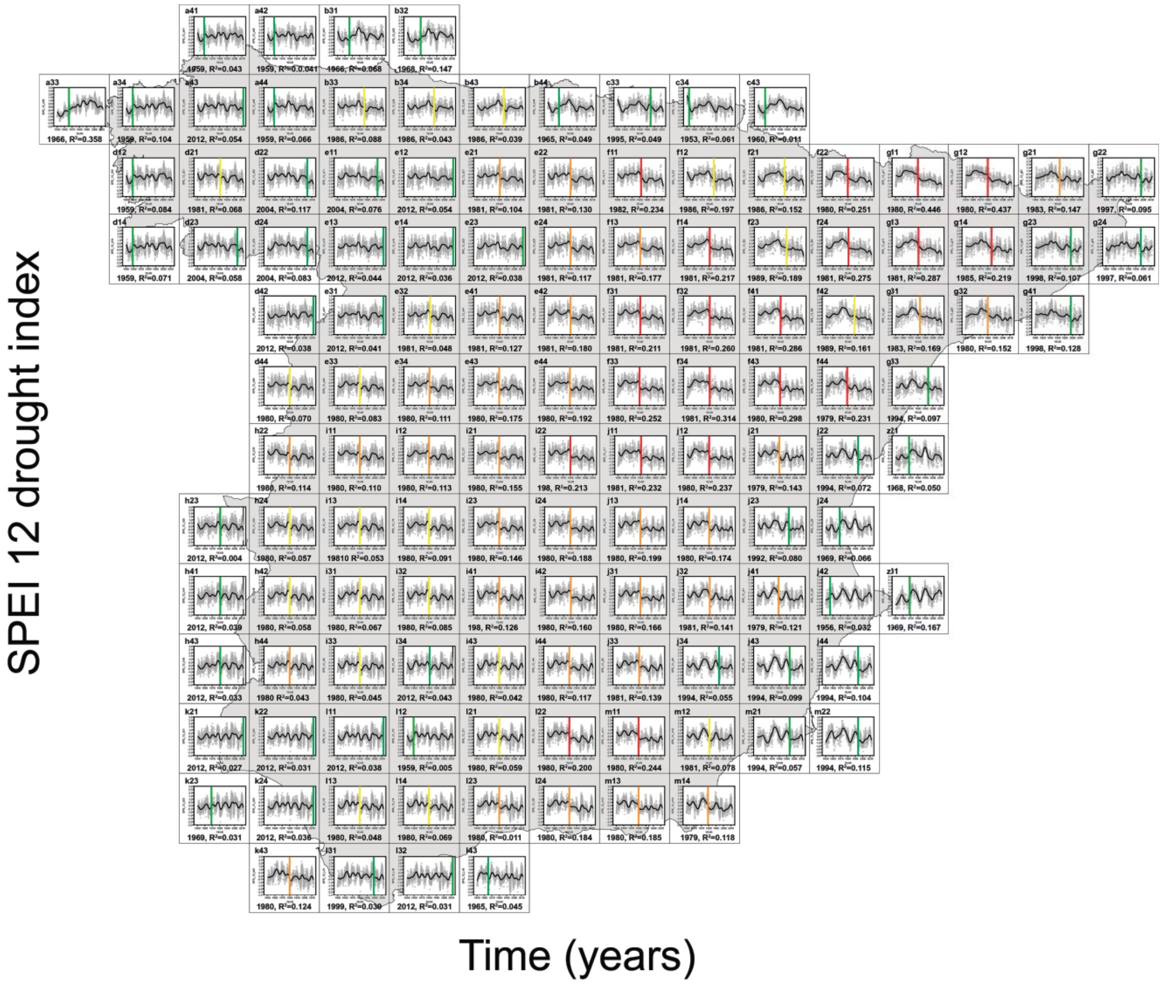
4.4.6 Supplementary materials



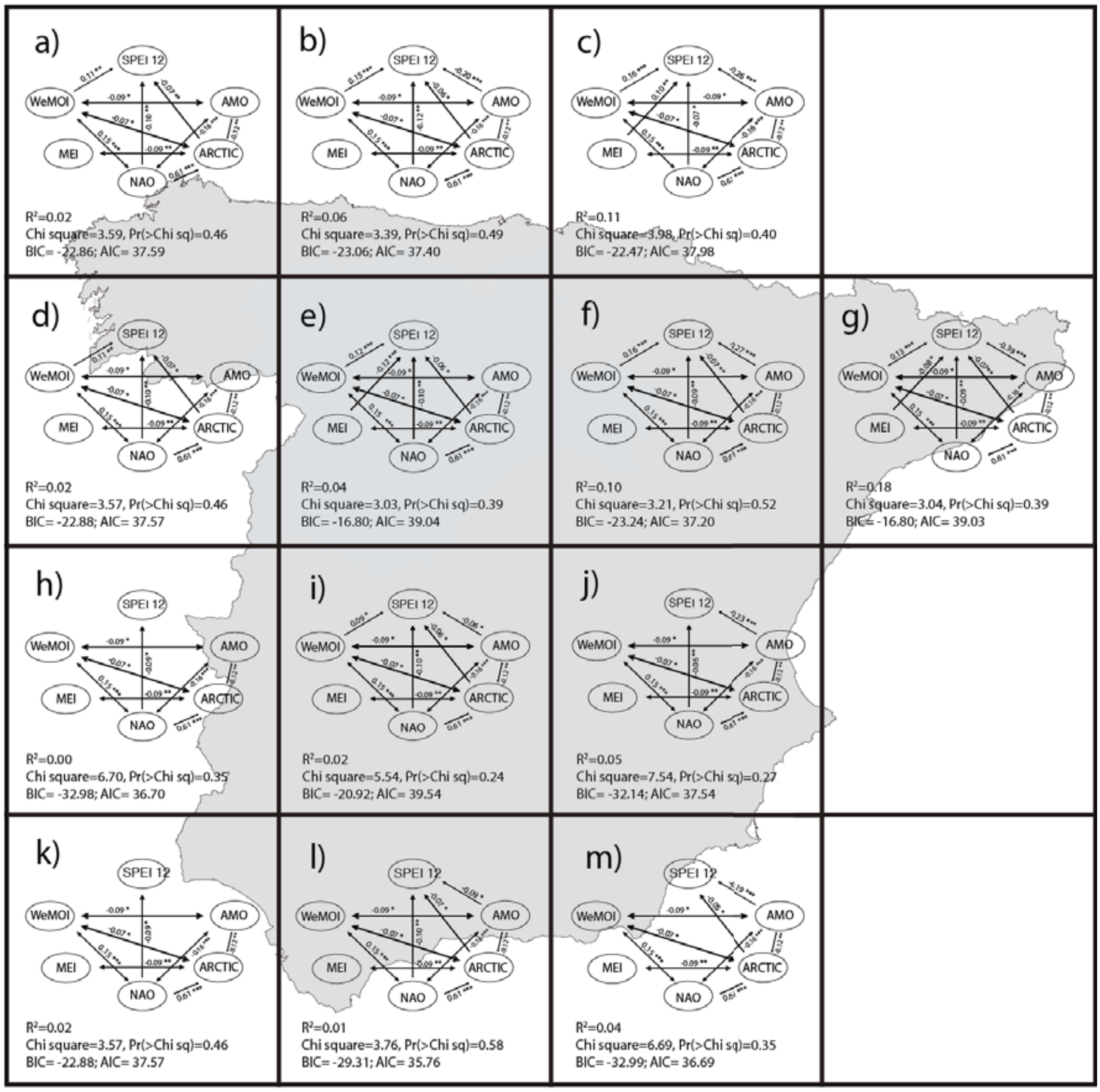
Supplementary Figure 4.4.6.1. Observed shifts in regression tree models for SPEI 3-36-month time series and for each grid cell (280 x 280 km^2 grid scale). A consistent large-scale pattern of shift in SPEI values was observed (affecting the following cells: e, f, g, i, j, l, m).



Supplementary Figure 4.4.6.2. Observed shifts in monthly SPEI 12-month time series for 140 x 140 km^2 grid. The splitting points obtained in regression tree analyses for the 1950-2012 time period are indicated by colored vertical bars. Red color illustrates strong shifts (i.e. regression tree R^2 values > 0.20); orange color indicates mid or intermediate shifting patterns (i.e. regression tree R^2 values ranging from > 0.1 to < 0.2). Yellow color indicates weak shifts (i.e. R^2 values < 0.1). Green color illustrates that the splitting point preferentially selected by the model clearly departed from the studied 1979-1981 focal period. The selected year of shift and the explained variance by the regression tree model are indicated



Supplementary Figure 4.4.6.3. Observed shifts in monthly SPEI 12-month time series for the 70 x 70 km^2 grid. The splitting points obtained in regression tree analyses for the 1950-2012 time period are indicated by colored vertical bars. Red bars illustrate strong shifts (i.e. regression tree models characterized by R^2 values > 0.2); orange bars indicate intermediate shifts (i.e. regression tree models with R^2 values ranging from > 0.1 to < 0.2). Yellow color bands illustrate weak shifts (R^2 values < 0.1). Green color illustrates that the splitting point preferentially selected by the model clearly departed from the studied 1979-1981 focal period. The selected year of shift and the explained variance by the regression tree model are indicated in each panel.



Supplementary Figure 4.4.6.4. Structural equation modeling (SEM) for each grid cell (280 x 280 km^2). Observed standardized coefficients and fitting parameters obtained in the SEM models for SPEI 12-month.

AMO	GRID CELLS (a-m)			
	a	b	c	
	St. Coef ± St.Error	St. Coef ± St.Error	St. Coef ± St.Error	
SPEI 03	-0.083 ± 0.156 *	-0.141 ± 0.145 ***	-0.202 ± 0.149 ***	
SPEI 06	-0.079 ± 0.156 *	-0.139 ± 0.143 ***	-0.218 ± 0.147 ***	
SPEI 09	-0.072 ± 0.156 *	-0.173 ± 0.137 ***	-0.245 ± 0.143 ***	
SPEI 12	-0.054 ± 0.154	-0.191 ± 0.133 ***	-0.258 ± 0.139 ***	
SPEI 18	-0.055 ± 0.152	-0.202 ± 0.128 ***	-0.245 ± 0.137 ***	
SPEI 24	-0.100 ± 0.150 **	-0.252 ± 0.126 ***	-0.286 ± 0.135 ***	
SPEI 36	-0.071 ± 0.148 *	-0.240 ± 0.124 ***	-0.315 ± 0.133 ***	
	d	e	f	g
	St. Coef ± St.Error	St. Coef ± St.Error	St. Coef ± St.Error	St. Coef ± St.Error
SPEI 03	-0.070 ± 0.160 *	-0.081 ± 0.157 *	-0.187 ± 0.147 ***	-0.247 ± 0.146 ***
SPEI 06	-0.061 ± 0.162 *	-0.066 ± 0.159 *	-0.214 ± 0.147 ***	-0.305 ± 0.143 ***
SPEI 09	-0.038 ± 0.161	-0.055 ± 0.158	-0.242 ± 0.145 ***	-0.348 ± 0.140 ***
SPEI 12	-0.016 ± 0.161	-0.042 ± 0.155	-0.273 ± 0.142 ***	-0.393 ± 0.136 ***
SPEI 18	0.010 ± 0.156	-0.016 ± 0.149	-0.253 ± 0.142 ***	-0.395 ± 0.133 ***
SPEI 24	-0.027 ± 0.155	-0.076 ± 0.150 *	-0.304 ± 0.076 ***	-0.434 ± 0.132 ***
SPEI 36	-0.006 ± 0.154	-0.044 ± 0.147	-0.325 ± 0.138 ***	-0.474 ± 0.132 ***
	h	i	j	
	St. Coef ± St.Error	St. Coef ± St.Error	St. Coef ± St.Error	
SPEI 03	-0.125 ± 0.164 ***	-0.121 ± 0.160 ***	-0.204 ± 0.145 ***	
SPEI 06	-0.096 ± 0.167 **	-0.095 ± 0.163 **	-0.209 ± 0.146 ***	
SPEI 09	-0.060 ± 0.168	-0.079 ± 0.163 *	-0.219 ± 0.146 ***	
SPEI 12	-0.034 ± 0.168	-0.065 ± 0.162 *	-0.229 ± 0.145 ***	
SPEI 18	0.001 ± 0.164	-0.050 ± 0.161	-0.201 ± 0.143 ***	
SPEI 24	-0.009 ± 0.165	-0.064 ± 0.160 *	-0.221 ± 0.144 ***	
SPEI 36	0.018 ± 0.164	-0.068 ± 0.160 *	-0.265 ± 0.014 ***	
	k	l	m	
	St. Coef ± St.Error	St. Coef ± St.Error	St. Coef ± St.Error	
SPEI 03	-0.139 ± 0.165 ***	-0.175 ± 0.158 ***	-0.200 ± 0.151 ***	
SPEI 06	-0.085 ± 0.170 *	-0.131 ± 0.162 ***	-0.183 ± 0.152 ***	
SPEI 09	-0.047 ± 0.171	-0.101 ± 0.162 **	-0.196 ± 0.149 ***	
SPEI 12	-0.023 ± 0.171	-0.086 ± 0.162 *	-0.190 ± 0.147 ***	
SPEI 18	0.015 ± 0.168	-0.071 ± 0.162 *	-0.175 ± 0.146 ***	* p < 0.05
SPEI 24	0.024 ± 0.171	-0.064 ± 0.160 *	-0.178 ± 0.147 ***	** p < 0.01
SPEI 36	0.046 ± 0.173	-0.083 ± 0.160 *	-0.245 ± 0.143 ***	*** p < 0.001

Supplementary Figure 4.4.6.5. Structural equation modeling (SEM) results. Observed geographical variation in the standardized coefficients linking AMO and SPEI in each grid cell (a-m, 280 x 280 km^2 scale). Significantly higher standardized coefficient values are observed at longer SPEI time scales and at northeastern grids. **p* value < 0.05; ** *p* value < 0.01; *** *p* value < 0.001.

Chapter 5

A REMOTE-SENSING CONTRIBUTION TO DROUGHT STUDIES

From MODIS surface reflectances' to vegetation indices

5 THE CONTRIBUTION OF REMOTE-SENSING TO DROUGHT STUDIES. From MODIS surface reflectances' to vegetation indices

This chapter contains a modified version of the article submitted to Remote-sensing of Environment (Domingo-Marimon, C., Pesquer, L., Cristóbal, J., & Pons, X.) and a modified version of the chapter published in:

Domingo-Marimon, C., Pesquer, L., Cristóbal, J., & Pons, X. (2015). Integration of climate time series and MODIS data as an analysis tool for forest drought detection. In J. Andreu, A. Solera, J. Paredes-Arquiola, D. Haro-Monteagudo, & H. A. J. Van Lanen (Eds.), Drought. Research and Science-Policy Interfacing (p. 514). CRC Press, Taylor & Francis Group.

As has been discussed in Section 2.3, drought plays an important role in natural ecosystems around the globe because its natural, economic and social impacts. Nonetheless, a lot of uncertainty still exists about the drought affliction of forests at the global scale. In Chapter 4, the capacity of drought indices, such as SPEI, for characterizing meteorological drought patterns has been demonstrated. Even thought, the scientific understanding of the impact of drought on forests should be both climatic and biological, taking into account e.g. phenological and hydrological state. Climate-based patterns do not entirely explain the real physiological state of vegetation, which is the most important variable for understanding the vulnerabilities of forest ecosystems to drought. A deliberation on the potential of remote-sensing for monitoring of drought effects on vegetation was undertaken in Section 1.2.

The present Chapter includes an overview of the MODIS products (Sections 5.1, 5.2, 5.3 and 5.4) subsequently used for evaluating the integration of climate data and remote-sensing data as an analytical tool for detection of forest drought (Section 5.5). Finally, there are several problems with the spatial heterogeneity of MODIS 8-day composites (introduced in Section 5.4); this is addressed in the present thesis by the presentation of a new methodology for generating 8-day products (Section 5.6).

5.1 The Moderate resolution Imaging Spectroradiometer sensor

Launched on December 18th 1999 and having a design life of 6 years, the Moderate-resolution Imaging Spectroradiometer, MODIS, onboard the Terra (EOS/AM-1) satellite is currently one of the favorite instruments of the remote-sensing research community. This reflects the versatility of the instrument and the scientific achievement of its design: a fascinating equilibrium between temporal, spectral, spatial and radiometric resolutions that allow interesting finds and analysis of land, ocean and atmosphere processes (Huete et al. 2002; Kaufman et al. 2005; Miller and McKee 2004). Evidence of its successful application can be seen in MODIS distribution metrics. Over the last 14 years (from 2000 to 2014) the NASA Land Processes Distributed Active Archive Center (LPDAAC) has distributed more than 7 000 TB of MODIS data to remote-sensing users in over 355 million MODIS scenes/files. The maximum was reached in 2014, with around 1 800 TB of information and more than 70 million scenes/files distributed (Meyer and Maiersperger 2015). Indeed, from the total number of remote-sensing publications included in the Scopus database from 2004 to 2014, 14.9 % are related to MODIS, compared to 19.4 % relating to Landsat or 2.2 % to MERIS (MEdium Resolution Imaging Spectrometer), demonstrating that the MODIS sensor plays a key role in current remote-sensing research.

One of the reasons for the success of MODIS is the large variety of processed products being distributed. Users are able to find and handle more than 100 products, from raw radiances, sea surface temperature or aerosol products, to derived vegetation indices or particulate organic/inorganic carbon. Products are arranged in several ways, from daily or annual to multi-date composites (8-day and 16-day), like the ones used, for example, in Hilker et al. (2015) and Wardlow and Egbert (2010).

Nevertheless, the research community continues identifying some issues to be improved on. For instance, the MOD35 product which is the MODIS cloud mask product, has certain properties which lead to uncertainties regarding overdetection or residual clouds (R. Liu and Liu 2013; Tang et al. 2013). Therefore, any MODIS product inheriting the MOD35 cloud quality control (QC) layer may present errors in cloud detection. This is the case of surface reflectance products (MOD09) (Leinenkugel, Kuenzer, and Dech 2013; Tan et al. 2006; Whitcraft et al. 2015), although they have been broadly validated (Kotchenova and Vermote 2007; Kotchenova et al. 2008; Kotchenova et al. 2006; Vermote and Kotchenova 2008).

5.2 MODIS Daily Land Surface Reflectance (MOD09GA)

The MODIS “Land Surface Reflectance Daily L2G global 500 m and 1 km”, MOD09GA, is a 500 m spatial resolution daily product that provides an estimation of the surface reflectance as it would have been measured at ground level if there were no atmospheric scattering or absorption. The Science Data Set (SDS) is composed of 7 reflectance bands (459–479 nm, 545–565 nm, 620–670 nm, 841–876 nm, 1230–1250 nm, 1628–1652 nm and 2105–2155 nm) together with their Quality Assurance Reflectance Data State (QA) and Quality Control (QC) bands and geolocation statistics. The QA, at 1 km spatial resolution, contains information about the state of the pixel (flag type: land, ocean, containing cloud, aerosol quantity or snow and fire; the QC, at 500 m spatial resolution, informs about the quality of the atmospheric correction of each pixel, aerosol retrieval data and data for assessing the aerosol retrieval algorithm (Vermote, Kotchenova, and Ray 2011).

5.3 MODIS 8-day Composite Surface Reflectance (MOD09A1)

A reported by NASA specifications, MOD09A1 is an 8-day composite estimating surface reflectance as it would have been measured at ground level if there were no atmospheric scattering or absorption (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod09a1). It has a nominal spatial resolution of 500 m with the same 7 spectral configuration of MOD09GA and a Quality Assurance Science Data Set (QA-SDS): Reflectance Data State (QA) and Reflectance Bands Quality (QC), which inform about the quality of each pixel. Composites combine observations of 8 days and select the best pixel available depending on several criteria. According to the MODIS Surface Reflectance User's Guide (Vermote, Kotchenova, and Ray 2011) the compositing criteria for selection include observations with the highest coverage followed by the assignation of scores corresponding to whether the pixel is flagged for cloud, cloud shadow, high or low aerosol, or contains high view angle or low solar zenith angle (less than 60 degrees). The observation with highest score and the lowest view angle is selected as output.

Certainly, the generation of the best possible product in a feasible time span is a major challenge. Indeed, the processing chain is crucial at all levels and a substantial effort has been made in order to produce a high quality set of products. However, some issues have been found in compositing products, which are explained in detail in the next Section (5.4).

5.4 MOD09A1 problem rationale

Some authors have already highlighted several issues regarding multi-date composites which present room for improvement. For instance, Cihlar (2000) mentions the effects of existing built-in-noise between adjacent composite pixels on radiometric properties, sometimes resulting in different reflectance values for the same land cover type. Also, it should be noted that in 8-day composite products, the real temporal resolution for each pixel in two consecutive 8-day composite images can vary up to 15 days (Guindin-Garcia et al. 2012). As a result, contiguous pixels may present significant reflectance shifts having a decisive implication in, for example, detecting and monitoring phenology and introducing errors when estimating temporal characteristics (Colditz and Ressl 2013).

A selection of these issues is illustrated below as examples of what an improved product should target.

5.4.1 Number of dates per 8-day composite

In 8-day surface reflectance composite products the aim is to have each pixel contain the best possible daily surface reflectance observation during an 8-day period, selected on the basis of several conditions (mentioned in Section 5.3). Therefore, resulting composites may include pixels from up to 8 different dates, and these have a distribution which is spatiotemporally independent, potentially resulting in undesirable highly patchy pixel aggregations (Figure 5.1).

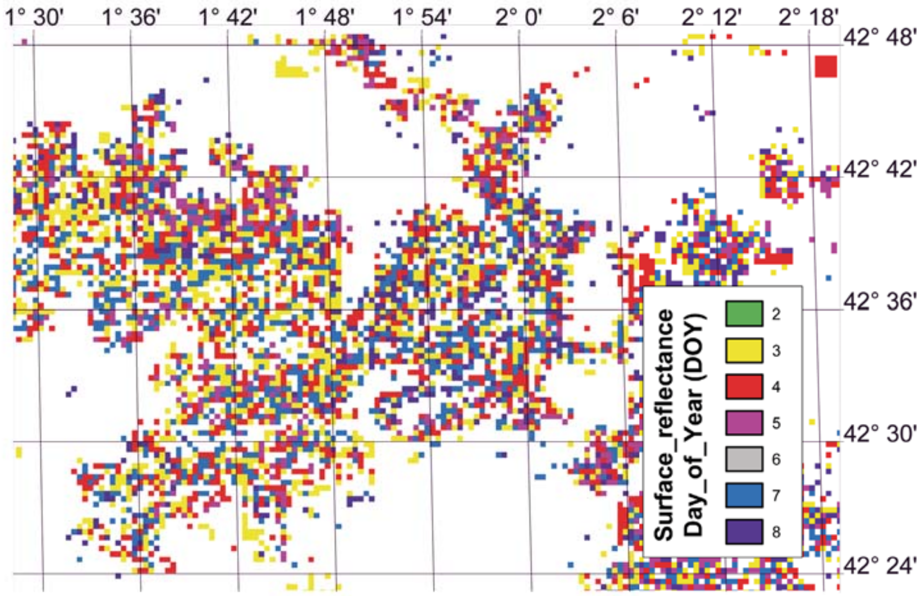


Figure 5.1. Salt and pepper distribution of the different days in a MOD09A1 8-day composite (01/01/2009). White areas correspond to cloud flagged pixels according to MOD09A1 cloud mask. Figure 5.2 demonstrates that this is usual throughout the year.

Spatiotemporal independence occurs because pixels are selected from within the 8-day sequence irrespective of neighbor pixels' day in the same 8-day sequence. As a result, pixels and their neighbors are often derived from different days. This is demonstrated by analyzing the number of dates per 8-day composite for the whole year, shown in Fig. 2. The example corresponds to a region of the Mediterranean falling within MODIS tile h18v04 (Northeast Spain). The average number of days used to generate the 8-day composite is 7.52 days, so each daily image is used for the majority of 8-day composites. It is notable that the original method uses up to 8 dates to generate the composite in a sunny Mediterranean area characterized by its low cloud cover during many months of the year. In fact, July 2009 had a median cloud state of 17.6 % per day according to MODIS cloud masks, and the minimum being 0.93 % on July 26th, reinforcing the idea that using 8 dates for the July 20th-28th composite should not be necessary.

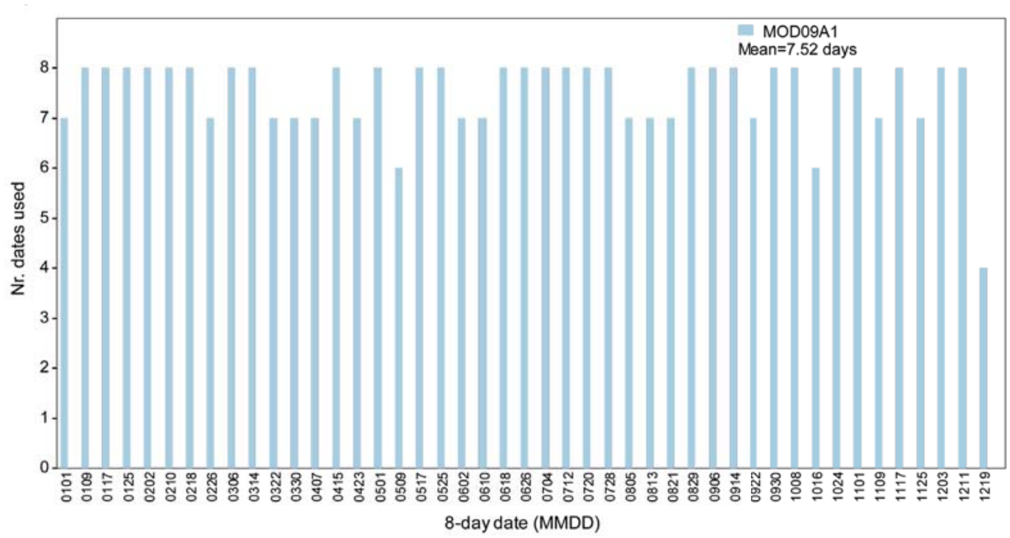


Figure 5.2. Number of days per 8-day composite in 2009 for MODIS tile h18v04 located in the study area detailed in Section 5.6.2.1.

This issue manifests itself in reflectance heterogeneity, corresponding to a salt and pepper noise effect as illustrated in Figure 5.3, becoming a major inconvenience when the land cover of neighbor pixels is the same.

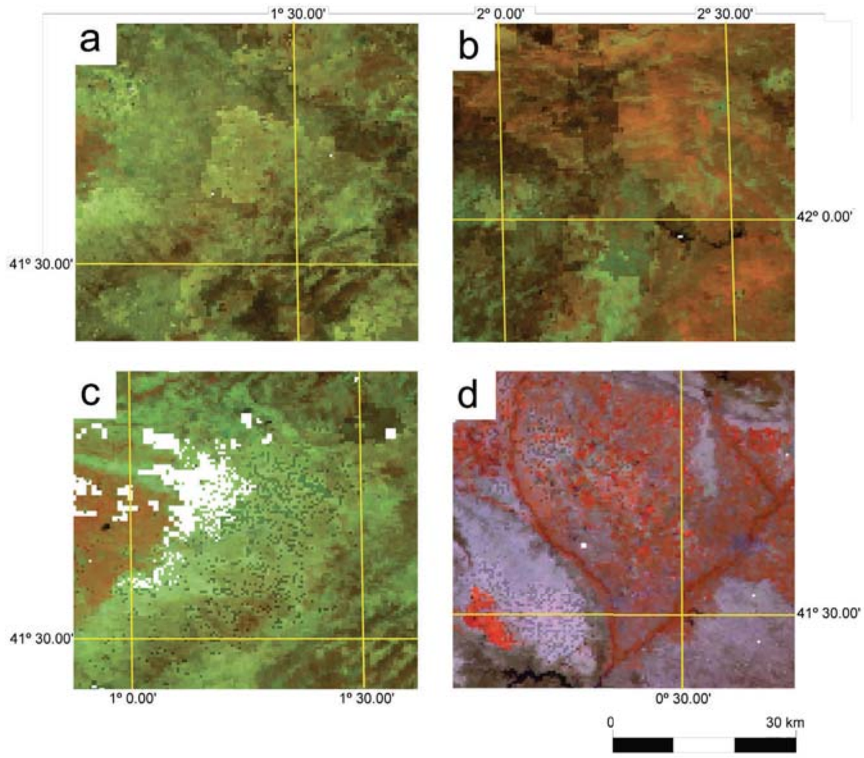


Figure 5.3. Examples of patchy and salt and pepper artifacts present in several parts of MOD09A1 products. a) 18th June 2009; b) 5th August 2009; c) 4th July 2009; d) 12th July 2009. (RGB compositions bands 2-6-1). Meridians and parallels are shown every 0.5°.

5.4.2 Reflectance shifts between contiguous pixels

Some work based on monitoring of agricultural production has concluded that compositing data collected within a maximum of 8 days is acceptable (Bolton and Friedl 2013; Johnson 2014; Sakamoto, Gitelson, and Arkebauer 2013). However, date shift may lead to significant differences in reflectance between contiguous pixels for the same land cover due to abrupt changes in e.g. vegetation phenology or crop harvesting, or it may also lead to inconsistencies in radiometric correction. Indeed, reflectance values may oscillate by up to 10 % (Figure 5.4). Concern about this issue was voiced by Cihlar (2000) who noticed the impact of these radiometric differences on classification.

At this point we have introduced the problems of compositing by a brief literature review, and these problems have also been demonstrated through a set of specific examples: these evidences support the idea that heterogeneous reflectance compositing products can lead to undesirable results. Later in this Chapter, a new methodology for generating 8-day products is presented (Section 5.6).

5.5 Integration of climate time series and MODIS data: an exploratory analysis

The analysis of time series of climatic anomalies indices, such as SPEI together with vegetation indices (VI) derived from satellite imagery could define a useful methodology to identify the most vulnerable areas affected by droughts. This Section contains the published article "*Integration of climate time series and MODIS data as an analysis tool for forest drought detection*" (Domingo-Marimon et al. 2015) in which such indicators were combined to characterize drought patterns. For this purpose, several vegetation indices were computed in order to ascertain the potential of remote-sensing data to determine drought events on forest areas. An exploratory analysis was conducted and results showed the capability of the methodology to identify and characterize drought patterns on forests and its potentiality for the identification of vulnerable areas.

As seen in previous section 5.4, MOD09A1 8-day product presents a series of artifacts which question the quality of the product. For this reason, the following study, *Integration of climate time series and MODIS data as an analysis tool for forest drought detection*, was based on MODIS daily surface reflectance data (MOD09GA).

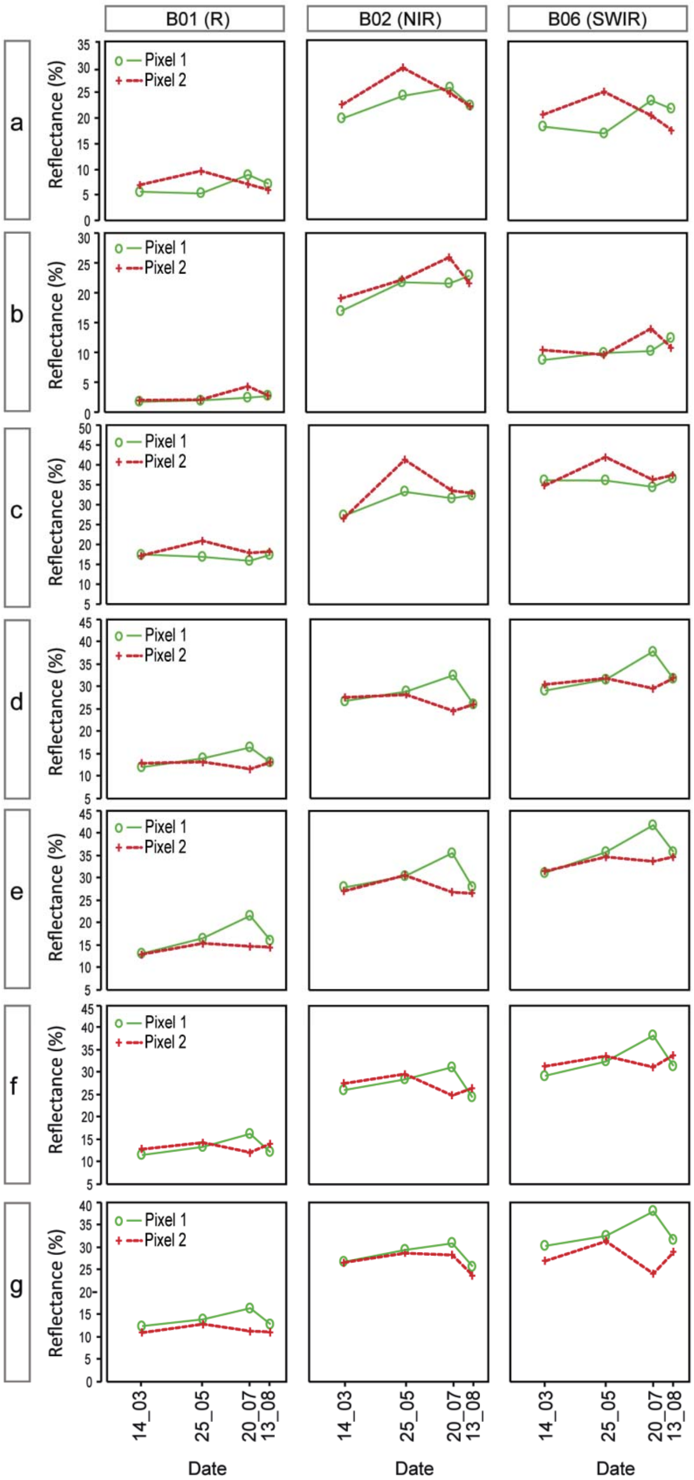


Figure 5.4. Spectral signatures from MODIS bands 1, 2 and 6 between contiguous pairs of pixels (Pixel 1 and Pixel 2) for 7 different locations (a-g) located in the same land cover according to official 1:5000 cartography. Note the significant shifts in reflectance values on a given date between contiguous pixels pairs (Pixel 1: P1 and Pixel 2: P2). Pixel coordinates in degrees: a) P1 (1.3659, 42.0311) P2 (1.3712, 42.0311) b) P1 (2.9427, 41.9230) P2 (2.9477, 41.9230) c) P1 (1.6057, 41.3105) P2 (1.6115, 41.3105) d) P1 (0.3874, 40.7232) P2 (0.3819, 40.7232) e) P1 (0.3869, 40.6939) P2 (0.3814, 40.6939) f) P1 (0.3098, 40.5898) P2 (0.3041, 40.5898) g) P1 (0.3093, 40.5768) P2 (0.3046, 40.5768).

5.5.1 Introduction

Drought plays an important role in natural ecosystems around the globe because of its natural, economic and social impacts. These impacts, widely recognized as a serious concern, have increasingly become an important topic for many management and policy decisions. In recent years there has been an increasing interest in droughts effects and monitoring due to the current situations of extreme climatic events. Such drought events have implications on many Societal Benefit Areas (SBAs) that GEOSS (Global Earth Observation System of Systems) addresses; and this phenomena set up an interconnection between different fields, such as health, food security, agriculture sustainability, ecosystem functions, biodiversity, carbon stocks, water resources, and wildfires, among others.

The most recent Intergovernmental Panel on Climate Change Fifth Assessment Report, WG1 AR5 (IPCC 2013) states that especially in the Mediterranean basin, the reduced precipitation is projected to be coupled with warmer temperatures, resulting in a decrease in water availability for natural and agricultural systems and human needs.

Drought research to date has tended to focus on agricultural systems and grassland environments rather than on other natural ecosystems such as forests, because agriculture is generally the first economic sector to be affected by a drought (Wilhite, Hayes, and Svoboda 2000). Traditionally, agricultural drought has been assessed by focusing on precipitation shortages and differences between actual and potential evapotranspiration, among others. Until now, several drought indices have been defined, and reported as successful (Hayes et al. 1999). During the last years, research in drought indices has advanced in the integration of timescales, universality and effortless computation. For instance, the Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano, Beguería, and López-Moreno (2010), emphasized climatic anomalies, using precipitation data, and integrating temperature as potential evapotranspiration as well as dealing with time frames.

Unfortunately, much uncertainty still exists about the global affection of droughts on forests. Nevertheless, forest drought is also meaningful because the invaluable ecosystems services they provide to society (Jacob, Wilson, and Lewis 2014). Forest management and forest decision support services are based on several key inputs, usually related to spatiotemporal drought patterns and to the identification of areas vulnerable to potential drought impacts. Clearly, the agricultural drought, although akin to the forest one, it is not the appropriate framework to follow. The different characteristics that both ecosystems present in terms of duration, intensity and spatial affection of droughts force to analyze forest drought from different perspectives. Therefore, the scientific approach to drought impact on forests should be done, from a climatic point of view as well as from a biological one, but climate-based patterns do not entirely explain the real physiological state of vegetation, which is the most important variable that is required in order to understand the vulnerabilities of forest ecosystems to drought.

Nowadays, Earth Observation satellites provide relevant long time-series of imagery that are crucial for forest monitoring and offer large possibilities on forest applications (Deshayes et al. 2006). The analysis of time series of climatic anomalies indices, such as SPEI together with vegetation indices (VI) derived from satellite imagery could define a useful methodology to identify the most vulnerable areas affected by droughts. Such a methodology can then be used to describe trends, lags, responses and intensity of drought effects, as well as the time required for forest recovery.

The aims of this paper are to show the necessity to understand biological spatiotemporal drought patterns for drought monitoring by integrating both climate and remote-sensing data by means of:

1. Investigating drought patterns which have been derived from a continuous spatiotemporal climate data interpolated from single stations.

2. Ascertaining the potential of remote-sensing data to determine drought events on forest areas.

5.5.2 Material and methods

5.5.2.1 Climate data and drought indicators

Meteorological station data distributed all over Spain for the years 1950-2012 was assembled from the State Meteorological Agency (AEMET) of Spain. Daily mean temperature and daily total precipitation were derived from these measurements and climate gridded maps were prepared according to an improved version of the procedure used by Ninyerola, Pons, and Roure (2007), refining the method in robustness, accuracy and spatial and temporal resolution. These data was structured in a Big Climate Data Cube set of approximately 6000 Standardized Precipitation Evapotranspiration Index surface maps of 100 m resolution, obtained from the interpolated meteorological variables in order to identify traditional climate-based drought anomalies. SPEI, which quantifies precipitation deficits at different time scales, was used as a drought indicator. This index is computed fitting a probability function to the frequency distribution of precipitation and evapotranspiration summed over the time scale of interest (3, 6, 9, 12, 18, 24, 36 and 48 months). The more negative the index value, the higher the intensity of drought. Thus, drought begins when the index rises below zero, increasing the intensity as it becomes more negative and cease with positive values of the index.

5.5.2.2 MODIS processing methodology

Changes in phenological state and biological damage of vegetation for the study area, Catalonia's forests (northeast of the Iberian Peninsula), are assessed using remote-sensing time-series of MODerate-resolution Imaging Spectoradiometer (MODIS) VI. Two time series of Terra MODIS Daily Surface Reflectance 500m product (MOD09GA) and Daily Land Surface Temperature 1km (MOD11A1) images were obtained through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS (https://lpdaac.usgs.gov/data_access). MOD09GA was chosen because of its multiple noteworthy advantages over other similar products available. For instance, products with higher spatial resolution have fewer bands designed for vegetation monitoring available. Alternatively, other products, such as MODIS Surface Reflectance 8-Day L3 Global at 250 m, are the best possible pixel observation of 8-day period composition. However, the real temporal resolution varies for each pixel in the image (Guindin-Garcia et al. 2012) exceeding up to 15 days in those cases where, for example, the image composed at day of the year (DOY) 1 and DOY 8 have a day of pixel composite (DPC) at day 2 and 16 (Colditz and Ressl 2013). The information of DPC is included in some products, but is missing in some others. Moreover, the real temporal resolution may have a significant implication in detecting and monitoring phenology (Guindin-Garcia et al. 2012) and using composites without taking into account the day of observation may introduce errors when estimating temporal characteristics (Colditz and Ressl 2013). Daily MOD09GA data allows user to deeply control data quality and temporal resolution given its associated Quality Assurance (QA) Science Data Sets: the Surface Reflectance Band Quality (QC) containing information about the quality of the atmospheric correction of each pixel, aerosol retrieval data and algorithm; and the Reflectance Data State band (QA) which contains information about the state of the pixel, configuring altogether a 21 layer product (Vermote, Kotchenova, and Ray 2011).

A total of 4331 images of available daily data for tile h18v04 were downloaded to cover the study area in Catalonia from 1st January 2001 until 31st December 2012. In order to ensure the highest quality data, best images are automatically selected following the methodology defined by Pesquer, Domingo-Marimon, and Pons (2013) which is based on two aspects: technical artifacts and natural phenomena. Regarding the first aspect, the above mentioned methodology considers the acquisition geometry to reject pixels being affected by the bow tie effect (sensor zenith angles higher than 35º) or with radiometric artifacts such as stripping noise in band 5. Furthermore, it takes into account an illumination condition criterion to elude shadow pixels as well as those that do not exhibit a Lambertian behavior for most surfaces (Pons et al. 2014). The second aspect considers the QA masks information to select only those pixels free of clouds, fire and snow. Altogether is complemented with a geostatistical spatial pattern analysis of images based on variogram tools. In addition, masking of some natural phenomena was improved due to its initial low quality (R. Liu and Liu 2013). Therefore, 1 km buffer to all masks, an extra fire areas mask provided by the Fire Prevention Service of Catalonia and a new Normalized Difference Snow Index (Cea, Cristobal, and Pons 2007) were also computed and added in the final analysis. The completion of the masking results in a final set of 1204 images

Finally, five VI are computed from the original MODIS reflectance bands: the Normalized Difference Vegetation Index (NDVI) (Chuvieco 2010), the Vegetation Condition Index (VCI) (Kogan 1995), the Normalized Difference Water Index (NDWI) (Gao, 1996), the Normalized Difference Drought Index (NDDI, high values indicate drought) (Gu et al. 2007) and the Temperature Vegetation Dryness Index (TVDI, high values indicate drought) (Sandholt, Rasmussen, and Andersen 2002). Median monthly data composites were generated obtaining a time series of 144 images from 2001 to 2012. The use of median monthly data is an effective way of rejecting outliers, improving data stability and controlling precisely the acquisition date. The advantage of monthly composites is to increase the likelihood of cloud-free pixels improving, thereby, the quality of the data set and diminishing the amount of images to deal with.

5.5.3 Results and discussion

5.5.3.1 Comparative analysis of the temporal characteristics of SPEI

The first set of analysis examined the climatic anomalies profiles for 18 forest sample points spread over Catalonia. SPEI profiles at 3, 6, 9, 12, 18, 24, 36 and 48 month time-scales were plotted and analyzed (Figure 5.5). Figure 5.5 shows different interpretations according to different time scales. As it can be seen, small time periods (3, 6 or 9 months) define an intense below zero and above zero patterns. Negative peaks denote short-term droughts relative to Mediterranean summer or winter precipitations shortages. Indeed, summer 2003 (sustained along 3 months), 2005 and 2006 were notably dry, achieving a minimum SPEI value of -2.23, while 2004, 2008-2009 and 2011 were rainy periods. Additionally, SPEI 3 showed another important dry event during late winter 2007 that lasts until spring 2008. Finally, SPEI values decreased steadily after 2010. When the time period was extended to 12 month or more, the index responded more slowly denoting fewer but longer and persistent drought events that were independent from the Mediterranean climate normal oscillations. Certainly, long time-scales are characterized by its significant and persistent negative values episode which lasts from 2005 to 2010. Therefore, the analysis of long time-scales is crucial to identify hidden dry periods that combined with any short-term drought might develop into a fatal event for forests such as forest fires.

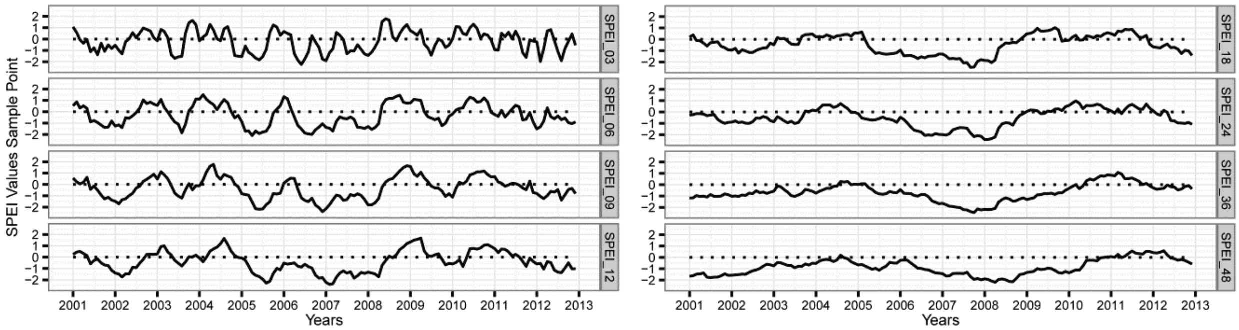


Figure 5.5. SPEI time series of 3, 6, 9, 12, 18, 24, 36 and 48 months for a forest sample point.

5.5.3.2 MODIS vegetation indices time-series

The second set of analysis examined MODIS VI profiles for the same 18 points. To this effect, NDVI, NDWI, NDDI, VCI and TVDI time-series were plotted and analyzed (Figure 5.6). Response during a drought event is expected to be different among indices. Therefore, NDVI, VCI and NDWI should decrease their values when decreasing rainfalls while NDDI and TVDI should present an inverse behavior, increasing their values during a dry event.

From the data in Figure 5.6 it is apparent that the VI pattern differed among years. Interestingly, NDVI and VCI presented a steep drop during August 2003, July 2005 and July 2007, reaching the summer minimums for the whole 12 year period. Thereby, NDVI and VCI revealed that, during winter and early spring 2008, there was a lower photosynthetic activity, thus vegetation was affected. Conversely, maximums of photosynthetic activity were found along 2010. Although NDWI presented a similar pattern, is also worth noting that minimum vegetation water content was achieved exactly in April 2003, 2005, 2007 and 2008. Also, 2008 outlines for its sustained low NDWI during the firsts months of the year. Far from being a coincidence, NDWI spring minimums were highly related to summer droughts. Again, highest NDWI values were found along 2010. In addition, NDDI and TVDI patterns concurred with NDWI and NDVI. NDDI presented its maximum value, indicating drought, in April 2003, 2005, 2007 and 2008 whilst TVDI still stood out among others for its continuous maximums since the beginning of 2008. TVDI showed high water deficit during 2003 while for 2005, 2007 and 2008 indicated moderate water stress. Anew, year 2010 outstood in general for its good level values. It is noteworthy that although SPEI 3-months identified a 2003 strong drought episode, the VI do not show significant changes in vegetation response of the study point. This result indicates that both types of data and their related information are necessary and complementary for determining whether a meteorological drought event identified by SPEI has effects on forests.

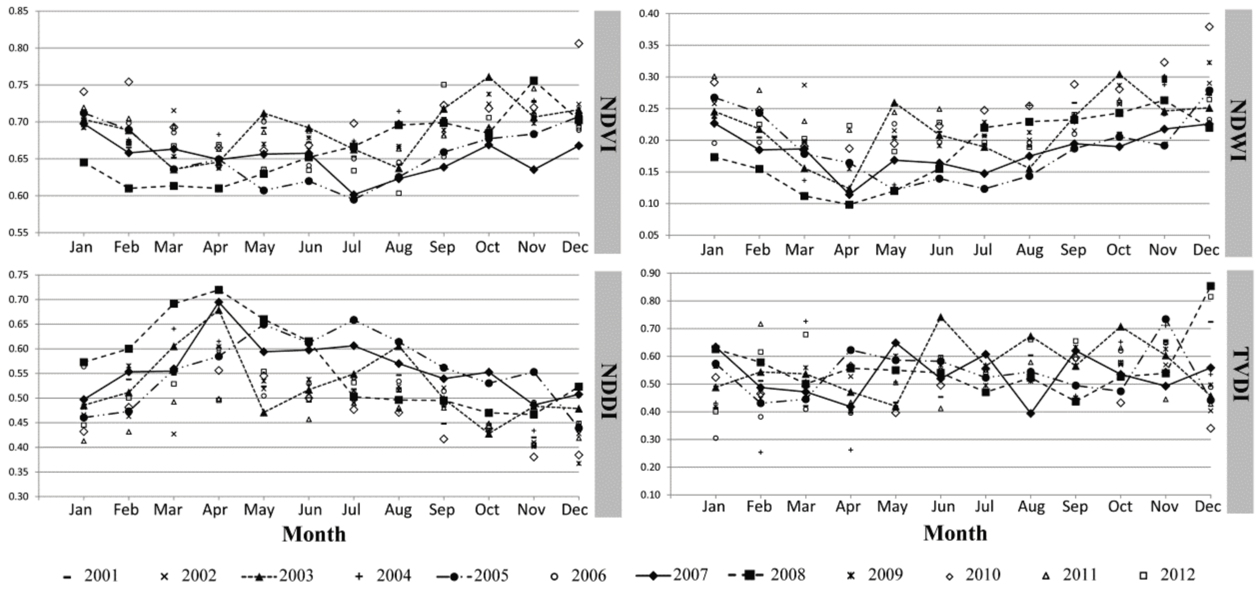


Figure 5.6. MODIS Vegetation Indices time series for a sample point.

5.5.3.3 Relationship between climate anomalies and MODIS data

Regression analysis was used for modeling the relationship between remote-sensing data and climate data for each point, using the VI as dependent variables and SPEI at several timescales as independent variables, in a year by year basis. In general a positive correlation was found between SPEI and 3 of the indices, the NDVI, the NDWI and the VCI while a negative relationship appeared between the NDDI, TVDI and LST and SPEI indices (Figure 5.7). VCI and TVDI appeared as the clearest indices related to water deficit conditions presenting the most significant relationship with droughts. However, some apparent contradictions between SPEI and VCI was observed, such as the one in 2010, when VCI fell to a value of 30 while SPEI remained at a normal level. Discrepancies are indicative of the different nature of the two indices (VI include seasonal patterns) and highlight the importance of the interpretation of SPEI. SPEI is referred to the mean rainfall of the point and, actually, might correspond to low amount of precipitation, not significant in terms of water shortage. Moreover, the graph also shows time lag responses of some months between VCI and SPEI, for example in 2010, when SPEI achieves its maximum values during early summer presenting a lag response of approximate 3 month with the VCI maximum peak.

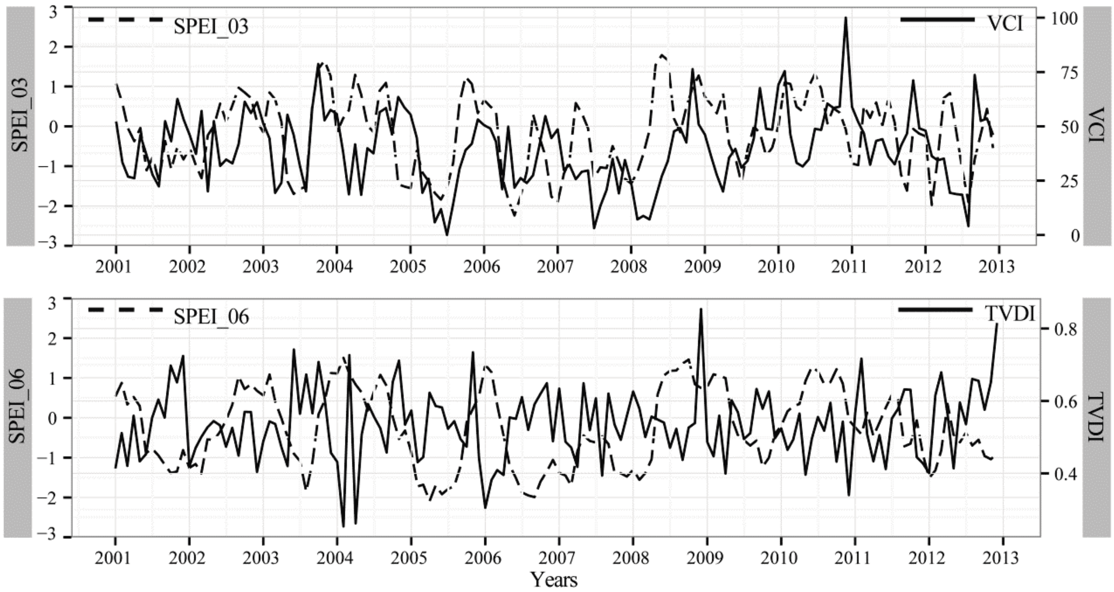


Figure 5.7. Three month SPEI and VCI monthly median (Top) and six month SPEI and TVDI monthly median graphs for a sample point.

5.5.3.3.1 Correlation according to time-scales

Table 5.1 presents an overview of the best regression coefficients of determination. The results obtained from the regression analysis indicate the shorter the time-scale, the better the temperature indices correlate.

SPEI_03		SPEI_06		SPEI_09		SPEI_12		SPEI_18	
R^2	Index	R^2	Index	R^2	Index	R^2	Index	R^2	Index
0.5665	LST	0.5598	LST	0.2653	LST	0.6121	LST	0.2799	NDDI
0.3070	LST	0.4693	LST	0.2323	VCI	0.3814	VCI	0.2488	NDWI
0.3052	LST	0.2885	LST	0.2240	NDVI	0.2565	LST	0.2457	TVDI

Table 5.1. Regression analysis coefficients of determination for 3, 6, 9, 12 and 18 month SPEI (*p* values < 0.01).

Therefore, better correlations at time-scales of 3, 6 and 9 months corresponded to the TVDI and LST indices, explaining at the most the 56% of the variability. When time-scales increased, VI related to photosynthetic activity and vegetation water content gained importance achieving R^2 values of ~0.38. For time-scales longer that 24 months, the relationship became lower.

5.5.3.3.2 Correlations according to years

Results showed a significant difference between years with negatives and positives SPEI. In fact, a number of significant regressions increased for years 2003, 2005 and 2008 while remained close to 0 for 2002, 2004 and 2006. Moreover, coefficients of determination improved for years that presented a winter drought, such as 2008, reaching the highest correlations for years 2003 and 2005 which, according to SPEI indices, experienced spring and summer droughts. Taken together, these results indicate that SPEI indices are suitable to explain up to 60% of the variability of the VI.

5.5.4 Conclusions

Our approach uses both, climate data and remote-sensing data to account for the characterization of drought on forests. It is highly recommended to complement MODIS quality and State QA bands together with extra detailed masks. Additionally, it has been demonstrated that SPEI is an appropriate index to characterize drought distribution patterns and intensity affection on forest areas although remote-sensing data is necessary and complementary for determining whether a meteorological drought event identified by SPEI has effects on forests. With shorter SPEI time-scales, almost-real-time drought events are monitored while longer timescales are functional to identify long-term precipitation deficit. Simultaneous short-term and long-term water scarcity may trigger fateful consequences on forests. Moreover, regression analysis results confirm the suitability of VI derived from MODIS daily reflectance as good representatives of SPEI when drought periods required to be identified. Therefore, the use of satellite data for mapping and monitoring drought events on forest become encouraging.

To sum up, both SPEI and VI clearly respond to the drought situations of 2003, 2005, 2007 and 2008 although a 40% of variability remains still unexplained. More research is needed to better understand the influence of seasonal trends of vegetation on MODIS data and the integration of ground truth data, such as defoliation, into the analysis; elements that might improve correlation with SPEI. The results of this study show the capability of such a multi-indicator and multi-source methodology to identify areas affected by droughts. It is specially indicated to monitor large regions or areas with difficult access or suitable to drought vulnerability. This methodology can then be used to describe trends, lags, responses, and intensity of the drought effects, as well as about the time required for forest recovery.

5.6 An improved methodology for generating 8-day surface reflectance composites from MODIS data

The previous analysis integrating climate time-series and MODIS data as a tool for forest drought detection led to interesting results encouraging its application to other regions. Notwithstanding, the use of daily data, like product MOD09GA, involves a Big Data processing approach that might be inoperative at some scales. This time-consuming situation would be improved using multiple date composites, such as MODIS 8-day product MOD09A1 that would reduce 8 times the processing effort. Unfortunately, as has been introduced in Section 5.4, MOD09A1 8-day product presents issues related to spatial heterogeneity deriving in a significant salt and pepper noise effect that question its own quality. A solution to overcome these issues is focused on generating a new 8-day product composite free of spatial heterogeneity. Therefore, an improved methodology for generating 8-day surface reflectance products from MODIS daily surface reflectance data is provided. The proposed approach entails enhancements regarding not only spatial and temporal homogeneity by exploiting the richness of the spatial context in the compositing process, but also radiometric homogeneity.

The improved product is achieved in two operations. First, a topographic correction is applied during the image processing. Second, the day of year (DOY) selection for each pixel of the multi-date product is made under a criterion which minimizes spatial heterogeneity. The improvement of the resulting product is evaluated through classification and spectral signature analysis. Moreover, its success is measured in terms of lowering the number of different daily images, and on the improvement of homogeneity of the reflectance surfaces (less salt and pepper effects). These improvements result in more coherent analyses for vegetation phenology or spectral monitoring.

Finally, similarities between daily derived data and improved 8-day derived data are analyzed to assess the feasibility of the new product in drought analysis.

5.6.1 Improved 8-day product methodology

The approach presented in this paper for generating improved 8-day composites is based on the quality masks of MODIS products and on additional variogram analysis, following a method developed by Pesquer, Domingo-Marimon, and Pons (2013) and consolidated in Pons et al. (2014). Both approaches, the original from the MODIS team and the improved method presented here (referred to as “original” and “improved”, respectively), share the use of daily surface reflectance product as starting data. However, they differ in two ways:

The presented improved methodology is a geostatistical approach instead of being a pixel-by-pixel score assignation.

The presented improved methodology prioritizes spatial homogeneity, while spatial coverage is a second criterion.

The methodology involves carrying out an analysis based on the image variogram in order to define a spatial pattern model (Fig. 5). The variogram, defined as the semivariance function (spatial variance between points) against the lag distance of pairs analyzed, is a tool for characterizing the spatial pattern, and has been widely and successfully used in remote-sensing studies (Berterretche et al. 2005; Curran and Atkinson 1998; Pesquer et al. 2013; Tarnavsky, Garrigues, and Brown 2008).

The variogram range needs to be analyzed in order to identify the distance at which the variogram is saturated: pixels separated more than the distance at saturation can be considered to not be spatially autocorrelated. Images are divided into sub-tiles according this distance, and the variogram analysis is applied at the sub-tile level. The sub-tile division might not be necessary in some study regions.

Next, all sub-tile images are geostatistically analyzed. Variograms of the sub-tile images with more than 70 % of valid land pixels are then used to define a representative variogram, which is key for rejecting sub-tile images presenting different types of problems (Figure 5.8).

Finally, the variograms of the remaining sub-tile images are compared with the representative variogram. The definitive selection criterion is that all three typical structure variogram parameters (nugget, sill and range) must be within the range of two and a half standard deviations from the mean, whereas the mean is calculated from the representative variogram.

In order to account for seasonal changes of the landscape, analyzed data was grouped into seasonal trimesters (winter: December to February; spring: March to May; summer: June to August; autumn: September to November). With this, the analysis avoids making comparisons between sub-tiles presenting highly different temporal patterns, such as snow cover during winter.

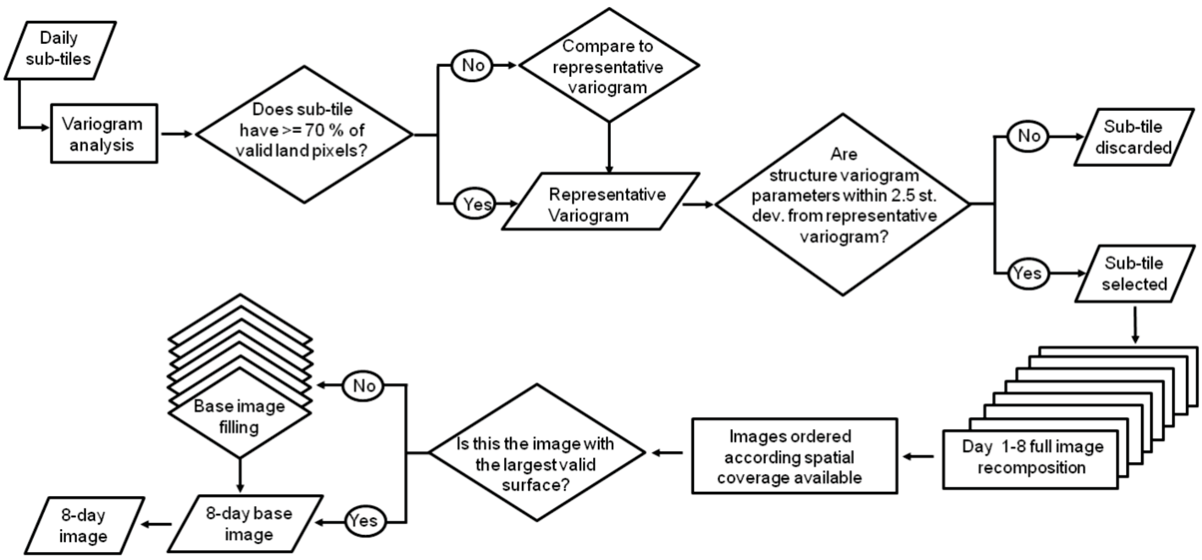


Figure 5.8. Geostatistical analysis workflow.

Once sub-tiles are selected, each daily image is recomposed. Note that each image will present different spatial coverage according to the sub-tiles that the geostatistical approach has selected.

For the final 8-day composite, the recomposed daily images of the period are ordered according to the spatial coverage available. The image with largest valid surface is used as the starting image and its missing values are filled with information from the second image presenting more spatial coverage, and so on successively.

Prior to data input and for the purpose of improving its quality, a topographic correction was performed taking into account incidence angle and discarding self-shadowed and cast-shadowed pixels by means of an analysis of the corresponding digital elevation model (Vanonckelen, Lhermitte, and Van Rompaey 2013). Also, a 35-degree maximum sensor zenith angle threshold was applied, removing pixels subject to heavy geometric distortion and lower spatial resolution. It is important to remember that the MODIS imagery present a bow-tie effect artifact which causes oversampling (the same data is imaged twice) and images seem distorted near the edges because pixels are bigger (a maximum of 6 times wider and 4 times longer (Yang and Di 2004). For example, pixels having a spatial resolution of 500 m at nadir might turn into 2415 m in size, covering a surface 23 times larger (Pons & Arcalís, 2012). Indeed, Tan et al. (2006) describe how overlapped dimensions begin to be noticeable when view zenith angle is approximately 27 degrees for 500 m data, and as a consequence the quality of MODIS data is degraded at high view zenith angles (Wolfe, Roy, and Vermote 1998).

5.6.2 Experimental design

5.6.2.1 Study area

The method was tested in Catalonia, a 32 000 km^2 region located in the Northeast of the Iberian Peninsula, covered by MODIS tile h18v04. Topography stands out for its wide altitudinal range, from 0 to more than 3 000 m above sea level, and due to a heterogeneous landscape with several mountain ranges (the Pre-Coastal Mountain Range, the Coastal Mountain Range and the Pyrenees). Its interesting mosaicked land cover reflects a great deal of human history, composed of agriculture lands mixed with areas of natural and semi-natural vegetation, including coniferous, sclerophyllous and deciduous forests. Moreover, the study area has freely available base map datasets, including the high quality multitemporal Land Cover Map of Catalonia, LCMC (Ibáñez and Burriel 2010). Following the methodology explained in Section 5.6.1, the study area was divided into sub-tiles of 25 km x 25 km.

5.6.2.2 MOD09A1 and MOD09GA product processing

Terra MODIS 8-day composite surface reflectance (MOD09A1, collection 5) and daily surface reflectance (MOD09GA, collection 5) products for year 2009 (January to December) covering tile h18v04 were used in this study. Both image datasets were obtained through the online Data

Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS (United States Geological Survey) (https://lpdaac.usgs.gov/data_access). The original Sinusoidal projection was kept. Study year 2009 was selected given the concurrent availability of the LCMC (Ibáñez and Burriel 2010). Moreover, as the MODIS land science team strongly suggests, embedded QA-SDS were used for a meaningful processing of MODIS imagery (Colditz et al. 2006; Roy et al. 2002; Wilson, Parmentier, and Jetz 2014).

In this study, a total of 45 images of the 8-day product MOD09A1 were masked using embedded QA State and QC quality bands. Pixels containing clouds (State QA band bit 0-1 described as “cloudy”, “mixed” or “not set”), cloud shadows (State QA band bit 2 described as “yes”), cirrus (State QA band bit 8-9 described as “small”, “average” or “high”) and fire (State QA band bit 11 described as “fire”) were discarded. Moreover, only pixels classified as “corrected product at ideal quality” in the QC quality band (bit 0-1) were saved. The 8-day image corresponding to the last week of the year (27th December 2009) was not used given that the composite includes the first days of the following year.

A total of 364 images of the MOD09GA daily surface reflectance from 2009 (except 16th November 2009 due to internal errors) were downloaded and masked following the same procedure as product MOD09A1. Pixels containing clouds, clouds shadows, cirrus, and fire, or presenting errors during correction were discarded. Additionally, to improve data quality, two new conditions, already explained in Section 5.6.1, were considered: a topographic correction was performed and the threshold of a maximum of 35 degree sensor zenith angle was applied. In the present study, the variogram was applied using the MOD09GA as the variable to be modeled. The variogram analysis was not carried out on full MODIS tiles (as this would not be useful), but at the sub-tile level. Sub-tile size was defined at 25 km x 25 km after analyzing the autocorrelation pattern over the study area, as explained in Section 5.6.1.

5.6.2.3 Improved 8-day product evaluation: spatiotemporal and spectral homogeneity and image classification

Spatial homogeneity was evaluated by analyzing and comparing the percentage of spatially discontinuous neighbor pixels (different days) in the images processed by the original and the improved methods. Similarly, temporal homogeneity was assessed by studying the number of days used to create each 8-day composite. Both of these properties were examined for all of the images.

In order to evaluate radiometric coherence, spectral signatures for reflectance bands 1, 2 and 6 were extracted from MODIS imagery, for both original 8-day and improved 8-day products. A total of 7 sites including different land cover types (coniferous forests, sclerophyllous forests, vineyards and fruit trees) were analyzed.

In addition, performance of the improved 8-day versus the original MOD09A1 8-day product was evaluated by applying two different land cover classifications, resulting in four thematic maps. A hybrid classification ((Serra, Pons, and Saurí 2003) and a maximum likelihood supervised classification (Richards and Jia 2005), each previously applied in other studies, were selected (Ortega-Huerta et al. 2012; Paneque-Gálvez et al. 2013; Pons et al. 2012; Zabala and Pons 2011). A total of 11 categories (Table 5.2) were selected according to the following criteria: a) categories were well adapted to the characteristic landscape of the study region; b) categories were suitable to MODIS spatial resolution; c) categories were compatible with previous cartography such as the CORINE Land Cover (*CLC2006 Technical Guidelines* 2007).

	Categories		**Categories**
Artificial	Artificial surfaces	**Croplands and mosaics**	Non-irrigated arable land
Forests	Coniferous forest		Permanently irrigated land
	Deciduous forest		Vineyards
	Sclerophyllous forest		Fruit trees
Grasses	Natural grasslands	**Seasonally or permanently inundated**	Rice fields
			Water bodies

Table 5.2. Categories included in classifications.

A total of 28 input variables covering the full growing season of vegetation for most categories were selected. These were then applied to each classification method from four composites in 2009 (14th March, 25th May, 20th July and 13th August). MODIS reflectance bands 1, 2, 4, 6, 7 and two vegetation indices, the Normalized Difference Vegetation Index (Chuvieco, 2010) and the Normalized Difference Water Index (Gao 1996), were chosen as variables given the importance of spectral diversity (Carrão, Gonçalves, and Caetano 2008). MODIS reflectance bands 3 and 5 were discarded due to a high correlation with band 1 (R^2=0.98) and strip noise band issues (Wang 2011), respectively.

Both training and test areas subsets required in the hybrid classification were obtained from the LCMC. At MODIS coarse spatial resolution, land cover homogeneity is hardly guaranteed given that most pixels are likely to contain features from different classes (Carrão, Gonçalves, and Caetano 2008), therefore, only pixels with a cover homogeneity of at least 80 % were selected to guarantee area representativeness. The two subsets (Figure 5.13) were independent. The training subset had 28 365 pixels (60 887.9 km^2) and the test subset had 12 078 pixels

(25 926.5 km^2). The test subset was used as ground truth in the assessment of accuracy of each classification.

An extra round of classifications was carried out evaluating only those areas with the steepest slopes in order to assess topographic correction usefulness.

5.6.3 Results and discussion

5.6.3.1 Improved 8-day product quality and spectral signatures

Following the new method, a set of 45 MODIS 8-day products from 2009 was processed. As indicated before, this methodology was designed to ensure high quality in terms of composite spatial homogeneity. Results showed a reduced salt and pepper effect when applied to the MOD09A1 product, generating a more robust and spatially homogeneous product (Figure 5.9). Indeed, the patchy appearance of MOD09A1, a consequence of the reflectance jump between contiguous pixels, also disappeared. The improved 8-day product presented better reflectance homogeneity, demonstrating the high adequacy of the geostatistical approach. However, some residual clouds, originally from improvable clouds masks, remained in the composites, indicating the need for cloud mask improvement.

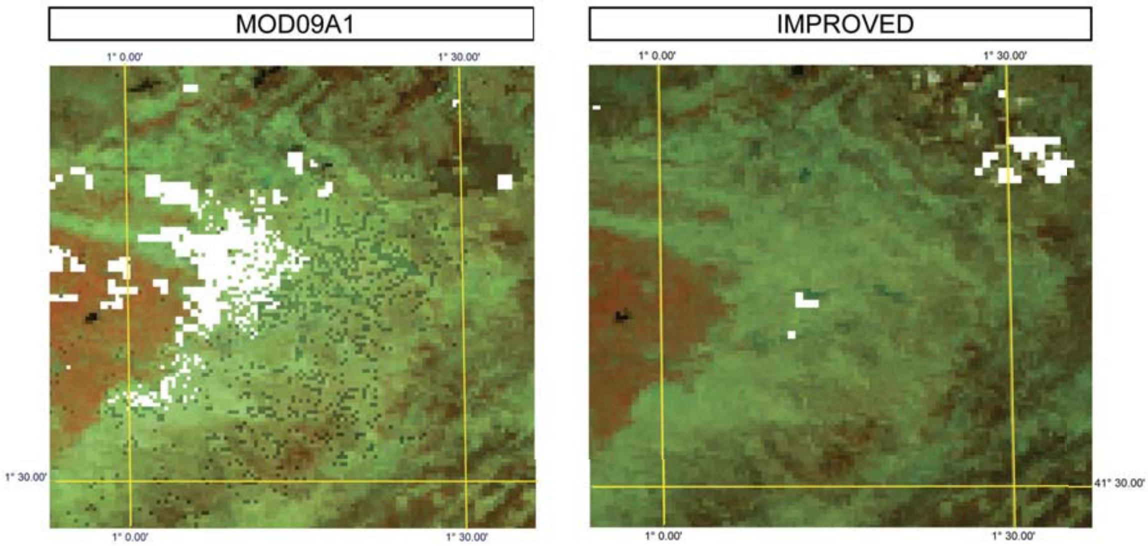


Figure 5.9. Salt and pepper noise effect comparison from original MOD09A1 8-day product (left panel) and improved 8-day product (right panel) for 4th June 2009 (white pixels correspond to missing values, mainly coming from cloud masks).

The reflectance differences between the original MOD09A1 and the improved 8-day products were evaluated through the assessment of spectral signatures for the same 7 locations in Figure 5.4 (original reflectance differences repeated here for the sake of clarity). A comparison of results revealed the degree to which the improved product maintained reflectance stability (Figure 5.10).

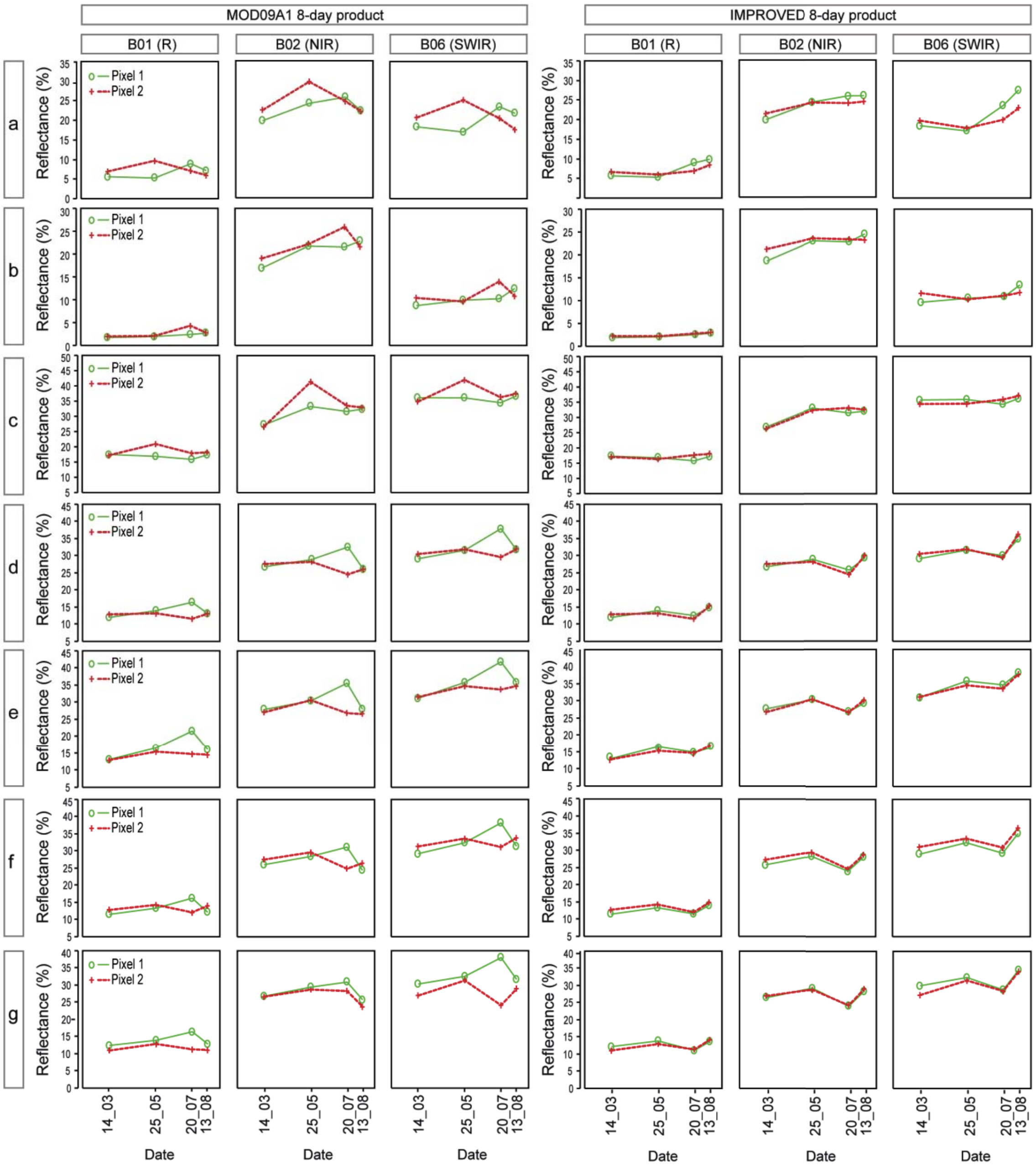


Figure 5.10. Comparison of spectral signatures extracted from MOD09A1 and the improved 8-day product for bands 1, 2 and 6 between contiguous pairs of pixels for 7 locations (a-g).

These findings highlight a better suitability of the new improved product for monitoring vegetation phenology, and that some inconveniences (Section 5.4) presented by the original MOD09A1 are solved in the improved product. The findings also show that results based on the original MOD09A1 could be erroneous. Notwithstanding, in order to dissipate any doubts concerning the use of convenient examples, another two indicators, distribution in the number of days used per each composite and the percentage of neighbor pixels from different days, were studied.

The number of days used for each of the composites was examined. Just as demonstrated in Figure 5.2, the original MOD09A1 8-day product used an average of 7.52 days per composite. The greater the number of individual days used per composite, the larger the number of spatial discontinuities. The methodology proposed in this study creates composites with higher spatial homogeneity, providing an average of only 3.96 dates per 8-day product (Figure 5.11).

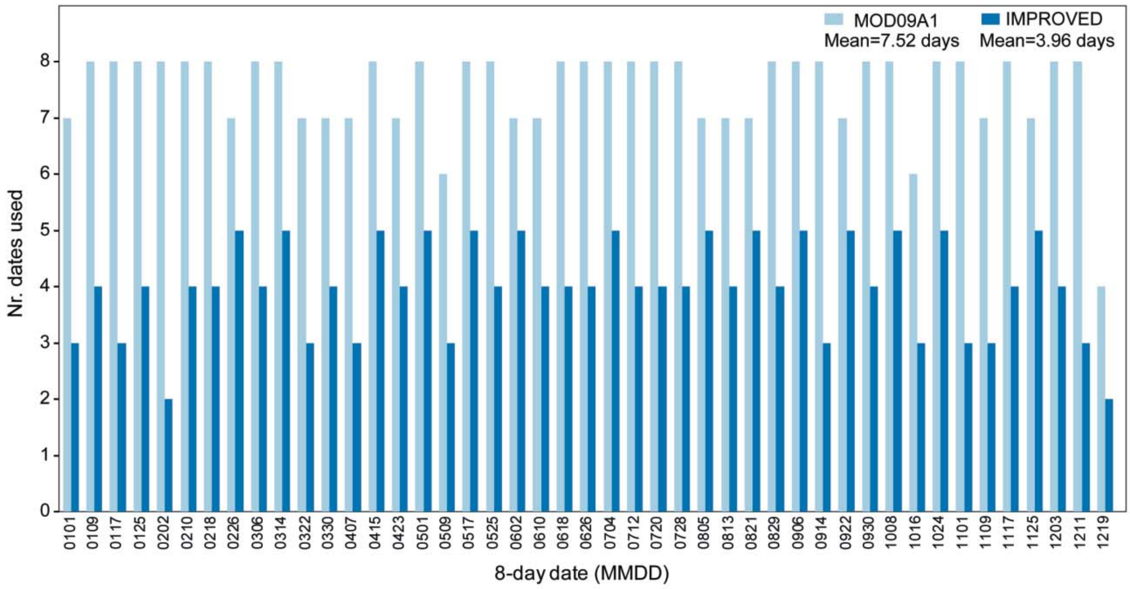


Figure 5.11. Number of days per 8-day composite for original MOD09A1 and improved product. The average of the improved product is substantially lower, reducing spatial heterogeneities.

Over the whole year, the new product included data from a maximum of 5 different days, contrasting with the original maximum of 8 dates per composite; the maximum of 8 was reached in 28 composites (62.2 % of the year), and 7 days was reached 14 times (31 %; note that the resulting sum of 7 or 8 dates composites is 93.3 % of the year).

In order to ascertain if the improved composites substantially reduce the number of times a given pixel and its neighbor in any direction belong to different days, a second analysis was performed. For this, the percentage of pairs of pixels from different days was computed for each composite image and the original and improved products were compared. When analyzing the "discontinuous pixels" in the original images, an average of 6.5 % of the surface (a maximum of 12.1 %) was composed of several dates, causing the reflectance issues demonstrated above. On the other hand, an average of only 1.7 % (a maximum of 6.2 %) was found in the series of improved composites (Figure 5.12).

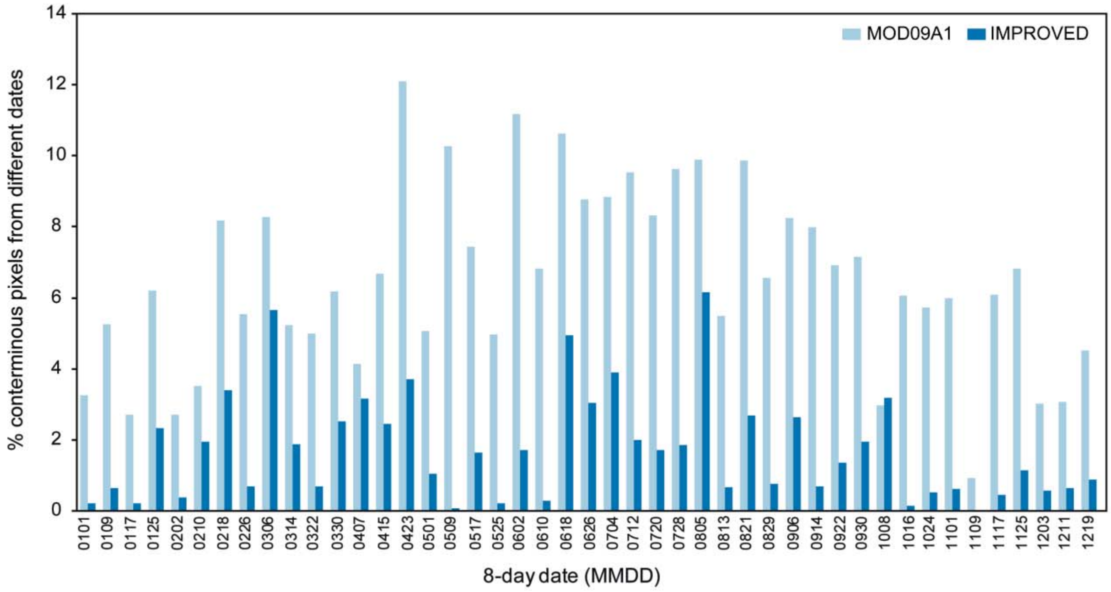


Figure 5.12. Percentage of neighbor pixels from different days per composite. Note that the improved product substantially reduces this percentage, resulting in composites which have a greater spatial homogeneity.

In all cases but one (8th October 2009), improved products presented less variability in the number of different days used. These results show that the improved 8-day composite method significantly heavily reduces spatial heterogeneity and avoids the salt and pepper noise effect and reflectance shifts.

5.6.3.2 Classification: overall accuracy

Results in Table 5.3 and Figure 5.13 show that the accuracy of categorical maps obtained from the improved 8-day product is higher than that of the original product for both classification methods. Also, hybrid classification and maximum likelihood maps resulting from the improved 8-day dataset had better accuracies in most categories.

Global accuracy (%)	*Original MOD09A1 product*	*Improved product*
Hybrid classifier	85.8 %	86.7 %
Maximum likelihood	89.5 %	90.0 %

Table 5.3. Comparison of overall accuracies of 2009 classifications using the original MOD09A1 product and the improved 8-day reflectance product.

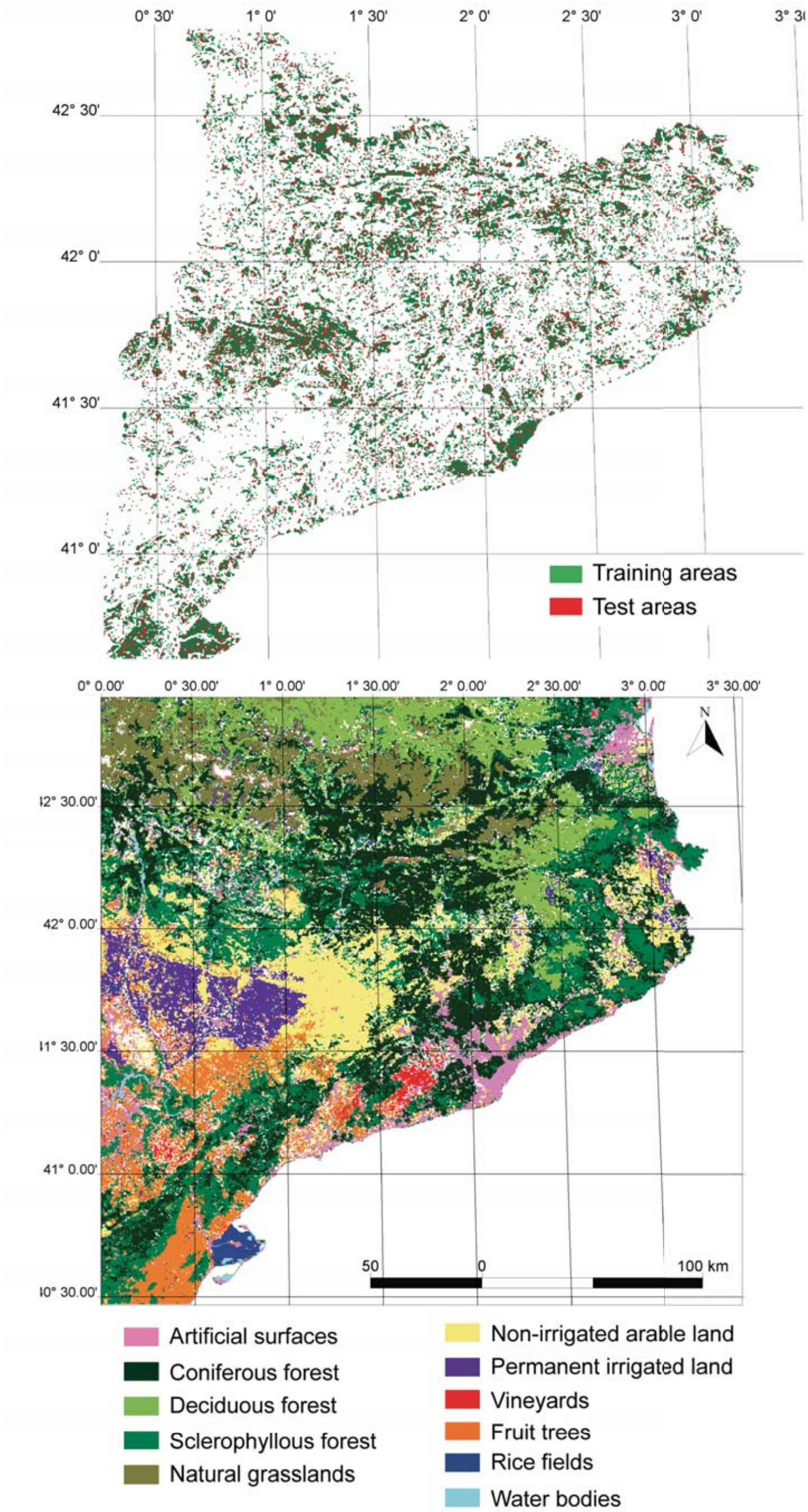


Figure 5.13. Distribution of training and test areas (top panel) and result of hybrid classification from improved 8-day product (bottom panel).

A closer look at the hybrid classification from the improved 8-day product confusion matrix (Table 5.4) shows that basically two categories (sclerophyllous forests and natural grasslands) presented results which were not very good (producer's accuracies, PA, of 73.5 % and 74.7 % respectively), whereas the remaining categories yielded producer accuracy scores above 80 %. This result agrees with Carrão, Gonçalves, and Caetano (2008), who reported mismatching between natural grassland, barren ground and shrublands in Portugal (having a similar landscape to the study area) and also with Hansen et al. (2000) who reported confusion among woodland and grassland categories. Regarding user accuracy, all categories presented values equal to or above 80 %. Improved 8-day product hybrid classification omission and commission errors were smaller than those obtained with the original MOD09A1 product (average 2 % and 4 %, respectively).

Moreover, the hybrid classification producer accuracy mismatches disappeared in maximum likelihood classification, achieving PA above 82 % in all categories (Table 5.5). By contrast, user accuracy of water bodies decreased to 60 %. We consider this fact insignificant given that water bodies of the study area are mainly water reservoirs, presenting an elongated shape which difficult classification at MODIS spatial resolution. Also, the fact that the hybrid classifier is non-parametric, supporting several statistical classes (in this case reservoirs and their surrounding variable dry-wet areas) per thematic class (water bodies), leads to better results in this class.

If we restrict the classification analysis to map areas with the steepest slopes (10 % or higher, obtained from a digital elevation model) the difference between the results of each 8-day product classification favors the improved composites even more, increasing maximum likelihood classification global accuracy figures by 2.1 percentage points. This suggests that the topographic correction applied to each daily image also improves the final 8-day composite.

Logically, this improvement has only modest effects on overall accuracy since the steepest areas are just 10 % of the 32 000 km^2 analyzed in this study, but it is also important to note that it is essential to have good results in steeper areas, frequently characterized by natural vegetation and forest land covers.

	IMPROVED / MOD09A1	1	2	3	4	5	6	7	8	9	10	11	Total	CE	UA
0	NODATA	21	51	13	47	10	17	3	0	1	12	1			
		44	33	38	61	24	30	48	0	13	68	2			
1	Artificial surfaces	743	13	0	17	9	7	18	0	15	24	0	846	12.2	87.8
		726	8	1	12	4	5	6	0	12	2	0	776	6.4	93.6
2	Coniferous forests	5	3616	31	492	2	0	0	0	0	1	4	4151	12.9	87.1
		12	3601	24	489	7	5	1	0	0	0	2	4141	13.0	87.0
3	Deciduous forests	0	19	576	39	12	4	0	0	0	0	0	650	11.4	88.6
		1	17	569	21	8	1	0	0	0	0	0	617	7.8	92.2
4	Sclerophyllous forests	10	275	31	1616	15	6	0	0	0	23	0	1976	18.2	81.8
		15	316	21	1634	15	5	5	0	0	15	1	2027	19.4	80.6
5	Natural grasslands	2	9	12	38	209	12	3	2	0	1	0	288	27.4	72.6
		0	6	10	30	215	6	5	1	1	2	0	276	22.1	77.9
6	Non-irrigated arable lands	6	1	1	4	4	1575	134	0	0	14	0	1739	9.4	90.6
		7	6	2	8	3	1585	136	0	0	22	0	1769	10.4	89.6
7	Permanently irrigated lands	11	0	0	8	36	43	758	1	10	74	0	941	19.4	80.6
		7	1	0	3	31	38	748	2	6	80	0	916	18.3	81.7
8	Rice fields	0	1	0	0	1	0	0	260	0	0	0	262	0.8	99.2
		0	0	0	1	1	0	0	259	0	0	0	261	0.8	99.2
9	Vineyards	7	0	0	0	1	0	5	0	127	8	0	148	14.2	85.8
		2	0	0	0	0	0	1	0	121	3	0	127	4.7	95.3
10	Fruit trees	30	1	1	22	12	29	57	0	7	689	0	848	18.8	81.3
		21	2	0	24	4	18	28	0	7	654	0	758	13.7	86.3
11	Water bodies	0	6	0	0	1	0	0	0	0	0	46	53	13.2	86.8
		0	2	0	0	0	0	0	1	0	0	46	49	6.1	93.9
	Total	814	3941	652	2236	302	1676	975	263	159	834	50	11902		
	Total	791	3959	627	2222	288	1663	930	263	147	778	49	11717		
MOD09A1	**OE**	8.7	8.2	11.7	27.7	30.8	6.0	22.3	1.1	20.1	17.4	8.0			
	PA	91.3	91.8	88.3	72.3	69.2	94.0	77.7	98.9	79.9	82.6	92.0			
	Overall accuracy	85.8%													
IMPROVED	**OE**	8.2	9.0	9.3	26.5	25.3	4.7	19.6	1.5	17.7	15.9	6.1			
	PA	91.8	91.0	90.7	73.5	74.7	95.3	80.4	98.5	82.3	84.1	93.9			
	Overall accuracy	86.7%													

Table 5.4. Comparison of hybrid classification results using the original MOD09A1 (grey) and the improved 8-day product. OE: Omission errors. CE: Commission errors. PA: Producer Accuracy. UA: User accuracy.

Class		Product	1	2	3	4	5	6	7	8	9	10	11	Total	CE	UA
0	NODATA	MOD09A1	212	408	56	60	138	6	6	62	6	11	12			
		IMPROVED	77	898	139	378	168	108	36	1	0	60	7			
1	Artificial surfaces	MOD09A1	576	3	0	2	0	2	13	1	4	14	0	615	6.3	93.7
		IMPROVED	717	5	0	6	0	7	13	1	4	10	0	763	6.0	94.0
2	Coniferous forests	MOD09A1	4	3193	3	193	0	0	0	0	0	1	1	3395	5.9	94.1
		IMPROVED	3	2619	3	59	0	0	0	0	0	0	1	2685	2.5	97.5
3	Deciduous forests	MOD09A1	0	140	576	75	2	1	0	0	0	0	0	794	27.5	72.5
		IMPROVED	0	35	497	33	7	2	0	0	0	0	0	574	13.4	86.6
4	Sclerophyllous forests	MOD09A1	6	220	23	1872	11	4	1	0	0	8	0	2145	12.7	87.3
		IMPROVED	12	397	23	1748	11	2	1	0	0	6	0	2200	20.5	79.5
5	Natural grasslands	MOD09A1	0	11	7	31	144	8	1	1	0	0	0	203	29.1	70.9
		IMPROVED	0	12	2	18	108	3	1	2	0	0	0	146	26.0	74.0
6	Non-irrigated arable lands	MOD09A1	1	6	0	8	0	1581	79	0	0	4	0	1679	5.8	94.2
		IMPROVED	1	4	1	5	0	1500	56	0	0	7	0	1574	4.7	95.3
7	Permanently irrigated lands	MOD09A1	17	1	0	1	5	77	870	1	5	56	0	1033	15.8	84.2
		IMPROVED	12	1	0	0	7	60	860	0	5	54	0	999	13.9	86.1
8	Rice fields	MOD09A1	0	0	0	0	0	0	0	198	0	0	0	198	0.0	100.0
		IMPROVED	0	0	0	0	0	0	0	255	0	0	0	255	0.0	100.0
9	Vineyards	MOD09A1	11	0	0	0	0	2	2	0	142	11	0	168	15.5	84.5
		IMPROVED	7	0	0	0	0	2	2	0	148	22	0	181	18.2	81.8
10	Fruit trees	MOD09A1	5	3	0	39	12	12	6	0	3	741	0	821	9.7	90.3
		IMPROVED	4	4	0	30	11	9	8	0	3	687	0	756	9.1	90.9
11	Water bodies	MOD09A1	3	7	0	2	0	0	0	0	0	0	38	50	24.0	76.0
		IMPROVED	2	17	0	6	0	0	1	4	0	0	43	73	41.1	58.9
	Total	MOD09A1	623	3584	609	2223	174	1687	972	201	154	835	39	11101		
	Total	IMPROVED	758	3094	526	1905	144	1585	942	262	160	786	44	10206		
MOD09A1	OE		7.5	10.9	5.4	15.8	17.2	6.3	10.5	1.5	7.8	11.3	2.6			
	PA		92.5	89.1	94.6	84.2	82.8	93.7	89.5	98.5	92.2	88.7	97.4			
	Overall accuracy		89.5%													
IMPROVED	OE		5.4	15.4	5.5	8.2	25.0	5.4	8.7	2.7	7.5	12.6	2.3			
	PA		94.6	84.6	94.5	91.8	75.0	94.6	91.3	97.3	92.5	87.4	97.7			
	Overall accuracy		90.0%													

Table 5.5. Comparison of maximum likelihood classification results using the original MOD09A1 (grey) and the improved 8-day product. OE: Omission errors. CE: Commission errors. PA: Producer Accuracy. UA: User accuracy.

5.6.4 Conclusions and future work

The main goal of this study was to provide an improved method for generating 8-day surface reflectance products from MODIS daily surface reflectance data by reducing the spatiotemporal heterogeneity of original products. Input data was topographically corrected and a compositing method based on a geostatistical approach was designed. The method improved the resulting composite in several ways. First, the resulting composite was robust and presented higher spatial homogeneity. Second, the variability of contiguous pixels from different days was reduced, and as a consequence (third), reflectance shifts from the same land cover in composites were decreased. Finally, (fourth), the topographic correction was found to be useful if improvements in steep areas are desired.

The improved product was suitable for land cover classification, presenting better results than the original MOD09A1 product. Similarly, the improved product is recommended for monitoring vegetation phenology given the reflectance stability between contiguous pixels. Moreover, the method may benefit from further enhancement in terms of the geostatistical selection, which can sometimes result in low spatial coverage in images and areas suffering extreme land cover changes. On the basis of the authors' experience, it would also be interesting to improve cloud masks or to apply a buffer around existing ones since they are often affected by omission errors. Fortunately, MODIS Collection 6 will improve the quality of cloud masks (Wilson, Parmentier, and Jetz 2014), which will also benefit the present method.

Further research will validate this methodology with other MODIS products and will try to balance date selection towards a more real 8-day temporal resolution. Finally, the authors invite researchers using the MODIS sensor onboard the Aqua (EOS/PM-1) satellite to apply this method in order to investigate if it may also be beneficial for its 8-day composites.

5.7 About the use of improved 8-day products *vs.* daily products

As has been demonstrated in the last Section, the new 8-day product is clearly better than the original since it do not present suspicious artifacts which might question its use on drought monitoring applications. This new product opens the possibility for less time-consuming operational processing. A first prospection of its adequacy to drought studies is carried out in this Section to evaluate a feasible replacement of daily data, such the one used in the integration analysis presented in Section 5.5, by the improved 8-day product.

5.7.1 Methodology

Three of the indices used in the integration analysis (Section 5.5), the NDVI, the NDWI and the NDDI, were computed for Catalonia for year 2009. These indices were chosen as an example of widely used surface reflectance derived data. Two different sets were created to compare both approaches. The first set was computed from MOD09GA daily surface reflectance filtered data. Next, median monthly composites were generated for each index obtaining monthly NDVI and monthly NDWI (36 images). The second set was computed from the improved 8-day product and median monthly composites were also generated (36 images as well). Finally, correlations between the two sets were made for each pair of monthly images.

5.7.2 Results and discussion

The results showed extremely high correlations for the NDVI index (median R^2=0.97) (Figure 5.14). NDWI also presented high correlations (median R^2=0.98) except for May, indicating slight differences between monthly data originated from daily data and monthly data generated through the improved 8-day composite (Figure 5.14). This disagreement is due to the spring variability of the study area. By the beginning of May, snow cover is still significant while by the end of May residual snow patches remain. These remaining patches are due to uneven process of the corresponding snow masks. The NDDI, being a ratio of both, the NDVI and the NDWI, present the same behavior, with high correlations (median R^2=0.89).

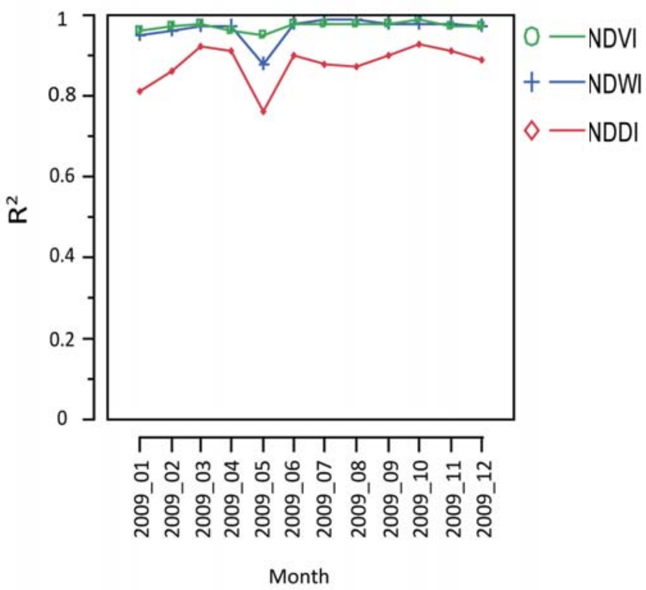


Figure 5.14. Correlations between pairs of monthly NDVI, NDWI and NDDI calculated from daily surface reflectance and improved 8-day composites.

These results suggest that improved 8-day product data could be used as a substitute for daily products, thus reducing the processing effort. .

Chapter 6

FINAL CONCLUSIONS

(Català / English)

6 FINAL CONCLUSIONS (Català / English)

6.1 Conclusions finals

En aquest darrer capítol s'ofereix una síntesi de les conclusions més rellevants obtingudes al llarg d'aquesta recerca.

L'objecte principal sobre el qual s'ha desenvolupat aquesta recerca ha estat la realització d'aportacions al coneixement dels patrons espacio-temporals de la sequera de la Península Ibèrica des de la perspectiva de la Ciència de la Informació Geogràfica, amb especial atenció a la sequera forestal.

L'estudi s'ha concretat a partir d'una sèrie d'objectius, exposats a la Secció 1.3, als quals s'ha anat donant resposta al llarg de la recerca i les principals conclusions dels quals s'exposen a continuació.

Proposta d'un nou marc teòric de la sequera on s'inclogui la sequera forestal a partir de la seva contextualització.

Al llarg d'aquesta tesis s'ha evidenciat la necessitat de definir un nou marc de sequera on la sequera forestal tingui el seu propi paper i se'n reconegui la seva importància. A partir d'aquí s'ha proposat la inclusió d'aquest tipus de sequera en la classificació tradicional.

Millora en la modelització espacio-temporal de dades meteorològiques in-situ i en la capacitat de gestió massiva d'aquestes (enfoc Big Data).

Un dels majors reptes a l'hora de caracteritzar la sequera és arribar a disposar de la informació a un nivell de detall que vagi més enllà de l'actual i, doncs, permeti abordar als investigadors, planificadors i gestors veure el territori de forma més nítida. Bona part de la recerca presentada s'ha centrat en el desenvolupament d'una base de mapes climàtics i de sequera a una alta resolució espacial (100 m) i temporal (mensual), i durant un període considerablement llarg (1950-2012), en base a un tractament molt curós de la major part d'informació de base disponible. Aquest nova base cartogràfica climàtica compren al voltant de 3000 mapes climàtics i més d'11 000 mapes de sequera, amb quasi 600 000 milions de cel·les o valors disposats al llarg d'aquest hipercub de diverses variables en l'espai geogràfic i les diferents finestres temporals. La computació massiva (Big Data) per a obtenir aquest enorme volum d'informació i la seva expressió i anàlisi cartogràfica ha estat possible mitjançant la implementació en un entorn SIG (MiraMon), el qual facilita una aproximació multidisciplinar que comprèn filtratge de les dades originals per garantir-ne el millor equilibri entre qualitat i representativitat espacio-temporal, mètodes d'interpolació espacial, l'obtenció de representacions cartogràfiques i, finalment, l'extracció i anàlisi estadística de les dades.

Pel què fa a la cartografia climàtica, l'homogeneïtzació de les dades *in-situ* i la selecció d'unes òptimes variables independents per a la modelització han estat punts claus per assolir un alt nivell en l'exactitud dels mapes finals els quals presenten un mediana dels errors RMS de 23.5 l/m^2 (mín: 4.1 l/m^2; màx: 66 l/m^2) per a la precipitació i d'1.2°C (mín: 0.7°C; màx:2.1°C) per a la temperatura mitjana.

En el cas del mapes de sequera, s'ha adoptat l'SPEI (Standardized Precipitation Evapotranspiration Index) com a índex de treball. El seu càlcul a partir de ràsters climàtics ofereix una visió espacial que és absent en l'aproximació a partir de dades discretes en l'espai. L'SPEI ha demostrat ser un índex altament informatiu i ofereix gran potencial a l'hora d'analitzar els episodis de sequera a nivell multidimensional.

Caracterització de les sequeres meteorològiques ocorregudes a la Península Ibérica espanyola a partir de patrons climàtics i espacials i identificació de les seves possibles causes.

Gràcies a l'adopció de l'SPEI com a índex de sequera que estandarditza les dades, permetent una visió comparativa entre zones, i que integra informació temporal a diferents escales, s'ha efectuat una anàlisi preliminar de les sequeres meteorològiques a la Península Ibèrica espanyola en base a la cartografia detallada produïda. En aquesta anàlisi s'ha identificat aquelles àrees afectades per episodis de més de 4 i de més de 7 mesos consecutius de sequera tant a curt com a llarg termini. Els episodis continuats de sequera a llarg termini són especialment interessant per poder determinar quines zones han estat més persistentment castigades. Aquesta anàlisi ofereix una perspectiva fins ara difícil de percebre on certes àrees de la Península no tradicionalment considerades com a afectades per la sequera es revelen com a tals, i que invita a reflexionar sobre els models d'unitats climàtiques de la Península Ibèrica.

Per altra banda, s'ha detectat un increment significatiu de la superfície afectada per sequeres en les últimes dècades. L'episodi sec més extens va tenir lloc l'any 2005 i va afectar gairebé el 89 % del territori (SPEI < -1). És important destacar que aquests patrons no són homogenis en tot el territori estudiat: mentre que els sectors nord i oest presenten un menor nombre d'episodis, les àrees afectades amb sequeres més intenses corresponen al sud i est de la Península Ibèrica.

L'anàlisi multidimensional realitzada gràcies a la continuïtat espacio-temporal de les dades i de les diferents escales temporals a les quals han estat generats els mapes permet disposar d'una visió innovadora i integradora complementaria a la informació tradicional. Aquesta nova perspectiva permet caracteritzar el fenomen de les sequeres en moviment (drought moving waves) per una regió extensa com és l'Espanya peninsular, reconèixer el seu moment d'inici i final, així com la seva extensió tant a nivell espacial com temporal. Un aspecte destacable és la fàcil identificació de la simultaneïtat de diversos episodis de sequera, la present en un moment donat i la resident d'un episodi anterior, que juntes poden desencadenar conseqüències encara més importants. Considerar la visió integrada del fenomen pot comportar millors resultats a l'hora de definir plans de gestió i mitigació.

L'ús de l'SPEI com a índex apropiat per la caracterització de la sequera ha estat demostrat un cop més, i també a nivell espacial detallat, ajudant a descriure la distribució del fenomen i la intensitat del seus patrons. Les tendències de les sèries temporals de l'SPEI a diverses escales temporals també han estat analitzades i s'ha identificat un canvi de règim abrupte entre els anys 1979 i 1981 amb afectació a la part centre-est de la Península Ibèrica. El canvi apareix de forma consistent en una amplia gamma d'escales temporals i també en diverses escales espacials (quadrícules de 70 km fins a 280 km de costat).

Per tal d'identificar les causes d'aquest canvi de tendència s'ha avaluat diversos índexs de teleconnexió. Els resultats han mostrat que la variabilitat de l'SPEI està significativament associada a l'Oscil·lació Multidecadal Atlàntica (AMO), indicant que aquest índex és, dels diferents estudiats, el predictiu més fort del canvis abruptes en els patrons de sequera ibèrics. També s'ha identificat consistents senyals d'alerta anticipada al llarg de la sèrie.

Finalment, s'ha avaluat els possibles impactes dels canvis de règim de sequera en la fixació de carboni dels boscos mediterranis de *Pinus halepensis*. Els resultats també han identificat reduccions significatives en els guanys de les reserves de carboni en la majoria de parcel·les forestals, alhora predits per l'AMO.

Aquests resultats indiquen que l'AMO està significativament associat a canvis multidecadals en serveis ecosistèmics claus com pot ser la fixació de carboni, un servei ecosistèmic clau, tot suggerint una possible reducció en l'activitat d'embornal de carboni als boscos semi-àrids de l'est de la conca Mediterrània durant les pròximes dècades a causa del debilitament previst de la Circulació Termohalina (Atlantic Meridional Overturning Circulation - AMOC).

L'ús potencial de les eines de la Ciència de la Informació Geogràfica en la detecció de canvis fenològics en boscos deguts a sequeres. Avaluació de les potencialitats i limitacions de les dades de MODIS i els índexs derivats per l'estudi de la sequera forestal.

Si bé s'ha demostrat que a través dels índexs climàtics es pot preveure i determinar els efectes de la sequera sobre els sistemes forestals, és evident que l'ús de la teledetecció ens pot aportar un major nivell de comprensió d'aquest fenomen, o com a mínim una comprensió complementària donat que integra la resposta de les pròpies plantes en la resposta a l'oscil·lació del clima.

Així doncs, dos productes de reflectàncies de MODIS, el diari (MOD09GA) i el de 8 dies (MOD09A1) han estat els escollits per validar el seu ús en aplicacions de sequera forestal. La literatura científica fins ara existent avala l'ús d'índexs de vegetació derivats de dades de teledetecció com a informació suficientment representativa de l'estat de la vegetació però és imprescindible conèixer l'origen de les dades i escollir el producte més adequat a les necessitats definides.

Atesos els problemes d'heterogeneïtat radiomètrica, espacial i temporal que presenta el producte de 8 dies de MODIS i que en aquesta recerca han estat quantificats, el primer estudi comparatiu de dades MODIS i climàtiques s'ha realitzat a partir del producte diari.

Integració de dades de sèries climàtiques i dades del sensor MODIS com eines d'anàlisi per a la detecció de sequera dels boscos. Són les dades MODIS adequades pel seguiment de la sequera forestal en l'àrea d'estudi? Són ambdues necessàries?

Els resultats de la regressió entre diversos índexs de vegetació derivats del producte diari de MODIS (MOD09GA) i del SPEI a diverses escales temporals han demostrat que:

- Les dades de teledetecció, i concretament els índexs de vegetació derivats de MODIS, són sensibles a canvis en la vegetació i són indispensables per determinar si un episodi de sequera meteorològica identificat a través del SPEI té algun tipus d'efecte sobre els boscos. Per tant, ambdós tipus de dades són necessàries i complementàries.
- S'observa un període de latència entre el SPEI i la resposta de la vegetació a determinades escales temporals. El coneixement del desfasament entre el factor sequera i la possible resposta de la vegetació a aquest és vital per poder pronosticar la resposta de la vegetació a canvis climàtics sobtats.
- La correlació més significativa es dóna entre escales temporals petites de l'SPEI i els índexs de vegetació relacionats amb la temperatura (R^2~0.56). A mesura que les escales temporals incrementen, les regressions amb els índexs de vegetació relacionats amb el contingut d'aigua i verdor són les que proporcionen coeficients de determinació més alts (R^2~0.38). Les anàlisis amb les escales de més de 24 mesos no presenten pràcticament significació estadística.
- Malgrat l'evident interès de les dades de teledetecció, l'SPEI explica fins quasi un 60 % de la variabilitat del índexs de vegetació en anys de sequera, com el 2005 o el 2008 fent

que sigui una important informació complementària a la teledetecció en temps actuals, i un indicador prou vàlid en èpoques prèvies a la percepció remota.

Explorar la possibilitat de millorar el producte actual de compostos de 8-dies de MODIS.

Amb la finalitat de disminuir el temps de processament necessari en l'ús de les imatges diàries i atesos els problemes que presenta el compost de 8 dies de MODIS, s'ha desenvolupat un nou algorisme per tal de generar compostos de reflectàncies de 8 dies a partir d'imatges diàries de reflectàncies. El mètode es basa en una aproximació geostadística, els resultats de la qual presenten una alta homogeneïtat espacial, disminueixen la variabilitat en la reflectància de píxels veïns que pertanyen al mateix tipus de coberta i finalment milloren la qualitat en àrees amb diferents pendents i orientacions gràcies a l'ús d'una correcció topogràfica. Els productes derivats del nou compost millorat de 8 dies presenten una alta correlació estadística amb aquells derivats de les imatges diàries, indicant que també podrien ser útils per estudis de sequera forestal i, doncs, es podria reduir substancialment (uns 8 cops) l'esforç de processament.

Addicionalment a les contribucions detallades fins ara, l'aportació més important d'aquesta tesi és la creació d'una gran base de dades climàtica i de sequera d'alta resolució espacial i extensió temporal, que confiem que serà útil en molts d'altres camps de la recerca de la sequera que aquesta tesi no pot abordar. Així mateix, aquest enorme volum d'informació obre la porta a nous dubtes i inquietuds, a formular-se noves preguntes. A continuació se'n perfilen algunes com a futures línies de recerca.

6.2 Mirant endavant: futures línies de recerca derivades

La recerca exposada en aquesta tesi avança en diversos aspectes de l'estudi de la sequera, tant a nivell climàtic com a nivell forestal. Tanmateix al llarg de la investigació han aparegut nous aspectes que susciten interès. La nova perspectiva de zones recurrentment afectades per sequera invita al replantejament del model d'unitats climàtiques definides a la Península Ibèrica i presenta un interessant camí per investigar. D'altres aspectes, com per exemple l'anàlisi detallada de la integració de les dades de clima i sequera i les de teledetecció a una escala forestal més detallada, també resulten atractius per tal de poder conèixer com afecten els episodis de sequera a diferents espècies forestals o quina és la resposta a la sequera en funció de la distribució d'una mateixa espècie.

D'altra banda, les dades de MODIS continuen proporcionant un gran potencial en el món de la recerca i és necessari segui avançant en el desenvolupament de nous productes d'alta qualitat que facilitin i donin més robustesa a les anàlisis posteriors. També caldrà tenir en compte les noves generacions de sensors, com per exemple els embarcats a missions com ECOSTRESS, o els de la sèrie Sentinel, les dades dels quals plantejaran nous reptes a assolir.

Però per sobre de tot, els investigadors, hem de continuar treballant amb la integració espacio-temporal dels índexs climàtics i les dades de teledetecció, amb la finalitat d'obtenir indicadors globals de qualitat, comprensibles i, sobretot, fàcilment accessibles i útils pels responsables finals de la presa de decisions en la gestió de les sequeres.

6.3 Final considerations

This final Chapter gathers the most important conclusions obtained during this research.

The main aim of this research was to contribute to the knowledge of the multitemporals spatial patterns of the Iberian Peninsula droughts from a Geographic Information Science perspective, with special attention to drought on forests.

The study resulted from a number of goals detailed in Section 1.3, which have been address throughout this manuscript and the main conclusions of which are detailed below.

Proposal for a new theoretical framework for drought including context-based forest drought.

This thesis showed the need for a new conceptual framework where forest drought had its own role and recognition. A new scheme for drought types modifying the traditional classification was discussed and proposed.

To improve spatiotemporal modeling of in-situ meteorological data and improve its massive management (Big Data approach).

One of the biggest challenges for drought characterization is to provide data at detailed spatial resolution beyond the current, giving a crispy view of the territory to researchers, planners and managers. Much of the presented research focused on the development of climate and drought map databases at a high spatial (100 m) and temporal (monthly) resolution for a considerable long period (1950-2012), based on a thorough processing of the most information available. This new cartographic database includes around 3 000 climate maps and more than 11 000 drought maps, with almost $600\,000 \cdot 10^9$ cells or values arranged along this hypercube of several variables in the geographic space and at different timescales. Massive computing (Big Data approach) of such amount of information and its mapping was only possible through its implementation in a GIS environment (MiraMon), which facilitated an interdisciplinary approach between original data filtering to guarantee an optimum equilibrium between quality and spatiotemporal representation, spatial interpolation methods, obtaining cartographic representations and, finally, the extraction and statistical analysis of data.

Regarding climatic cartography, the homogenization of *in-situ* data and the selection of optimal modeling independent variables were key to achieving high accuracy final maps which presented a median RMSE of 23.5 l/m^2 (min: 4.1 l/m^2; max: 66 l/m^2) for precipitation and 1.2°C (min: 0.7°C; max: 2.1°C) for mean temperature.

The SPEI (Standardized Precipitation Evapotranspiration Index) was used as the index for drought mapping. Its computing from climate rasters offered a spatial vision which was not possible in an approach based on discrete data. The SPEI proved to be a highly informative index and offered a great potential in analyzing drought events at a multidimensional level.

Characterization of past meteorological drought events (1950-2012) affecting the Spanish Iberian Peninsula through climatic and spatial patterns and the identification of their possible causes.

The use of the SPEI index, which standardizes data allowing a comparative view between different areas and which integrates information at different timescales, allowed a preliminary analysis of meteorological droughts in the Spanish Iberian Peninsula based on the detailed drought database. This analysis identified those areas affected by drought episodes longer than 4 or 7 consecutive months, at short-term and long-term timescales. The continuous drought episodes were interesting to determine which areas were persistently affected. This analysis provided a new perspective, where areas traditionally considered unaffected by droughts were revealed as affected. The analysis also invites to consider new climate units models in the Iberian Peninsula. Moreover, the area affected by drought in recent decades significant increased. The most extensive episode took place in 2005 and affected almost the 89 % of the territory (SPEI <-1). It is noteworthy that these patterns are not homogeneous throughout the studied territory: while the drought regime of the northern and western areas of the Iberian Peninsula was characterized by effects leading from fewer drought episodes, the southern and eastern parts experienced the most intense events.

The spatiotemporal continuous data and the several timescales used in the analysis allowed a multidimensional approach which provided an integrative and innovative vision complementary to traditional information. This new approach enabled the characterization of the phenomenon of drought moving waves for such a wide region such as Spain: the start and end periods and also their spatiotemporal duration were identified. The most remarkable achievement was that the approach facilitated the identification of several simultaneous droughts, i.e. the drought episode of the period considered and the resident drought of a previous episode, which together can trigger even greater consequences. This integrated vision of drought phenomena may lead to better results when defining mitigation and management plans.

The suitability of SPEI for characterizing droughts was demonstrated once again, also at a detailed spatial resolution, helping in the description of the distribution of the phenomena and the intensity of their patterns. Trends of SPEI time-series at different timescales were analyzed and an abrupt regime shift was identified between 1979 and 1981 affecting the central-eastern part of the Iberian Peninsula. The shift consistently appeared in a wide range of timescales and at different spatial scales (grids from 70 x 70 km to 280 x 280 km). In order to identify the drivers of this trend several teleconnection indices were evaluated. The results showed that SPEI variability was significantly associated with the Atlantic Multidecadal Oscillation (AMO), indicating the AMO as the strongest predictor of the abrupt regime shift, among other indices evaluated. Consistent early warning signals anticipating the shifts were also identified. Finally, the potential impacts of drought regime-induced shifts in forest carbon sequestration of Mediterranean *Pinus halepensis* forests were evaluated. The results identified significant reductions in carbon stock accumulation rates in most of forest plots, also predicted by the AMO. The results also indicated that the AMO is significantly associated with multi-decadal shifts in key ecosystem services such as carbon sequestration, suggesting a future reduction in the carbon sink activity of semi-arid forests across extensive areas in the Western Mediterranean Basin over the next decades due to the expected weakening of the Atlantic Meridional Overturning Circulation (AMOC).

To use potential GI Science tools for detecting phenological changes in forests due to drought events. To evaluate potential and limitations of MODIS data and its derived VI in forest drought studies.

While it was demonstrated that climate indices can predict and determine the effects of droughts on forest systems, it is clear that the use of remote-sensing can provide a higher level or at least a complementary understanding of these phenomena, given that integrates the direct response of plants to climate oscillations.

To this effect, two MODIS surface reflectance products, the daily (MOD09GA) and the 8-day (MOD09A1) were validated for forest drought studies. The existing scientific literature supports the use of vegetation indices derived from remote-sensing as sufficiently representative of the state of vegetation. However, the origin of the data and the selection of an appropriate product for the analysis are essential issues which need to be taken into account. Given the problems of radiometric, spatial and temporal heterogeneity present in MODIS 8-day product, which were quantified in this thesis, a first exploration of the use of MODIS data was based on the daily product.

Integration of climate series and MODIS data as an analytical tool for the detection of forest drought. Is only MODIS data suitable for monitoring forest drought or are both necessary?

Results of the regression between different vegetation indices derived from the MODIS daily surface reflectance (MOD09GA) and SPEI at several timescales demonstrated that:

- Remote-sensing data, and specifically vegetation indices derived from MODIS, were sensitive to changes in vegetation and were essential for determining whether a meteorological drought event identified by SPEI has effects on forests. Therefore both types of data and their related information are necessary and complementary.
- A lag period between the SPEI at certain timescales and the response of vegetation was observed. The understanding of this lag is essential for predicting the response of vegetation to abrupt changes in climate.
- The most significant regression was found between small SPEI timescales and vegetation indices involving temperature (R^2~0.56). As the time scales increased, regressions with vegetation indices involving water content and greenness improved (R^2~0.38). Regression involving SPEI longer than 24-month timescales were not statistically significant.
- Despite the obvious interest of remote-sensing data, the SPEI explained up to 60 % of the variability of vegetation indices for drought years, such as 2005 and 2008 identifying SPEI as important complementary information to current remote-sensing and as a valid indicator in periods prior to Earth Observation.

To explore the possibility to improve current 8-day MODIS surface reflectance composites.

In order to reduce the cost of daily data processing time and given the problems presented by the MODIS 8-day product, a new algorithm for generating 8-day composite from MODIS daily data was developed. The method was based on a statistical approach and the results presented higher spatial homogeneity, reducing the variability of reflectance of neighboring pixels for the same type of land cover. Eventually, it also improved the product quality in the areas with the steepest slopes thanks to the use of a topographic correction. Indices derived from the new 8-day composite products had high statistical correlations with those derived from daily data, confirming their suitability in forest drought studies thus reducing up to 8 times the processing costs.

In addition to the contributions detailed so far, the most important aspect of this thesis was the generation of a big climate and drought database with high spatial resolution and temporal extent, undoubtedly useful in many other fields of research which this thesis has not addressed directly. This huge volume of information also opens the door to pursuit of new questions and concerns that are outlined below as future research lines.

6.4 Looking forward: future research arising

The research presented in this manuscript furthers many aspects of drought studies, meteorological studies and forest studies. Also, new interesting aspects appeared over the course of the research. The new perspective of the recurrent affected areas invites to consider the current climate unit models defined in the Iberian Peninsula, and opens a new interesting research line to research in.

Other aspects such as the detailed analysis of the integration of climate and remote-sensing data at fire scale are with the goal of understanding how drought episodes affect different forest species and their distributions are also attractive.

Moreover, MODIS data still presents a great potential for research and it is necessary to continue the development of new high-quality products to give more strength to the subsequent analysis. New generations of sensors, such as the ones onboard missions as ECOSTRESS or the Sentinel, must be taken into account, given that their data present mew challenges.

Above all, researchers must continue working on the spatiotemporal integration of climate indices and remote-sensing data in order to obtain high-quality global indicators which are understandable, easily accessed and useful for decision makers and drought management.

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