Universitat de Lleida

Spatio-temporal analysis of human-caused fire occurrence patterns in Spain

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It is the possibility of having a dream
come true that makes life interesting.

- *Paulo Coelho* -

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Summary

Fire management in Spain focuses on fast and total control of all wildfire ignitions, independently of location and weather conditions. In order to optimize this process, I have focused on analyzing which factors determine: i. the amount of the deployed resources (Chapter 3) and, ii. the wildfire occurrence patterns (Chapters 4-6). Results from Chapter 3 show that the number of personnel, terrestrial and aerial units deployed increases in large crown fires, being constrained by multiple-fire occurrences, although these results vary by considering regional scales. Firefighting resources in Spain may already be under duress in complying with the current total suppression policy of the country.

Therefore, the prediction of wildfire occurrence, which in Spain is mainly caused by people (HCFs), is crucial for planning. Accordingly, the main objective of this thesis is to identify, analyze and characterize the spatio-temporal patterns of HCFs in Spain. Concern over HCFs has led to modeling for the prediction of their occurrence in other countries, so we have analyzed the state of the art of HCFs modeling (Chapter 4) globally, based on major habitat types. Wildfire occurrence has spatial and temporal similarities by major habitat types, but differences in vegetation composition and configuration patterns were found.

In this way, the Mediterranean vegetation pattern is highly influenced by human land use and settlements, thus it can be considered that pattern is a good proxy for human presence and activities, therefore, for HCF occurrence. In this context, in Chapter 5, we attempted to predict HCF occurrence by quantifying the landscape pattern in peninsular Spain and Balearic Islands. The best model suggests that the highest fire occurrence is associated to highly diverse areas in terms of land uses with compact and short patch edges.

In addition, HCF occurrence in multiple-fire-days suggests wildfire spatio-temporal aggregations. HCF aggregations were analyzed in 9 regions of Spain and related to weather, population density and landscape pattern of each region. Our results suggest the existence of maximum space-time structures around 4 km and 6 months that lose strength when spatial and temporal distances increase. HCFs seem to aggregate within fewer days in warm and dry regions than in milder Atlantic areas. Spatially, HCFs are clustered in shorter distances in diverse and fragmented landscapes of small patches and complex patches. Urban interfaces tend to spatially concentrate fire occurrence, while wildland-agriculture interfaces correlate to large aggregation distances.

Resum

La gestió d'incendis a Espanya es centra en el control ràpid i total de tots els esdeveniments, independentment de la seva ubicació i condicions meteorològiques. Per optimitzar aquest procés, aquesta tesi es centra en l'anàlisi dels factors que determinen: i. la quantitat de recursos empleats (Capítol 3) i, ii. els patrons d'ocurrència d'incendis forestals (Capítols 4-6). El Capítol 3 mostra que el nombre de mitjans d'extinció augmenten en els incendis grans i de copa, però estan limitats per l'ocurrència d'incendis simultanis, encara que aquests resultats varien segons la comunitat autònoma. Els mitjans d'extinció a Espanya poden ja estar sota coacció pel compliment de la política de supressió total d'incendis.

Per tant, la predicció de l'ocurrència d'incendis forestals, que a espanya estan causats principalment per persones (HCF, per les seves sigles en anglès), pel que és fonamental la seva planificació. En conseqüència, l'objectiu principal d'aquesta tesi és identificar, analitzar i caracteritzar els patrons espacio-temporals dels HCFs a Espanya. Aquesta inquietud ha donat lloc a models per predir la seva ocurrència en altres països, pel que s'ha analitzat el seu estat de l'art (Capítol 4) a nivell mundial, en base als tipus d'hàbitat. L'ocurrència d'incendis mostra analogies espacials i temporals en els diferents hàbitats, però també es troben diferències en la composició i configuració de la vegetació.

D'aquesta forma, el patró de la vegetació de la conca del Mediterrani està molt influenciada per les activitats agrícoles i forestals i pels assentaments humans. Per tant, es pot considerar que els patrons del paisatge són bons indicadors de la presència i activitats humanes i, per tant, per l'ocurrència dels HCFs. En aquest context, al Capítol 5, es prediu l'ocurrència dels HCFs mitjançant la quantificació dels patrons del paisatge a la península espanyola i les Illes Balears. El millor model suggereix que la major incidència d'incendis està associada a àrees amb alta diversitat d'usos del sòl, amb tessel·les compactes i perímetres curts.

A més, el Capítol 6 suggereix que els HCFs es troben agregats espacial i temporalment. En aquest sentit, s'analitzen 9 regions d'Espanya i es relacionen amb el clima, la densitat de població i la configuració del paisatge de cada regió. Els resultats suggereixen estructures espai-temps màximes al voltant de 4 km i 6 mesos i perden força a l'augmentar les distàncies espacials i temporals. Els HCFs s'agreguen en un menor nombre de dies en les regions càlides i seques. Les distàncies espacials dels HCF són menors en paisatges fragmentats amb alta diversitat d'usos del sòl i tessel·les petites i complexes. Les interfícies urbanes tendeixen a concentrar espacialment l'ocurrència d'incendis, mentre que la interfície agrícola-forestal està correlacionada amb distàncies llargues d'agregació.

Resumen

La gestión de incendios en España se centra en el control rápido y total de todos los eventos, independientemente de su ubicación y condiciones meteorológicas. Para optimizar este proceso, esta tesis se centra en el análisis de los factores que determinan: i. la cantidad de recursos empleados (Capítulo 3) y, ii. los patrones de ocurrencia de incendios forestales (Capítulos 4-6). El Capítulo 3 muestra que el número de medios de extinción aumentan en los incendios grandes, de copa pero están limitados por incendios simultáneos, aunque estos resultados varían según CCAA. Los medios de extinción en España pueden estar ya bajo coacción en el cumplimiento de la política de supresión total del territorio.

Por lo tanto, la predicción de la ocurrencia de incendios forestales, que en España están causados principalmente por personas (HCFs, por sus siglas en inglés), es crucial para su planificación. En consecuencia, el objetivo principal de esta tesis es identificar, analizar y caracterizar los patrones espacio-temporales de los HCFs en España. Esta inquietud ha dado lugar a modelos para predecir su ocurrencia en otros países, por lo que se ha analizado su estado del arte (Capítulo 4) a nivel mundial, en base a los tipos de hábitat. La ocurrencia de incendios muestra analogías espaciales y temporales en los diferentes hábitats, pero también se encontraron diferencias en la composición y configuración de la vegetación.

De esta forma, el patrón de vegetación de la cuenca del Mediterráneo está muy influenciada por las actividades agrícolas y forestales y los asentamientos humanos. Por consiguiente, se puede considerar que los patrones del paisaje son buenos indicadores de la presencia y las actividades humanas y, por lo tanto, para la ocurrencia de HCFs. En este contexto, en el Capítulo 5, se predice la ocurrencia de HCFs mediante la cuantificación de los patrones del paisaje en España y Baleares. El mejor modelo sugiere que la mayor incidencia de incendios está asociada a áreas con alta diversidad de usos del suelo, con teselas compactas y perímetros cortos.

Además, el Capítulo 6 sugiere que los HCFs se encuentran agregados espacial y temporalmente. Para ello, se analizan 9 regiones de España y se relacionan con el clima, la densidad de población y la configuración del paisaje de cada región. Los resultados sugieren estructuras espacio-tiempo máximas alrededor de 4 km y 6 meses y pierden fuerza al aumentar las distancias espaciales y temporales. Los HCFs se agregan en un menor número de días en las regiones cálidas y secas. Las distancias espaciales de los HCFs son menores en paisajes fragmentados con diversidad de usos del suelo y teselas pequeñas y complejas. Las interfaces urbanas tienden a concentrar espacialmente la ocurrencia de incendios, mientras que la interfaz agrícola-forestal está correlacionada con distancias de agregación largas.

Contents

Chapter 1.

Introduction

1. Introduction

Wildfire is the major disturbance in many regions around the world, and trends in number and burned area seem to increase over time according to climate change predictions. Fire is a relevant factor in forest stands processes of mortality (Catry *et al.* 2010), regeneration (Francos *et al.* 2016), species composition (Fornwalt and Kaufmann 2014) and spatial structure (Lloret *et al.* 2002). Worldwide, burned area rounds 360-380 MHa per year (Chuvieco *et al.* 2016) and more than 30% of the land mass already has significant and recurrent fire activity (Chuvieco *et al.* 2008). Africa and South America are the most active fire areas (Figure 1.1), being the Tropical and subtropical grasslands, savannas and shrublands, the Flooded grasslands and savannas and the Tropical and subtropical dry broadleaf forests (Olson *et al.* 2001) the most affected land habitats.

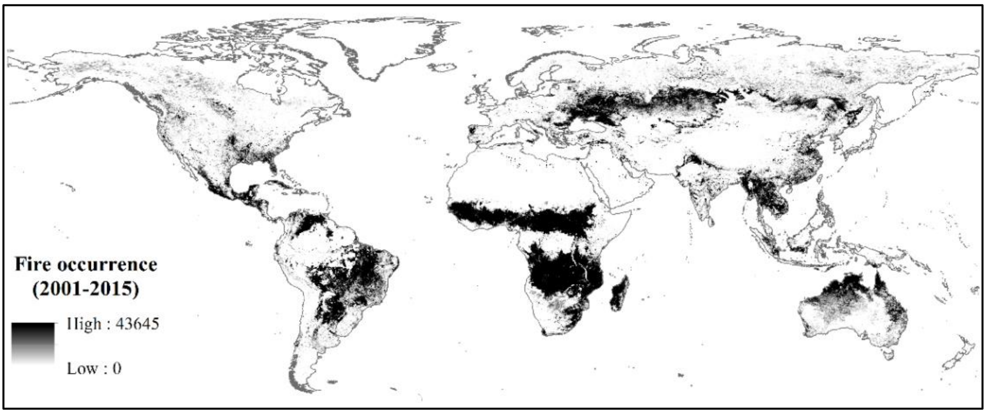

Figure 1.1. Global fire frequency between 2001 and 2015 based on the hotspots product of the sensor MODIS (http://neo.sci.gsfc.nasa.gov/)

Fire suppression has been implemented in most affected countries for many decades, under different organizational models, with varying results often linked to development status of the country. Suppression performance depends on the number and behavior of active fires (Haight and Fried 2007) in relation to resources allocated, though management agencies in a few regions (see, for instance, Canada, Hirsch and Fugelm 2006) may allow some fires to burn if they respond to conservation or management goals. Human technical resources and budgets may be comparatively more stressed in those countries that sustain a full suppression policy like Spain (Costafreda-Aumedes *et al.* 2015) or some US regions (Paveglio *et al.* 2010), because of their high values at risk in very populated regions. When lives and properties are threatened, firefighting managers must make crucial decisions on the amount, type and allocation of the required resources.

Spain organized professional fire suppression in the 1970's, and competences in fire management were transferred regionally (to the Autonomous regions, CCAA) after 1978 (Spanish Constitution approved). Managerial organizations in Spain differ by region, being generally linked either to general emergencies structures or to forest administrations. Different models and different budgets are applied regionally. In addition, these different regional budgets are constrained in the current economic recession (2010-2014) and often prevent maintenance of enough suppression resources that can manage active fires (Alonso-Betanzos *et al.* 2003). For instance, Andalusia and Castile and Leon (Spain) decreased their fire suppression budget in €12 million each (Garcia-Rey *et al.* 2014) from 2006 to 2014 (Andalusia) and 2009 to 2013 (Castile and Leon).

Moreover, whatever resources are available, firefighting efforts may be rendered insufficient (Castellnou *et al.* 2010) under extreme fire behavior conditions in the fire environment and/or high human risk levels. Worst-scenarios occur under extreme weather conditions that increase the probability of fires to scape and to become large (*i.e.* Portugal in 2005, Italy in 2007 or France and Greece in 2009, Cardil, Salis, *et al.* 2014), becoming catastrophic events beyond suppression capacity.

There are knowledge gaps on the relation between the amount on firefighting resources needed and characteristics in the fire physical and social environment, due to the regional variability in budgetary expenses, operational procedures and fire social perceptions. As fire management agencies worldwide have aimed to reduce expenses and damages without endangering human safety, a considerable amount of work has focused on simulating and improving the efficiency of the initial attack to fires and to optimize firefighting resources location from the 70's (Simard *et al.* 1978) to present (Katuwal *et al.* 2016). However, in these cases, the capacity to anticipate fire spatial and temporal occurrences is what allows: i. to take preventive actions, ii. to allocate firefighting resources in advance, and accordingly, iii. to reduce damages and to optimize firefighting resources use.

Consequently, the analysis of fire occurrence, its potential influence on deployment and its application to improved fire management is the focus of this thesis.

1.1. Human-caused fires

Worldwide, more than 90 % of wildfire ignitions are linked, directly or indirectly, to human risk (FAO 2007). These fires are designated as human-caused fires (HCFs) and include as causes all intentional and unintentional human actions, power lines and machinery. HCFs frequently show broadly recognizable spatial and temporal patterns (Padilla and Vega-Garcia 2011), which were perceived from the 50's onward. For instance, Crosby (1954) and Bruce (1963) where the first authors to consider that fire ignitions can be analyzed using mathematical methods. The interest of HCF modeling grew in the following years and is still active nowadays (Levi and Bestelmeyer 2016).

The highest amount of models of HCF occurrence and frequency is mainly located in the Mediterranean Europe and North America (Figure 1.2). However, from 2010 to present, China has been one of the countries with the highest number of fire research models. The first wildfire occurrence models were simple (linear regression, Crosby 1954; Haines *et al.* 1970) and comprised natural- and human-caused fires. In subsequent years, binary logistic (Donoghue and Main 1985) and Poisson logistic (Martell *et al.* 1985) models were introduced, and are still in use nowadays (Pan *et al.* 2016). In recent years, complex parametric and non-parametric methodologies, such as Classification and Boosted regression trees, Artificial neural networks, Support vector machines, Zero-truncated Poisson regression or Generalized additive models were introduced as an alternative to traditional statistical methods.

Figure 1.2. Number of fire occurrence studies by region

HCF occurrence modelling has aimed to identify which biotic and abiotic factors influence wildfire ignition. Fire ignitions depend on the presence, the type of ignition sources and the environment conditions. Temporal factors are based on weather and weather-derived indices related to drought or vegetation moisture. Physiography, land/vegetation cover or human presence are often termed as spatial variables, due to their inherent low temporal variability or the unavailability of frequently updated data.

Previous studies concluded that HCFs tend to occur with high temperatures (Padilla and Vega-Garcia 2011; Ancog *et al.* 2016) and low precipitation (Albertson *et al.* 2009), for instance. In addition, they frequently occur close to anthropic features, like (*i.e.*) settlements (Zhang *et al.* 2010; Chang *et al.* 2013) or roads (Badia-Perpinyà and Pallares-Barbera 2006; Dlamini 2010; Penman *et al.* 2013) and are linked to certain socio-economic activities (Kalabokidis *et al.* 2007; Martínez *et al.* 2009; Mann *et al.* 2016). However, these HCFs are closely connected to the causative agent (Curt *et al.* 2016): arson and negligence fires occur most often in gently slopes and populated areas in summer, while livestock fires are mainly located in mountain areas and take place more often in winter and early spring (González-Olabarria *et al.* 2015). Under these conditions, HCFs tend to aggregate (Vazquez and Moreno 1998) and increase their recurrence. Accordingly, the simultaneity of wildfires frequently occurs in these periods and causes.

For firefighting suppression resources, the simultaneity of two or more fires do create a challenge (Rachaniotis and Pappis 2006). Delays in the initial attack of new fires can happen when multiple fires are burning simultaneously, and the time required to extinguish them grows exponentially with detection and response time. Therefore, it is important to understand the occurrence pattern of HCFs to support prevention and pre-attack planning.

Fire occurrence has been developing successfully for decades now, but admits new developments. The occurrence pattern has been analyzed spatially by relating wildfire occurrence with spatial features, but the landscape structure has rarely been used as a proxy for human activities, and the rapid development of landscape ecology quantitative methods holds potential in fire analysis. Also, temporal aggregation has also been observed linked to human risk, so both the spatial and temporal aggregation of HCF observations must be considered, requiring new methods of analysis.

1.2. HCF occurrence patterns at the landscape level

Current landscapes composition and configuration are the result of historical disturbances on the environment we can observe nowadays (De Aranzabal *et al.* 2008). Thus, the spatial landscape pattern allows understanding natural and human processes like climate (Pickett and White 1985), pests and diseases (Hatala *et al.* 2010), human presence (Fuller 2001), land production activities (De Aranzabal *et al.* 2008) or wildfires (Naveh and Lieberman 1994; Chang *et al.* 2007; Moreno 2007).

In many major habitat types (MHTs), like Mediterranean forests, landscape has been modified by humans (Pausas 2006) and the footprint seems to start more than 6000 years ago (Kaal *et al.* 2011). Recent landscape structures are mainly created by direct human action through the design of margins between wildland and anthropic features (*i.e.* infrastructures or buildings) and productive activities (*i.e.* agriculture), becoming what Farina (2006) calls cultural landscapes. Consequently, landscape patterns can be considered as a source of information on human activities and their interaction with environment, and, accordingly, they have been largely analyzed by sets of metrics (*i.e.* Ferraz *et al.* 2009) like size, number, shape of patches or diversity of land uses. Landscape ecology has developed conceptual advances and empirical methods by which spatial land use patterns are related to ecological processes, such as HCFs.

Therefore, the quantification of landscape spatial patterns is a useful tool to infer HCF occurrence factors. Among the large number of studies that have dealt with wildfire occurrence (see Chapter 4 for an exhaustive review), some have modelled fires with sets of geographic or spatial variables, but only few studies have included metrics measuring landscape patterns. In this way, Henry and Yool (2004) related landscape metrics to historical wildfire occurrence (all causalities) in Arizona (US). Focusing on HCFs, Ruiz-Mirazo *et al*. (2012) analyzed the behavior of landscape metrics in relation to pastoral wildfire occurrence in Andalusia (Spain). Martinez *et al*. (2009) and Martinez-Fernandez *et al*. (2013) considered size, density and fragmentation indices with other socio-economical and spatial variables to predict HCFs in Spain. Building on the conclusions of these authors, this thesis aims to identify the metrics that could be considered more appropriate to characterize fire-prone landscape traits.

1.3. Spatio-temporal aggregations of HCFs

HCFs are usually considered within regular quadrates or irregular administrative divisions (areal units), and few studies analyze wildfires' points of origin as spatial explicit locations. Among these few, HCF occurrence models have been devised using geographically weighted regression models (de la Riva *et al.* 2004), ignition density estimates (Amatulli *et al.* 2007), log-Gaussian Cox processes (Serra *et al.* 2014) or the Ripley's K-function (Vega Orozco *et al.* 2012; Fuentes-Santos *et al.* 2013; Serra *et al.* 2013). Few studies have considered the temporal dimension. For instance, Gralewicz *et al.* (2012a) considered temporal trajectory metrics of ignition densities and, Tanskanen and Venäläinen (2008) analyzed fire weather indices of summer wildfires.

HCFs have also been evaluated as ignition points placed within novel spatio-temporal point process statistical tools (Figure 1.3). These methods comprise the analysis of inhomogeneous spatio-temporal structures of wildfire ignitions (Hering *et al.* 2009), cluster analysis of wildfire ignitions (Vega Orozco *et al.* 2012; Pereira *et al.* 2015), modelling of fire locations by spatio-temporal Cox point processes (Møller and Díaz-Avalos 2010), and spatio-temporal analysis of fire ignition points combined with geographical and environmental variables (Juan *et al.* 2012). However, none of them analyze the space-time configurations of HCF ignitions in relation to environmental patterns, which is the last goal of the thesis.

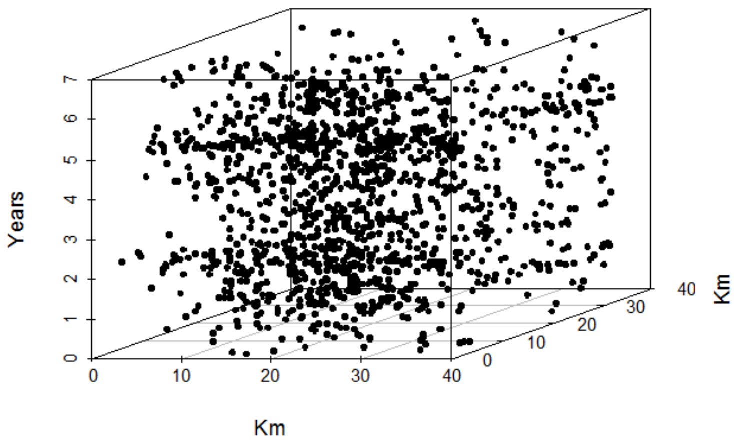

Figure 1.3. Spatio-temporal pattern of HCFs occurred in a 40 km x 40 km region of Badajoz (Spain) during the period 2007-2013

Chapter 2.

Objectives and structure

2. Objectives and structure

The main objective of this thesis is to identify, analyze and characterize the spatio-temporal patterns of HCFs in Spain in order to better inform and potentially improve wildfire management (prevention, pre-attack planning and suppression). The work is carried out under the hypothesis that the current levels of fire incidence affect wildfire management, and specifically, deployment to fires, which raises a need for a better knowledge on spatial and temporal patterns of fire occurrence to optimize decision making in fire organizations.

For this purpose, the followed specific objectives were formulated:

1. To identify what wildfire-incidence-related aspects are currently influential on deployment of suppression resources to fires, besides testing if multiple/simultaneous occurrence situations strain suppression resources, as hypothesized.
2. To review the state of the art in HCF occurrence prediction modeling.
3. To evaluate specifically the relationship between landscape patterns and HCF occurrence with a comprehensive array of landscape metrics, encompassing the wide range of landscape compositions and configurations in Spain.
4. To analyze space-time point patterns of HCF ignitions in relation to biotic and abiotic factors, including landscape metrics.

This thesis is structured in chapters, which have been written as scientific papers. The first study (Chapter 3) analyzes how size, type, duration and simultaneity of wildfires affect firefighting resources management in peninsular Spain. Chapter 4 resumes the state of art of HCF occurrence models in the world for major habitat types, showing trends and differences in wildfire spatio-temporal patterns. Chapter 5 predicts HCF occurrence (fire / no-fire) by using landscape metrics as proxy variables of the human impact of high-modified landscapes by socioeconomic activities in peninsular Spain. Chapter 6 identifies the spatial and temporal aggregations of HCFs in 9 windows of 40 km x 40 km in Spain and compares the trends with some weather, vegetation and human-related variables.

Chapter 3.

Factors in suppression use

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3. Analysis of factors influencing deployment of fire suppression resources in Spain using artificial neural networks

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ABSTRACT: In Spain, the established fire control policy states that all fires must be controlled and put out as soon as possible. Though budgets have not restricted operations until recently, we still experience large fires and we often face multiple-fire situations. Furthermore, fire conditions are expected to worsen in the future and budgets are expected to drop. To optimize the deployment of firefighting resources, we must gain insights into the factors affecting how it is conducted. We analyzed the national data base of historical fire records in Spain for patterns of deployment of fire suppression resources for large fires. We used artificial neural networks to model the relationships between the daily fire load, fire duration, fire type, fire size and response time, and the personnel and terrestrial and aerial units deployed for each fire in the period 1998-2008. Most of the models highlighted the positive correlation of burned area and fire duration with the number of resources assigned to each fire and some highlighted the negative influence of daily fire load. We found evidence suggesting that firefighting resources in Spain may already be under duress in their compliance with Spain's current full suppression policy.

3.1. Introduction

Wildland fires are one of the main threats for Mediterranean forests and cause their degradation (FAO 2013). Spain, one of the Mediterranean countries most affected, currently sustains a full suppression policy under which all fires are fought until extinguished. As in the US (Paveglio *et al.* 2010), the strategy generally applied is based mainly on a fast and aggressive attack on all ignition points in the territory, at every place and under all weather conditions. The strategy is justified by the high values at risk in this highly populated country. The results are usually outstanding in limiting most wildfires to very small burned areas. However, under certain conditions in the fire environment, fires do escape and became large, as happened in Portugal in 2003 and 2005, Italy in 2007, southeast France in 2003 and 2009 and Greece in 2000, 2007 and 2009 (Cardil, Salis, *et al.* 2014). These episodes demonstrate that even strong suppression resources and capabilities may be inadequate when faced, for instance, with extreme fire behavior (Castellnou *et al.* 2010) or multiple-fire starts linked to human risk (Rachaniotis and Pappis 2006). The challenges related to wildfires may increase with the predicted climate change, which could intensify fire propagation and increase burned areas, hamper fire suppression operations and increase costs (Raftoyannis *et al.* 2014), which will be further raised by the expansion of wildland-urban interfaces (WUIs - Liang *et al.* 2008).

In the Spanish recent past (1998-2009), budget was not supposed to be a constraint to forest firefighting. All available firefighting resources were used to minimize the damages, whatever the costs, even if these exceeded any budgetary limit (Velez 2009). However, budgets are a constraint in the current economic recession (2010-2014), as they will certainly be in the future. For instance, Andalusia decreased its fire suppression budget from €89 million in 2006 to €77 million in 2014, and Castile and Leon from €34.4 million in 2009 to €22.4 million in 2013 (Garcia-Rey *et al.* 2014). Consequently, there is a need to examine the amount and patterns of resource use in Spain under the current scenario, because we are already forced to re-think our strategies under rising climate induced danger, dramatic financial cutbacks and rising values at risk in WUIs.

There are certainly gaps of knowledge in Spain on many suppression-related issues, partly due to a great variability in budgets, operational procedures and social perceptions across the political regions in the country. As agencies responsible for fire management in other countries have aimed to optimize procedures to reduce costs and damages without jeopardizing human safety, a certain amount of work has been devoted to simulating optimal resource allocation and dispatching procedures, mainly for initial attack (Simard *et al.* 1978; Islam and Martell 1998). A comprehensive review may be found in Calkin *et al.* (2011). Rachaniotis and Pappis (2006) in Greece addressed the problem of scheduling a single firefighting resource in a multi ple-fire situation. Martin-Fernandez *et al.* (2002) optimized wildfire combat by using simulated annealing and Bayesian global optimization techniques in the Northwest Forest of Madrid (Spain). Rodriguez-Silva (2007) described the SINAMI model for selecting the optimal resource combination for a given fuel type, fire type and duration in Spain. Mendes (2010) used this model to illustrate the application of producer theory and linear programming to optimize suppression.

The anticipated complexity of modeling use of firefighting resources, and the fact that some successful applications had been developed before for other fire problems, led us to select artificial neural networks (ANNs) as a modeling technique. ANNs have been successfully applied to problems such as fire occurrence prediction (Vega-Garcia *et al.* 1996; Vasconcelos *et al.* 2001; Li *et al.* 2009; Vasilakos *et al.* 2009; Karouni *et al.* 2014), regional forest fire susceptibility (Dimuccio *et al.* 2011), forest fire risk prediction and firefighting management in Galicia (Alonso-Betanzos *et al.* 2003), burned area mapping (Mitrakis *et al.* 2012), fire-landscape structure relations (Vega-García and Chuvieco 2006; Ruiz-Mirazo *et al.* 2012), and the evaluation of forest regeneration after fire (Debouk *et al.* 2013). ANN models are a reliable alternative to traditional statistical methods because they are robust pattern detectors even for unpredictable non-linear relationships (Scrinzi *et al.* 2007), they are not affected by multicollinearity or non-normal distributions (Hilbert and Ostendorf 2001) like statistical techniques, and they are flexible in terms of structure.

In this study, we analyze the main factors influencing fire deployment decisions across Spain, especially the factors behind management decisions when resource limits are pushed during large wildland fires. Models for deployment and containment of large fires have very rarely been explored (Finney *et al.* 2009). Therefore, we studied fires larger than 100 ha because they cause the most serious problems to fire agencies and society, and because they account for a very high percentage of the total burned area (Cardil and Molina 2013). Furthermore, in large fires the fire behavior is usually more extreme, and this can influence the risk perception of managers, and hence their deployment decisions (Mills and Bratten 1988).

All publications cited above were used to identify selected factors that could influence demands on resources in this study. Regarding these factors influencing current deployment decisions across Spain, we aimed to answering the following questions: (i) was the final fire size a major factor in the number of resources involved? (ii) Were more resources used when there was crown fire activity? (iii) Did fire duration influence the amount of resources assigned to fire suppression? (iv) Were enough suppression resources available when simultaneous fires occurred? And finally, (v) if response was not swift enough, did a delayed fire suppression response mean that more resources would be needed later? Deployment of different types of resources to fight fires would be expected to depend on factors such as simultaneous fire occurrence (Rachaniotis and Pappis 2006) or fire size (Liang *et al.* 2008). However, the combined influence of these or other factors on fire management remained unknown in the literature, thus justifying this study.

3.2. Materials and methods

3.2.1. Study area

This study covered the whole area of Spain (17 autonomous communities - Figure 3.1) including the Canary and Balearic Islands. Most of the study area is dominated by a Mediterranean climate, and only the northern end has an Atlantic climate. The long summers of high temperatures and low rainfall increase the risk of wildfires in the Mediterranean area. However, even in the northwestern part of Spain, which has an Atlantic climate, forest fire incidence is high (Vázquez de la Cueva *et al.* 2006; Moreno and Chuvieco 2013). The different climatic regions, the complex topography and the socio-economic development over millennia resulted in a very uneven spatial distribution of the vegetation, combining the presence of medium-scale farming areas, areas with little natural vegetation cover (grasses and rangelands), extensive shrublands, park-like open forest structures with undergrowth, and high forests of variable densities. Verdú *et al.* (2012) characterized the relationships between different climatic, topographic and vegetation factors and wildfires in Peninsular Spain.

3.2.2. Historical fire data

The fire history data used in this study were obtained from the National Wildland Fire Statistics (EGIF) of the Agency for Protection against Wildfires (ADCIF) of the Spanish Ministry of Environment and Rural and Marine Affairs (MAGRAMA). This national agency is responsible for compiling statistics, supporting regional actions and coordinating fire suppression at national level.

However, fire prevention and suppression activities are carried out independently by the 17 autonomous communities.

The data were obtained from standard fire reports, which document each fire and contain information such as starting date and time, response time, fire duration, fire type (surface or crown fire), burned area of forest, shrubland or other land, and number of resources deployed. In our study, data for the period 1998-2008 were considered. It was decided to use only this subset of data because after 1998 the data collection procedures were deeply modified, they are considered generally reliable (Velez Muñoz 2000), and before 2008 the financial and economic crisis in Spain had not yet affected budgets.

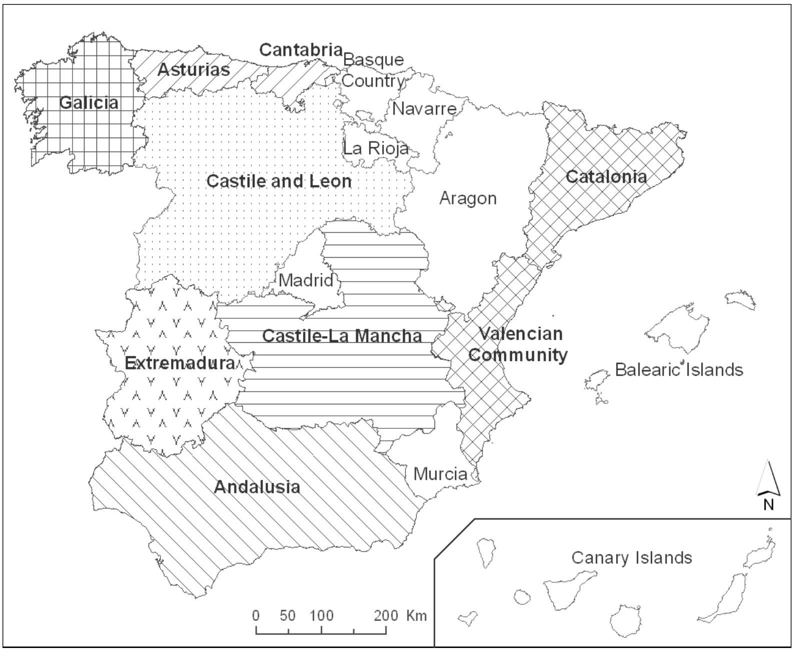

Figure 3.1. Location of the political regions of Spain. The regions of the study are indicated by different filling patterns.

The database underwent many screening and cleaning processes. We discarded all records that contained non-logical information (*i.e.* records with zero as the fire detection time, zero suppression resources, crown fire type and no wooded burned area, and control time equal to or previous to time of arrival) and records with little information (blanks). The 206,978 fire records for the period 1998-2008 were reduced to 170,422 fires in our database, and of these we selected all fires larger than 100 ha (100ha+), adding up to 1824 observations for the whole of Spain. The database was later divided for modeling according to regional location in Spain into either separate autonomous communities or combinations of adjacent communities with similar patterns in fire occurrence and suppression, in order to have enough cases for analysis across each territory (Figure 3.1). Combined regions were built on the basis of similarity in terms of weather conditions, fire regime and fire social implications, and the existing fire suppression systems (all-in-one emergency agencies or forest services). Autonomous communities without neighboring similarities and few large fires (fewer than 100) were discarded for individual models but their data were considered in a general model for the whole of Spain. The rationale for this multiple modeling approach was that we knew that resources differ among regional agencies, but not by how much. Different regions can adjust their resources to their fire problem and values at risk over fire seasons, hence requiring regional models. Those regions with less local suppression resources, though, receive more frequent and intense support from national agencies (the Ministry of Environment and Rural and Marine Affairs, Civil Protection of the Ministry of the Interior, and the Army Emergency Unit). Therefore, we assumed a common baseline in terms of suppression effort across the country for the national model.

3.2.3. Fire suppression resources in the reports: dependent variables

In the EGIF reports, three main categories of fire suppression resources are listed: personnel (*P*), terrestrial units (*TUs*) and aerial units (*AUs*). The *P* category includes all different types of personnel that were directly involved in fire suppression: forest and fire supervisors, forest rangers, professional firefighter crews, well-organized volunteer firefighter crews, other civil personnel, police officers, and army personnel. *TUs* include fire trucks, bulldozers, farm tractors and other heavy machinery used for fire suppression. Finally, *AUs* include amphibious airplanes, air tankers, suppression helicopters, fire crew helicopters and coordination aircrafts. For each of these groups, only the number of resources deployed is reported in the EGIF dataset.

Though available types of firefighting resources may change with the region, only a number of options are available in the EGIF fire report form, so the closest resource type is usually filled in, thus leading to inaccuracy of the data. Therefore, we only considered the three main categories (*P*, *TUs* and *AUs*) to avoid data noise. The database lacks any information about cost and length (working time) of suppression activities for each group. Therefore, it was impossible to transform suppression resources into one monetary dependent variable. We had to develop models capable of explaining jointly the three dependent variables measured in different units: the quantity of *P*, *TUs*, and *AUs* used from each group in each fire.

3.2.4. Individual fire characteristics in the reports: independent variables

To explore the relationships between individual historical fire (100ha+) observations and their recorded use of suppression resources, a series of independent variables were considered according to the previous literature and our stated goals. The list of the independent variables used in the models (Fire Load, Response Time, Fire Type, Fire Duration and Burned Area), their range of values, their description and their use in previous references are presented in Table 3.1. In selecting these variables we acknowledged that we could not analyze environmental conditions and fire behavior because they were not compiled in the database. These are factors that would influence deployment, firefighting strategies and techniques on-site. However, they are not routinely included in the official reports in Spain. Variables related to vegetation are included in the EGIF database marginally and descriptively, but are not spatially explicit. Weather variables are very limited (days from last rain, temperature, wind speed and direction and relative humidity, just one value for the fire, at only one time), and topography is not present in all the records. Every EGIF fire is classified according to type of fire, but the individual record does not contain information on behavior or spread (intensity, direction, flame length, etc.). Therefore, we selected Fire Type (surface or crown fire, also in the record) as the best proxy variable to account for general fuel and danger conditions in the fire environment.

Table 3.1. List of the independent variables used in our models, values range, their description and use in previous references.

Independent variables	Description	Previous references
Fire Load, FL (1-169 fires/day)	The number of fires occurring on the same day and in the same region	Islam and Martell (1998), Rachaniotis and Pappis (2006)
Response Time, RT (0-47.5 h)	Hours between the detection and arrival at the fire	Islam and Martell (1998)
Fire Duration, FD (0-236.5 h)	Hours between the detection and the control of the fire.	Not used. Conceptually related but not the same variable
Fire Type, FT (logical,1,2)	Surface or Crown fire (SF, CF)	Mees and Strauss (1992)
Burned Area, BA (100-19190.9 ha)	Wooded, non-wooded area and non-forest area affected	Liang *et al.* (2008)

3.2.5. ANN models

High correlations should be expected between the variables (*i.e.* fire duration and fire size). Fire suppression resources would be measured in different units, people, trucks, helicopters or air tankers, which could not be added, but would also be correlated. Multicollinearity and the consideration of different types of suppression resources as joint dependent variables in the same model made the choice of ANN optimal for modeling their use in large fires across Spain.

An ANN is an information processing system capable of identifying and fitting very complex non-linear patterns by iterative adjustment of the weights or connections between nodes (free parameters to store the relation between variables in the models) organized as input, hidden and output layers. Our models were feed-forward, multilayered, non-linear, fully connected cascade-correlation networks (Fahlman and Lebiere 1990) built using NeuralWorks Predict ® v.3.24 software (Neuralware 2013). The models were computed as in Alcázar *et al.* (2008) and Debouk *et al.* (2013), but with three output nodes (one for each of the suppression dependent variables). With the cascade-correlation method, the architecture of any network is not set beforehand. Training based on an adaptive gradient learning rule – a variant of the general algorithm of back-propagation (Werbos 1994) – started with no hidden layer, and then hidden units were tested and added during the training process, creating an optimal multi-layer structure (Fahlman and Lebiere 1990) by the time the best possible correlation between observed and predicted suppression variables was achieved. The independent variables (Fire Load, Response Time, Fire Duration, Fire Type and Burned Area) went through a comprehensive number of transformations (*i.e.* linear exponential, inverse, tanh, log, power functions), which were tested as possible inputs to the models with a genetic algorithm prior to model building (as in Alcázar *et al.* 2008). Also previous to model building, the national database of 1824 large fires was split into two subsets: 90% of the data were used for developing the networks (this sample was further divided into two: 70% for training and 30% for periodic testing and assessing of performance accuracy) and 10% for independent validation (data not used for building the model). To avoid the common problem of losing generalization capacity and the ability to perform well with new data in training a network model, it is customary to apply early stopping with a test set (Guan and Gertner 1991; Hasenauer *et al.* 2001; Corne *et al.* 2004). The database was divided according to regional location in Spain, and separate explanatory models were built for several regions. The regional databases were also split in two subsets: 10% for validation and 90% for developing the models (training 70%, testing 30%).

For each of the models several replicate networks were simulated by changing the random selections of fire observations falling within the validation, test and building datasets. We wanted to check for stability in the resulting models (convergence to the same solution). For each of these replicate networks, at least five different initial starting points (random weights assigned) were set for training, to avoid local minima. Given that some regions had a limited number of fires, a weight decay factor was applied to the learning rule for the corresponding regional models to inhibit the complexity of the models (Hasenauer *et al.* 2001; Neuralware 2013). Models for regions with a low number of fires should not have complex networks with many weights or connections, as rules are often applied regarding the number of cases needed per weight for a robust network.

If all the resulting networks (at least 15) converged to a similar result, we considered the solution robust and chose the best net model.

In selecting the best ANN model, we looked for a high Pearson correlation between observed and predicted fire suppression units, low root-mean-square error, balanced results between the three datasets and parsimonious architecture. A sensitivity analysis based on partial derivatives (Jutras *et al.* 2009) was used to determine which independent variable had the highest impact on the predicted variable, since networks were too complex for direct examination. Finally, the frequency of selection of each independent variable by the generic algorithm in each model was examined. The higher the frequency of the independent variable, the more relevant it was in explaining the dependent variable. The same independent variable might enter any network twice or more times, further emphasizing its importance in the corresponding model (Alcázar *et al.* 2008).

3.3. Results

The maximum values of the variables were 1833 for *P*, 173 for *TUs*, and 43 for *AUs*. Pearson's correlation between *P* and *TUs* was 0.72, 0.67 for *P* and *AUs*, and 0.56 between *TUs* and *AUs* ($p<0.01$). Therefore, the correlation between dependent variables was significant and more personnel implied more aerial and terrestrial units also being used.

Average values of resources used per fire and per burned area (100ha+) for the regions analyzed in Spain are presented in Table 3.2. In relation to the number of resources per fire, Aragon, Catalonia, the Valencian Community and Andalusia had the highest values and Cantabria and Asturias the lowest. Similar results were obtained considering the number of resources (*P*, *TUs* and *AUs*) per burned area (Table 3.2). Therefore, noteworthy differences were found among regions in Spain.

Table 3.2. Average values for each resource (personnel *P*, terrestrial units *TUs*, aerial units *AUs*) per each large fire and per 100 ha burned across regions in Spain. Values substantially over the Spanish average are shadowed

Regions	Num	P/F	TU/F	AU/F	P/100ha	TU/100ha	AU/100ha
Spain	1824	110.92 (153.92)	9.85 (13.82)	5.08 (5.5)	41.32 (48.96)	3.83 (5.4)	2.05 (2.43)
CL	507	90.28 (123.35)	7.08 (9.81)	3.72 (4.43)	34.95 (46.29)	2.77 (4.14)	1.45 (1.78)
AN	151	233.15 (210.03)	12.95 (10.48)	10.5 (7.12)	84.59 (58.88)	5.19 (4.74)	4.26 (3.34)
CM	134	112.48 (134.38)	11.63 (10.28)	5.42 (5.98)	39.66 (48.7)	4.32 (3.97)	1.93 (2.33)
CV	118	277.37 (279.7)	33.65 (32.5)	10.81 (7.38)	80.8 (86.77)	10.68 (13.26)	3.62 (3.47)
EX	181	82.8 (74.69)	7.69 (9.37)	3.91 (4.29)	34.66 (28.52)	3.07 (3.32)	1.51 (1.6)
GA	497	66.37 (57.56)	7.32 (6.48)	4.5 (4.26)	29.84 (23.96)	3.36 (3.32)	2.09 (2.32)
CA	127	27.97 (28.57)	1.7 (2.43)	1.41 (2.14)	13.59 (12.86)	0.85 (1.19)	0.69 (1.15)

CL: Castile and Leon; AN: Andalusia; CM: Castile-La Mancha; CV: Catalonia and Valencian Community; EX: Extremadura; GA: Galicia; CA: Cantabria and Asturias

No suitable ANN model could be designed for separately modeling Aragon, La Rioja, Madrid, Basque Country, Balearic and Canary Islands due to lack of sufficient data (fewer than 50 cases), so we focused our efforts on the other regional models with higher fire incidence.

Integrated models for the three dependent variables (*P*, *TUs* and *AUs*) were successfully built using different combinations of the independent variables Fire Load, Fire Duration, Fire Type and Burned Area. The variable Response Time was discarded early in the development of the models, as it showed no significance during any of the building processes. In total, we obtained eight models, one for each of the seven regions and one for the whole of Spain. General model diagnostics (Pearson's R and network architecture) for the best eight models are presented in Table 3.3, where the network architecture for all the best models is also listed, referring to the number of input, hidden and output nodes. ANN architectures were not too complex, but they were more substantial in Castile and Leon and Cantabria and Asturias, with a larger number of nodes in the hidden layer.

The ANN fittings (Pearson's R) between predicted and observed values of the Spanish model training data were 0.66 for *P*, 0.54 for *TUs* and 0.59 for *AUs*, with a

5-11-3 structure. Correlations between predicted and observed values of the Spanish model validation data were 0.70 for *P*, 0.65 for *TUs* and 0.60 for *AUs*.

Table 3.3. General diagnostic with Pearson's R and architecture of the best eight artificial neural network (ANN) models for all Autonomous Communities and for the whole of Spain for the period 1998-2008

ANN architecture		**Spain**	**CL**	**AN**	**CM**	**CV**	**EX**	**GA**	**CA**
		5-11-3	7-24-3	4-8-3	3-9-3	3-10-3	4-4-3	5-24-3	5-2-3
	Train	0.662	0.637	0.809	0.744	0.588	0.700	0.662	0.428
P	Test	0.699	0.508	0.805	0.773	0.779	0.582	0.560	0.685
	Valid.	0.698	0.851	0.357	0.944	0.599	0.571	0.574	0.397
	Train	0.542	0.522	0.706	0.666	0.601	0.720	0.596	0.244
TU	Test	0.545	0.528	0.677	0.745	0.380	0.370	0.456	0.668
	Valid.	0.651	0.808	0.412	0.908	0.505	0.733	0.395	0.740
	Train	0.594	0.567	0.741	0.784	0.494	0.616	0.513	0.323
AU	Test	0.606	0.628	0.706	0.739	0.483	0.641	0.448	0.447
	Valid.	0.600	0.866	0.644	0.931	0.628	0.687	0.500	0.441

CL: Castile and Leon; AN: Andalusia; CM: Castile-La Mancha; CV: Catalonia and Valencian Community; EX: Extremadura; GA: Galicia; CA: Cantabria and Asturias

By regions, Castile and Leon and Galicia showed the most complex architectures (24 nodes in the hidden layer), while the other models had a similar architecture to that of the global model. The best results by regions were obtained in Castile-La Mancha and Castile and Leon (0.80 and 0.66 Pearson's R values averaged over the three datasets and resource types) and the worst in Cantabria and Asturias (0.49). The average sensitivity indicates the direction of change (Table 3.4) and the factors that influence the number of resources (*P*, *TUs* and *AUs*). In order to more accurately illustrate the impact of inputs on outputs, we ran the network model for Spain with average input values for crown or surface Spanish fires, and then we shifted them up and down for crown fires (the most dangerous). The effects of changing Burned Area, and increasing or decreasing Fire Duration and Load (± 5 units) is reported in Table 3.5.

In the global Spanish model (all the data), the average absolute error was approximately 60 for P, 6 for TUs and 3 for AUs (all similar for training, testing and validation data samples). The variables with the highest weight for the fire suppression resources (*P*, *TUs* and *AUs*) were Fire Load (negative) and Burned Area (positive), followed by Fire Duration and crown Fire Type (both positive). Thus, the number of forest firefighting resources is higher in larger fires when regional fire frequency is low, and in long-duration crown fires.

Table 3.4. Simulation of Input-Output effects in the model for Spain

Sensitivity Spain model	FL	FD	SF	CF	BA	P	TUs	AUs
SF_{MEAN} values	21	20	1	0	301	49	4	2
CF_{MEAN} values	23	28	0	1	731	107	9	5
Crown fires sensitivities	**FL**	**FD**	**SF**	**CF**	**BA**	**P**	**TUs**	**AUs**
BA_{MEAN} + 1STD ha	23	28	0	1	2463.2	113	10	6
BA_{MIN} 100 ha	23	28	0	1	100	58	4	3
FL_{MEAN} +5 fires	28	28	0	1	731	102	9	5
FL_{MEAN} -5 fires	18	28	0	1	731	114	10	6
FD_{MEAN} +5 h	23	33	0	1	731	111	10	6
FD_{MEAN} -5 h	23	23	0	1	731	101	9	5

FL: Fire load; FD: Fire duration; SF: Surface fire; CF: Crown fire; BA: Burned area; P: Personnel; TUs: Terrestrial units; AUs: Aerial units

The average absolute error of the regional models is widely variable, being the highest in Catalonia and the Valencia Community and the lowest in Cantabria and Asturias. The value ranges were 15-135 for *P*, 1.5-20 for *TUs*, and 1.5-5 for *AUs*. The number of selected variables in each model is uneven, being only two (Fire Duration and Burned Area) for the Andalusian model. The behavior of their variables is similar to the global Spanish model, in which Fire Load was negatively related to the number of resources (or not affecting them), while Fire Duration, Burned Area and crown Fire Type were positive. Thus, the number of resources for extinguishing a fire was greater in large, long duration crown fires, as expected.

Table 3.5 shows some special patterns. In the Cantabria and Asturias region, more firefighting resources were allocated to surface fires than to crown fires. Fire Duration in Castile and Leon was negatively correlated with the number of *TUs*, and the correlation between Burned Area and *TUs* and *AUs* was stronger in Andalusia and Extremadura than in other regions.

3.4. Discussion

Cascade-correlation ANNs were used to model the relationships between suppression resources deployed in large wildland fires (100ha+) and several independent variables (Fire Load, Fire Duration, Fire Type and Burned Area) in Spain. Our models had a similar behavior and architecture, and replicates converged even when observations were randomly shifted in the training, testing and validation datasets. These findings agree with those of other works (Scrinzi *et al.* 2007; Alcázar *et al.* 2008) and indicate that the models were robust and the databases were suitable for identifying the trends in the data through the analysis of input/output relationships. However, it would be advisable to improve the data collected in order to obtain more accurate analyses in the future, including other information than the quantification of resources used by type (*i.e.* economic information).

Table 3.5. Interactions between independent and dependent variables in each region and the whole Spain. Values of average sensitivity for the period 1998-2008

		Spain	**CL**	**AN**	**CM**	**CV**	**EX**	**GA**	**CA**
				Personnel					
Fire Load		-1.03	-0.07	0	0	0	0	-0.21	-0.01
Fire Duration		0.21	0.17	0.64	0.19	0.11	0.0005	0.26	0.34
Fire type	Crown	0.05	0.03	0	-0.01	0.06	0.056	0.04	0
	Surface	0	0	0	0	0	0	0	0.06
Burned area		0.65	0.05	2.69	0.09	0.27	2.165	0.11	0.22
				Terrestrial units					
Fire Load		-0.80	-0.08	0	0	0	0	-0.20	-0.07
Fire Duration		0.06	-0.11	0.60	0.28	-0.07	0.0003	0.37	0.19
Fire type	Crown	0.05	0.03	0	-0.05	0.10	0.0306	0.05	0
	Surface	0	0	0	0	0	0	0	0.05
Burned area		0.78	0.06	3.24	0.35	0.47	1.0747	0.13	0.16
				Aerial units					
Fire Load		-1.34	-0.10	0	0	0	0	-0.28	-0.01
Fire Duration		0.51	0.86	0.85	0.372	0.12	0.0002	0.25	0.18
Fire type	Crown	0.07	0.06	0	-0.004	0.08	0.0418	0.03	0
	Surface	0	0	0	0	0	0	0	0.05
Burned area		0.88	0.05	5.66	0.153	0.52	2.127	0.07	0.09

CL: Castile and Leon; AN: Andalusia; CM: Castile-La Mancha; CV: Catalonia and Valencian Community; EX: Extremadura; GA: Galicia; CA: Cantabria and Asturias

As a general observation, modeling of *TUs* showed slightly worse results than that of *AUs* and *P*, and *P* showed the best prediction accuracy within the same model and across all models. Trends in dispatching *TUs* could be related to the proximity and accessibility of the *TUs* to the fire location. Local factors such as distance, access, the presence and steepness of forest roads are instrumental, as Mees and Strauss (1992) mentioned, and could explain the higher use of *TUs* in the densely populated eastern and southern Spanish regions in large wildland fires and the lower use in Castile and Leon. Castile and Leon is the largest region in both total area and total forest area, but it has one of the lowest population densities (27 inhabitants per square kilometer).

Different considerations may be applied to *P* and *AU*. According to Ganewatta and Handmer (2009), *AUs* are only justified when other resources cannot reach the fire site, but in Spain they are routinely used in many cases and scenarios. This means that *AU* dispatching could also depend on limited access to the fire site by other resources (interaction effects). *AU* use is usually restricted by weather conditions and geographic or socio-economic factors (Donovan and Rideout 2003; Gebert *et al.* 2007; Kaval 2009).

For the general model at the national level, the number of forest firefighting resources is higher in large, crown and long duration fires when regional fire frequency is low. The fire load negatively influenced deployment to large fires, as found in other environments for fire suppression in the US (González-Cabán *et al.* 1986; Donovan and Rideout 2003). Islam and Martell (1998) also found an effect of fire load on aerial initial attack range in Ontario. Our findings apparently contradict those of Hunter (1981), who concluded that response time and dispatching decisions were not affected by multiple-fire occurrences in Montana, US, though the US environment and the forest fire policy greatly differ from the current Spanish situation.

Not surprisingly, at the national level when the burned area increases, the number of dispatched resources increases, as was also found by Liang *et al.* (2008). The behavior of the independent Fire Type variable seemed to capture the general knowledge that crown fires are the most severe and destructive type of fires (Alexander and Cruz 2014), thus requiring most suppression resources (Dupuy 2009). The fire duration variable showed that the longer the fire, the more resources would be assigned for suppression activities. However, this was more likely for *AUs* than for *TUs*, in agreement with Castellnou *et al.* (2010). Sensitivity analysis of the national model shows, for instance, that a reduction from average Burned Area in crown fires (731 ha) to the minimum considered in the study of 100 ha saves 49 personnel, 5 machines and 2 aircraft from being deployed. An increase in simultaneous fire occurrence by 5 more fires in the same day and region means that 5 fewer people will be deployed to any crown fire. A delay of 5 hours in controlling a crown fire causes on average an increase of 4 people, one *TU* and one *AU*.

Our 7 regional models showed a similar behavior and structure to the national Spanish model, but not all of them achieved equally good results or used the same variables, indicating different regional trends in the use of firefighting resources across Spain. The NW regions (Galicia, Cantabria and Asturias) had lower goodness-of-fit (network Pearson's R correlation) values than central Spain (Castile and Leon and Castile-La Mancha) and the Mediterranean regions (Catalonia and the Valencian Community region). The NW regions also had lower average absolute errors, but this is a consequence of the lower number of resources usually deployed in these regions and not an indication of better model fit.

Regarding Fire Type, in the NW region of Galicia crown fires also appeared to be important for resource deployment, but Fire Load, Fire Duration, and Burned Area (the last one to a lesser extent) were far more influential variables in the best model. The model also confirmed that the influence of fire simultaneity in Galicia is the highest in Spain (Chas-Amil *et al.* 2010). Also, this NW region was more difficult to model in terms of fire occurrences (Padilla and Vega-Garcia 2011), indicating that the general fire environment (social and biophysical) and related patterns of use of suppression resources are more complex than elsewhere in Spain.

Although similar to other variables, the combined region of northern Cantabria and Asturias showed an opposite pattern in Fire Load (resulting negligible) and Fire Type, with more resources being dispatched to surface fires. Surface fires create the most relevant problems in these regions, where large tracts of shrub lands with the worst fire behavior have been created by abandonment of productive rangeland. Moreover, when compared with the nearby Galicia, Cantabria-Asturias exhibits more topographic complexity and lower forest property fragmentation, which favors lower transmittance of fire to tall forests (Rodriguez LA, Head of Prevention and Training of the Emergency Service of Asturias, pers. comm.). Castile and Leon showed a pattern similar to Galicia, but with lower influence of the Fire Load variable.

The individual patterns of Mediterranean regions were completely different, with Burned Area playing a major role in Extremadura and Andalusia. The relation between Burned Area and resources (both *TUs* and *AUs*) was stronger in southern Spain than in other regions. This finding may be explained by the fact that population density in the other regions is higher, therefore availability of local firefighting resources (especially personnel) is also higher.

Interestingly, daily fire load was not relevant in central-southern and eastern Spain. Fire Load did not imply a reduction in firefighting resources deployed to large, 100 ha+ fires in four of these regions. This finding may indicate that the occurrence threshold (number of fires) above which available resources are under duress may not yet have been reached, and that the national model is influenced by the high number of fires in NW Spain.

Some regional differences should be expected as different fire regimes in Atlantic (NW Spain) and Mediterranean Spain have been identified in previous studies (Verdú *et al.* 2012; Cardil and Molina 2013; Moreno *et al.* 2014), and agencies naturally adjust their deployment protocols to the different ignition and propagation conditions and the values at risk. Resource use in large fires in the Mediterranean areas was substantially above the Spanish average. Lower resource use in the Atlantic likely indicated that burning conditions were not as extreme as in the Mediterranean (assuming no budgetary restrictions for either regions in 1998-2008). However, the influence of fire load in three regional models in the northwest, and very especially in Galicia, proved that the occurrence of multiple fires reduced available resources for large fires in these Spanish regions.

Management implications for regions with high fire occurrence need to be considered in our current scenario of a full suppression policy. If fire load is high, temporal constraints in use may occur, meaning that late-arrival fires will use fewer resources or none. When these constraints are in place, there is the possibility of improving the efficiency by training fire managers in advanced analysis of fire behavior and meteorology (Molina *et al.* 2010) and by optimizing the selection and distribution of resources (Martin-Fernandez *et al.* 2002; Rodríguez y Silva 2007), even leaving lower priority fires watched but unattended. And when fire load is high, social preventive action is essential (Raftoyannis *et al.* 2014).

In the future, we can expect worse fire danger conditions in all regions, a more complex WUI environment and constrained budgets (Liang *et al.* 2008; Garcia-Rey *et al.* 2014; Raftoyannis *et al.* 2014), leading to the conclusion that new management strategies are required not only for Spain, but also for other Mediterranean countries with similar conditions (Mendes 2010). The potential impact on budgets should be carefully evaluated (Gebert and Black 2012) and anticipated. Environmental conditions and fire behavior factors that would influence deployment, firefighting strategies and techniques could not be included in our models because they were not available in the official Spanish fire database, but they should be included in future work. Some recent extreme behavior fires have already offered reduced opportunities for fire suppression, being beyond suppression capacity (Molina *et al.* 2010; Cardil, Salis, *et al.* 2014). The current pattern of adding suppression resources when fires grow in size or duration will not be the solution for future fire control, especially if resources are increasingly limited by higher human risk and lower budgets. It may be advisable to revise the current policy of suppression of all fires, as other countries have done before (US and Canada, for instance). The heterogeneous regional environmental and the managerial characteristics and fire regimes (Moreno and Chuvieco 2013) make fire prevention the focus for the future control of fires (Fernandes *et al.* 2013). Forest and fire prevention management alternatives for safer landscapes, including reduced fuel hazards arising from technical use of fire (Cassagne *et al.* 2011; Ager *et al.* 2013; Fernandes *et al.* 2013) and information and education campaigns (Raftoyannis *et al.* 2014), should be a priority for Spain.

3.5. Conclusions

ANNs were successfully applied to model regional patterns of firefighting resource deployment in Spain. Our models suggested that Spanish agencies generally respond to large fires by adding more resources as the fires grow either in size or duration, but in some regions (especially those in NW Spain) multiple-fire situations divert resources from their use on large fires. However, national level analyses may mask the fact that trends of regional firefighting resources differ across Spain. Efficiency can be improved by training decision makers on advanced analysis of fire behavior and meteorology, but in the future we can expect worse danger conditions, a more complex WUI environment and constrained budgets. The full suppression policy being applied should be reexamined. The current pattern of just adding suppression resources with extended fire duration or size will not be the solution for future fire control, thus fire prevention should be a priority for Spain.

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Chapter 4.

Human-caused fire occurrence modelling

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4. Human-caused fire occurrence modelling in perspective: A review

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ABSTRACT. The increasing global concern in the world about wildfires, mostly caused by people, has triggered the development of models for the prediction of occurrences in fire-prone regions, under the premise that a better knowledge of the underlying factors is critical for suppression, prevention-planning actions and guidance on fire policies. Here we analyze the state of the art on human-caused fire occurrence modelling since the first attempts until the present (1954-2016), with the purpose of establishing current and future research needs, stratifying our worldwide analysis by major habitat types that support different fire environments. Fire occurrence patterns present many spatial and temporal similarities, but we found regional differences responding to vegetation composition and configuration, closely linked to weather, human presence and activity that need to be considered regionally in model development.

4.1. Introduction

Wildfire is a major disturbance factor in many parts of the world and it is growing due to climate change (Wotton *et al.* 2010). More than 30% of the world's land mass already has significant and recurrent fire activity (Chuvieco *et al.* 2008). According to FAO (2010), which compiled a wildfire database with records from 64 countries (60% of the world's forest area), an annual average of 487,000 wildfires occurred during 2003–2007. Mozambique, United States, Madagascar, Poland, Portugal, Russia, Spain, Argentina and Hungary topped their list, all with averages over 10,000 fires/year. However, remote sensing has proved Africa and Latin America are the most active fire areas (Chuvieco *et al.* 2008), being the Tropical and subtropical grasslands, savannas and shrublands, the Flooded grasslands and savannas and the Tropical and subtropical dry broadleaf forests (Olson *et al.* 2001) the most affected major habitat types (MHTs). Worldwide, more than 90% of these fires are linked, directly or indirectly, to human activities like forest clearing, grasslands maintenance for livestock production, extraction of non-wood forest products, hunting, recreational areas, arson or resettlement (FAO 2007). These fires are usually termed as "human-caused fires" or HCFs. HCFs encompass intentional and unintentional human actions, power lines and machinery; fires are labelled as "natural" if mainly caused by lightning, and locally at certain regions, by volcanic eruptions or earthquakes.

HCFs often show broadly identifiable spatial and temporal patterns, which led to believe that forest fire occurrences could be modelled from the 1950´s onward. At that time, Crosby (1954) argued that "*Fire occurrence can be predicted*" and Bruce (1963) asked "*How many fires?*" occur considering that fire ignitions can be analysed by mathematical methods. New models of fire occurrence appeared during the following years. Donoghue and Main (1985) produced the first study focused on HCFs occurrence. It was soon recognized that the prediction of these fire occurrences could provide important information for prevention programs (Donoghue *et al.* 1987), optimizing resource allocation in strategic firefighting (Dlamini 2010) and generally guiding forest and fire policies (Chas-Amil *et al.* 2010). The interest of modelling HCFs grew in the following years and this interest remains active nowadays (Pan *et al.* 2016).

Fire occurrence modelling has tried to identify which biotic and abiotic factors influence fire ignitions, by using many modelling techniques. The aim of this review is to analyse the state of art of HCF occurrence modelling with the purpose of establishing current and future research needs to better inform and aid wildfire management. We have considered research papers written in English in widely available scientific journals, and reports published during the 50s and 60s when publishing in scientific journals was not as common as later on.

4.2. The causes of HCFs

138 research papers have been found between the first, Crosby (1954), to the most recent, Levi and Bestelmeyer (2016), and all are listed in Supplementary table 4.S1, with descriptive information on contents. The largest number of HCF papers has been published between 2012 and 2015, with an average of 12 studies per year, and this trend seems to increase in 2016 (13 studies published until July).

This review compilation considers general HCFs occurrence modelling (36 studies), but also studies on specific processes related to human behaviour, like arson (Donoghue and Main 1985; Vasconcelos *et al.* 2001; Prestemon and Butry 2005; Juan *et al.* 2012; Penman *et al.* 2013; Serra *et al.* 2013, 2014; Collins *et al.* 2015), negligence (Vasconcelos *et al.* 2001; Juan *et al.* 2012; Serra *et al.* 2013, 2014; Collins *et al.* 2015), livestock-related (Ruiz-Mirazo *et al.* 2012) or debris fires (Donoghue and Main 1985). HCF occurrence studies often focus on fire ignitions in human-dominated landscapes (FAO, 2007) because a reliable classification of specific causes (human/natural) is not always available. Consequently, we have also considered research papers that include ignitions from any cause or those that do not specify ignitions source, but state that human activity is the predominant causal factor for ignitions in the study area (93 studies).

All these HCFs occurrence models involve the selection and quantification of significant risk factors (predictive variables) used to characterize the occurrence of fire ignitions that are detected and reported, conducing to a fire record in a database for analysis (observed/predicted variable).

4.3. HCF occurrence and ignition data collection

HCF occurrence models rely on the analysis of historical data to describe past HCFs or to predict future events. Fire events are usually reported to a database by national forest departments, forest or fire agencies or forest administrations and usually include the location, date and time, cause and size of each fire, which are the basis for forest fire occurrence modelling (Finney 2005). However, undetected and/or unreported fires or missing fires are a common problem in many countries, due to lack of managerial resources, peak high fire loads, differing policies on minimum reporting size or occurrence in remote underpopulated regions with low values-at-risk (*i.e.* Lefort *et al.* 2004). When reliable fire records are unavailable, fire occurrence (Chuvieco *et al.* 2008) can yet be estimated from remote sensing sources from burned areas or hotspots (*i.e.* Venevsky *et al.* 2002; Vadrevu *et al.* 2006; Maingi and Henry 2007; Chuvieco *et al.* 2008; Garcia-Gonzalo *et al.* 2012; Marques *et al.* 2012; Zhang *et al.* 2013; Li *et al.* 2014; Bedia *et al.* 2015; Ancog *et al.* 2016). In this case, as with historical fire records, precise ignition locations are often uncertain.

Fire ignitions are usually reported within regular quadrats or irregular administrative divisions (areal units), and only a few studies have been able to analyze the spatial-specific location of each event as a point pattern in a certain location and date (Yang *et al.* 2007; Juan *et al.* 2012; Liu *et al.* 2012; Miranda *et al.* 2012; Fuentes-Santos *et al.* 2013; Serra *et al.* 2013, 2014).

HCFs occurrence models in grid or areal units are usually probabilistic and their output is a probability (of at least one fire) that ranges from 0 to 1. By classifying this probability with a cut-off value, fire occurrence can be modelled as binary (absence or presence of fires, coded 0 and 1, respectively) and the greatest amount of research papers have focused on the binary prediction of wildfires (*i.e.* Andrews *et al.* 2003; Reineking *et al.* 2010; Zhang *et al.* 2010, 2016; Arndt *et al.* 2013; Pan *et al.* 2016). A binary dependent variable implies accepting that fires are rare events (Vega-Garcia *et al.* 1995), hardly ever more than one takes place in the temporal and areal unit under study. However, this is not true across temporal and spatial scales, which demands estimations of the actual number of ignitions of each areal unit. Therefore, some studies have focused on the modelling of number of HCF in a certain time span (*i.e.* García Diez *et al.* 1994, 1999; Cardille *et al.* 2001; Knorr *et al.* 2014; Plucinski *et al.* 2014; Xiao *et al.* 2015)

Both binary occurrence and numerical HCFs prediction models have been developed for varying temporal spans. HCF models range from daily predictions (*i.e.* (Crosby 1954; Haines *et al.* 1983; Alonso-Betanzos *et al.* 2003; Lozano *et al.* 2007; Albertson *et al.* 2009; Wotton *et al.* 2010; Padilla and Vega-Garcia 2011; Sakr *et al.* 2011), to monthly predictions (Preisler *et al.* 2004; Boulanger *et al.* 2014), to yearly predictions (Todd and Kourtz 1991; Prestemon and Butry 2005; Karouni *et al.* 2014; Hu and Zhou 2014) or even longer time-span predictions (*i.e.* Pew and Larsen 2001; Chuvieco *et al.* 2008; Avila-Flores *et al.* 2010; Gonzalez-Olabarria *et al.* 2011; West *et al.* 2016).

Within a year, fire occurrence may differ seasonally (Albertson *et al.* 2009): there is a well-defined seasonality in some regions with a high peak of fire occurrence in summer (Ager *et al.* 2014), while in others there are two well-defined peaks of fire frequency in early winter and summer (Martell *et al.* 1989). Accordingly, some models only use fires recorded during the fire season because this is the period with the highest number of fires (*i.e.* Haines *et al.* 1970; Vega-Garcia *et al.* 1995, 1996; Dickson *et al.* 2006; Vilar *et al.* 2010).

After ignition, fires grow to a final size determined by topography, fuels, winds and suppression efforts, in a process that is usually modelled separately from occurrence, dependent on sources of ignition and fine fuels state. For this reason, HCF studies usually consider fires of all sizes. However, models built from remote sensing data have had to focus on large forest fires (LFFs), or consider a certain minimum size arising from technical limitations. Bradstock *et al*. (2009) considered fires larger than 1000ha, Preisler and Westerling (2007) and West *et al*. (2015) fires larger than 400ha, Drever *et al*. (2009), Gralewicz *et al*. (2012), Jiang *et al*. (2012) and Boulanger *et al*. (2014) fires bigger than 200ha; Sitanggang *et al*. (2013) and Zhang *et al*. (2013, 2016) fires larger than 100ha; Lefort *et al*. (2004) and Duane *et al*. (2015) fires over 50ha; Verdú *et al*. (2012) fires over 25ha; Dickson *et al*. (2006) and Hegeman *et al*. (2014) fires larger than 20ha; Garcia-Gonzalo *et al*. (2012), Marques *et al*. (2012) and Rodrigues *et al*. (2014) fires over 5ha; Parisien and Moritz (2009) fires over 4ha, Cardille *et al*. (2001) fires over 0.4ha; Stolle et al. (2003) fires over 0.25ha; or Miranda *et al*. (2012) fires larger than 0.1ha.

4.4. HCF occurrence modelling methods

The first fire occurrence and frequency models were simple, starting with linear regression (Crosby 1954; Haines *et al.* 1970, 1983; Altobellis 1983), modelling together natural- and human-caused fires. In the second half of the 1980s, Donoghue and Main (1985) and Martell *et al*. (1987) introduced, respectively, binary logistic regression for the HCFs binary occurrence and Poisson logistic regression for predicting the number of HCFs. Both methods have been frequently put to use since then (*i.e.* (Liu and Zhang 2015; Marchal *et al.* 2016; Levi and Bestelmeyer 2016), as they are easy to use and understand (Chang *et al.* 2013). In subsequent years, models evolved in parallel to mathematical applications and computing power. Complex techniques such as Classification and Regression Trees (CARTs, *i.e.* Amatulli *et al.* 2006; Sitanggang *et al.* 2013; Karouni *et al.* 2014; Argañaraz *et al.* 2015), Artificial Neural Networks (ANNs, *i.e.* Vasconcelos *et al.* 2001; Sakr *et al.* 2011; Ruiz-Mirazo *et al.* 2012), Support Vector Machines (SVMs, Rodrigues and De la Riva 2014) or Generalized Additive Models (GAMs, Penman *et al.* 2013) have been introduced as an alternative to traditional statistical methods, especially when dealing with large databases, non-linear patterns and not normally distributed or highly correlated variables. Currently, the observation that fires often occur in aggregated or clustered patterns (Pereira *et al.* 2015) has led to non-parametric models including the spatio-temporal relations between ignitions (Yang *et al.* 2007; Beccari *et al.* 2015).

Additionally, this methodological evolution has increased HCF prediction accuracy. While the linear regression model of Altobellis (1983) showed an accuracy of 0.27 for all fire causes, the Poisson mixed model accuracy of Boubeta *et al*. (2015) is 0.86 in HCFs. Padilla and Vega-Garcia (2011) reached 0.89 for one ecoregion in Spain. Higher accuracy should increase the reliability of HCFFs models for operational use by fire managers. Models predicting locations and weather conditions of new fires have the potential to aid in detection and initial attack. Fire suppression resources are often challenged by simultaneous occurrences of fires (Molina-Terrén and Cardil 2015) that can be predicted in advance by fire occurrence models. However, the current level of operational implementation of the majority of these models is scarce, though some fire management systems have made provisions for their use (*i.e.* Chuvieco *et al.* 2010).

4.5. Study areas by terrestrial ecoregions

Our analysis of previous work was geographically stratified from the Global Map of Terrestrial Ecoregions determining Major Habitat Types (MHTs) (Olson *et al.* 2001, https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world), which has been used in previous fire occurrence modelling studies (Bedia *et al.* 2015). MHTs are characterized from climate and, particularly, temperature and precipitation. Climate depends on i. latitude (related to temperature and seasonality), which define polar, subpolar, boreal, temperate, subtropical and tropical regions; ii. precipitation, which determines super-humid, humid, sub-humid, semiarid, arid and super-arid MHTs; and iii. altitude which determines basal, premontane, montane, subalpine, alpine and nival belts. MHTs provide an adequate basis for the stratification of HCFs studies because vegetation results from the interactions between climate, human activities and natural processes, including wildfires. For our analysis, we selected 14 ecoregions from the total 16 (Table 4.1), discarding *Water bodies* and *Rocky and Ice* areas because of their little or no vegetation presence. A minimum representation of 10% in area was set to consider that a publication pertained to a MHT.

Most of the 138 publications analyzed had study areas comprising two or more MHTs. 44 studies had their study area completely enclosed within one MHT, being 6 the number of MHTs in these cases. These 44 studies are distributed with a minimum of 1 and a maximum of 19 studies within the 6 MHTs, suggesting that: i. study areas are usually not based on major vegetation types, but political or administrative boundaries, and ii. some fire environments have received a lot more attention that others, particularly *Mediterranean Forests, Woodlands and Scrub*, and *Temperate Broadleaf and Mixed Forests*, though they are not the highest in fire incidence (Table 4.1). In terms of political boundaries, publications are mainly located in Southern Europe (49 publications, out of which 37 have been done in Spain and Portugal), and North America (US and Canada), with 29 and 16, respectively. In the last years (2010-2016), China has been the second country with the highest number of HCF occurrence modelling publications (14 studies), behind Spain with 22.

Table 4.1. Terrestrial major habitat types (Olson *et al.* 2001), with their world areal percentage and fire density between 2000 and 2015 based on the hotspots product of the sensor MODIS (http://neo.sci.gsfc.nasa.gov/)

Major habitat type	Area %	Fire density (fires/km^2)
Tropical and Subtropical Grasslands, Savannas and Shrublands	6.7	16.6
Flooded Grasslands and Savannas	0.4	16.2
Tropical and Subtropical Dry Broadleaf Forests	1.0	11
Tropical and Subtropical Coniferous Forests	0.3	7.4
Mangroves	0.1	6.4
Tropical and Subtropical Moist Broadleaf Forests	6.5	5.6
Temperate Grasslands, Savannas and Shrublands	6.4	3.4
Temperate Broadleaf and Mixed Forests	8.1	2.4
Mediterranean Forests, Woodlands and Scrub	1.5	2.2
Temperate Conifer Forests	2.7	1.8
Montane Grasslands and Shrublands	2.3	1.6
Deserts and Xeric Shrublands	11.7	1.3
Boreal Forests/Taiga	19.8	0.6
Tundra	22.8	0.1
Rock and ice	9.1	0
Inland water	0.7	0

4.6. Global driving risk factors of HCF occurrence

Human risk (or probability that a fire starts) (Merrill and Alexander 1987) depend on the presence and activity of ignition sources and the conditions in the environment in which fires take place. Environmental factors with high variability in time are mainly based on weather, and weather-driven indices related to drought or vegetation moisture, and are often called “temporal” factors. Factors derived from physiography, land/vegetation cover or human socioeconomic variables (*i.e.* census data) are often termed as “spatial” or “geographic” variables, and have inherent low temporal variability or frequently updated data is usually unavailable. Some studies only consider temporal or spatial variables, or specific groups (*i.e.* only weather, only landscape structure) for input variables (Plucinski 2012). Across the abundant research done until present, many spatial and temporal factors have been tested and been found to be related to, or to be able to explain, HCF occurrence at the MHTs level. The methodology of the analysis (Verdú *et al.* 2012) and the range values of the variables in each study area (Argañaraz *et al.* 2015) influence variable selection and their behavior in a model. However, the analysis of spatial and temporal variables selected in most studies (at least 10) within each MHT, in Table 4.2, shows coincidences in variables and their trends (positive or negative relation to fire occurrence), that allow to summarize some global patterns.

4.6.1. Weather factors

As should be expected when considering combustion requirements in the environment, variables reflect drought conditions, vegetation stress and upward changes in fuel availability. High mean and maximum temperatures (*i.e.* Chou 1992; Pew and Larsen 2001; Magnussen and Taylor 2012; Turco *et al.* 2014; Ancog *et al.* 2016), low precipitation (*i.e.* Lefort *et al.* 2004; Parisien and Moritz 2009; Oliveira *et al.* 2012; Barreal and Loureiro 2015; Guo, Su, *et al.* 2016) and low relative humidity (*i.e.* Mandallaz and Ye 1997; Oliveira *et al.* 2012; Chang *et al.* 2013; Karouni *et al.* 2014) favor fires and are often used. Evapotranspiration and insolation (*i.e.* Badia-Perpinyà and Pallares-Barbera 2006), lack of precipitation during fire-days and previous dry-days (Turco *et al.* 2014) also increase risk. However, annual precipitation, and especially spring precipitation, is related to an increase of HCFs (*i.e.* Donoghue and Main 1985; Cardille *et al.* 2001; Krawchuk *et al.* 2009; Parisien and Moritz 2009; Oliveira *et al.* 2012). Precipitation in spring increases vegetation biomass, especially in fine fuels like grasses or shrubs, that will be later available to burn.

Table 4.2. List and behavior of the most common variables per MHT, if at least a minimum of 10% of the study area belong to the MHT and if included in at least 10 research papers (Number of research papers, Num.RP).

MHTs	NumRP	Weather / danger	Physiography	Vegetation / fuel	Human-related	Other
Tropical and subtropical moist broadleaf forests	10	Mean / Max temp. (+)	Elevation (-)		Road dens. (+)	
		Precipitation (-)	Slope (+)		Dist. roads (-)	
		Relative hum. (-)	Aspect N (+)		Dist. settlements (+)	
		Wind Speed (+)			Population dens. (+)	
		ISI (+)			Dist. railroads (+)	
		FWI (+)			Dist. rivers (-)	
		FFMC (+)			Livestock dens. (-)	
Temperate Broadleaf and Mixed Forests	77	Mean / Max temp. (+)	Elevation (-)	Shrubland (+)	Road dens. (+)	Weekend (+)
		Precipitation (-)	Slope (-)	Wetland (+)	Dist. roads (-)	Bank holiday (+)
		Annual/Non-fire seas. P (+)	Aspect S (+)	WUI (+)	Dist. settlements (-)	
		Days without precip. (+)	Latitude (-)	Grassland (+)	Population dens. (+)	Recent fires (+)
		Relative hum. (-)	Ruggedness (-)	Forest (+)	Building dens. (+)	
		Low RH previous days (+)		Agriculture (+)	Dist. railroads (-)	
		ISI (+)		Dist. non-forests (-)	Railroad dens. (+)	
		FWI (+)			Public forests (-)	
		FFMC (+)			Unemploy. rate (+)	
		McArthur (+)			Poverty rate (+)	
		PDSI (-)			Dist. rivers (-)	
		Evapotranspiration (+)				

Table 4.2. Continued

MHTs	NumRP	Weather / danger	Physiography	Vegetation / fuel	Human-related	Other
Temperate Conifer Forests	34	Mean / Max temp. (+)	Elevation (-)	Forest (-)	Road dens. (+)	No-fire days (-)
		Precipitation (-)	Slope (-)	Dist. WUI (-)	Dist. roads (-)	Bank holiday (+)
		Annual/Non-fire season P (+)		Grassland (-)	Dist. railroads (-)	Weekend (+)
		Relative humidity (-)		Shrubland (-)	Dist. settlements (-)	Time of day (+)
		Low RH previous days (+)		Urban (-)	Population den. (+)	Julian (∩)
		Evapotranspiration (+)		WUI (+)	Unemploy. rate (-)	
		FFMC (+)		Fuel 1000h (-)	Police presence (-)	
		FWI (+)			Poverty rate (-)	
		McArthur (+)			Dist. campgrounds (-)	
		KBDI(+)			Forestry operations (+)	
		DMC (+)			Pasture land holding (+)	
Boreal Forests/Taiga	20	Mean / Max temp. (+)	Elevation (-)	Forest patch edge (-)	Population dens. (+)	Fire season (+)
		Precipitation (-)			Dist. settlements (-)	
		Annual precipitation (+)			Dist. roads (-)	
		Wind Speed (+)			Road dens. (+)	
		Water balance (-)			Per capita GDP (+)	
		FFMC (+)				
		DMC (+)				
		DC (+)				
		FWI (+)				
		ISI (+)				

Table 4.2. Continued

MHTs	NumRP	Weather / danger	Physiography	Vegetation / fuel	Human-related	Other
Temperate Grasslands, Savannas and Shrublands	17	Mean / Max temp. (+)	Elevation (-)	Shrubland (+)	Population dens. (+)	Summer (+)
		Precipitation (-)	Slope (+)	Grassland (+)	Dist. settlements (-)	
		Relative humidity (-)	Latitude (-)	Forest (+)	Dist. roads (-)	
		Radiation (+)	Topog. rough. (∩)	NDVI (+)	Dist. railroads (-)	
		FFMC (+)		WUI (+)	Dist. water bodies (∩)	
		ISI (+)		WAI(+)	Dist. waste dispos. (-)	
		FWI (+)		Sparsely veget. (-)	Prosecutions (-)	
Mediterranean Forests, Woodlands and Scrub	62	Mean / Max temp. (+)	Elevation (-)	Shrubland (+)	Dist. roads (-)	Municipality (+)
		Precipitation (-)	Slope (-)	Dist. Shrubland (-)	Road dens. (+)	Workday (-)
		Annual/Non-fire seas. P (+)	Aspect SW (+)	Forest (+)	Dist. settlements (-)	Weekend (+)
			Topog. Position (+)	WUI (+)	Urban dens. (+)	DoY (∩)
		Days with precip. (-)		WAI(+)	Population dens. (+)	Recent fires (+)
		Relative humidity (-)		Non-flammable fuel (-)	Dist. railways (-)	
		Insolation (+)		Number of trees (-)	Railroad dens. (+)	
		FWI (+)		DBH (-)	Protected areas (+)	
		FFMC (+)		Agriculture (+)	Dist. protected areas (-)	
		FMC (+)		Land fragmentat. (+)	Livestock dens. (-)	
		DC (+)		Shannon's diversity (+)	Agric. machin. dens. (+)	
				Grassland (-)	Dist. recreation areas (-)	
				Mean Patch Edge (-)	Dist. powerlines (-)	
				Mean Shape Index (-)	Power lines (+)	
				Patch density (-)	Unemploy. rate (-)	

Table 4.2. Continued

MHTs	NumRP	Weather/danger	Physiography	Vegetation / fuel	Human-related	Other
Desert and Xeric Shrublands	19	Temperature (+) Annual precip. (+) FWI (+)	Topog. rough. (+) Aspect N (+)	Shrublands (+) NDVImax (+) Coniferous (+) Mean Shape Index (-) Mean patch size (+) Patch size coeff. var. (-) Shannon's diversity (-)	Population dens. (+) Dist. settlements (-) Per capita GDP (+) Road dens. (+) Dist. roads (-)	$NDVI_{DATE}$ (-)

Fire science has developed methods to estimate the decrease of the moisture content caused by weather on litter and fine fuels, medium compact organic layers and deep organic soil layers or heavy fuels for fire danger rating (Dimitrakopoulos *et al.* 2011). Among them, we found very frequent use of Fine Fuel Moisture Content (FFMC, Cunningham and Martell 1973; Martell *et al.* 1989; Chuvieco *et al.* 2009; Carvalho *et al.* 2010; Lee *et al.* 2012), Drought Code (DC, Drever *et al.* 2009; Wotton *et al.* 2010; Bedia *et al.* 2014) and Duff Moisture Code (DMC, Wotton *et al.* 2003; Magnussen and Taylor 2012; Wu *et al.* 2014), Fire Weather Index (FWI, *i.e.* Martell *et al.* 1987; Carvalho *et al.* 2008; Ager *et al.* 2014; Beccari *et al.* 2015), Initial Spread Index (ISI, Haines *et al.* 1983; Vega-Garcia *et al.* 1996), McArthur (Crosby 1954; Bradstock *et al.* 2009; Penman *et al.* 2013), Keetch-Byram Drought Index (KBDI, Prestemon and Butry 2005), Palmer Drought Severity Index (PDSI, Preisler and Westerling 2007; Miranda *et al.* 2012), Energy Release Index (Andrews *et al.* 2003) and Angstrom (Reineking *et al.* 2010).

The Canadian codes and indices FFMC, DMC, DC and FWI, are the most significant indices in all MHTs, followed by the American KBDI, ERC and PSDI and the Australian McArthur. These indices were selected in most of models in which were included, often with preference to other weather variables.

Weather conditions favorable to fire occur mainly in summer (Albertson *et al.* 2009; Ager *et al.* 2014), but also happen, to a lesser extent, in early or late winter in those regions with marked seasonality (Maingi and Henry 2007; Reineking *et al.* 2010; Zhang *et al.* 2010). In some regions, like Europe (Mandallaz and Ye 1997; Reineking *et al.* 2010; Ganteaume *et al.* 2013), fires have two well-defined peaks, one higher in summer, and another lower in winter. They may associate to specific fire causes, *i.e.* arson, agricultural burnings and accidental fires are more frequent in summer (Ganteaume *et al.* 2013), fires caused by shrub removal for regenerating pastures and feeding livestock in winter and early spring (DeWilde and Chapin 2006).

4.6.2. Physiography variables

Elevation and slope are considered in most of MHTs. Usually, decreases in elevation increases HCFs occurrence (*i.e.* Sebastián-López *et al.* 2008; Kwak *et al.* 2012; Narayanaraj and Wimberly 2012) and slope (*i.e.* Syphard *et al.* 2008; Dondo Bühler *et al.* 2013; Argañaraz *et al.* 2015; Najafabadi *et al.* 2015). As temperature decreases (average variation of -0.65 °C / 100m) while relative humidity increases with elevation (*i.e.* in mountain ecoregions), these variables may be reflecting climatic conditions. As HCFs tend to occur in lowlands and gentle slopes, where population tends to cluster, topographic variables may also be proxies for human presence and activity. However, this depends on the activity, Gonzalez-Olabarria *et al*. (2015) found fires related to pastures and forests are mainly located in the mountain areas. Arson (Vasconcelos *et al.* 2001) and negligence fires (Juan *et al.* 2012; Serra *et al.* 2013) occur most often in flat or moderate slopes.

4.6.3. Fuel risk factors

Even though vegetation, and hence fuel availability, differ by MHTs, it is possible to identify some trends around the world with regard to landscape composition. Conifer forests seem more prone to burning (Badia *et al.* 2011; Verdú *et al.* 2012; Duane *et al.* 2015), being some examples in the literature Ponderosa pine (Dickson *et al.* 2006), Jack pine (Cardille and Ventura 2001), Aleppo pine (Kalabokidis *et al.* 2007), black pine (Kalabokidis *et al.* 2007) and maritime pine (Barreal and Loureiro 2015).

As for landscape configuration (Farina 2006), land uses interfaces seem to favor HCF occurrence in those MHTs in which it has been considered. Particularly, the wildland-urban interface (WUI), areas with less than 50% vegetation and at least 6 houses per km^2 of an area over 500 ha (Faivre *et al.* 2014) and the wildland-agriculture interface (WAI) (Vilar del Hoyo *et al.* 2011), are significant factors in, respectively, 4 and 2 of the 7 MHTs in Table 4.2. Urban, forest, and agriculture land uses coexist and intermix in these anthropic landscapes.

Configuration metrics have not been applied as extensively as composition or land cover variables, but fire prone landscapes often present high fragmentation (Martínez *et al.* 2009; Ruiz-Mirazo *et al.* 2012; Martínez-Fernández *et al.* 2013) and non-complex shapes linked to the artificial boundaries set by humans (Henry and Yool 2004; Gralewicz *et al.* 2012b; Costafreda-Aumedes *et al.* 2013).

Wildfire patterns differ between MHTs according to vegetation changes; tree or forest structure variables influence the occurrence process (González *et al.* 2006), but not always in a similar way. *Temperate conifer forest* and *Temperate broadleaf and mixed forest* in cold and wet regions usually show high tree density and a moist understory composed mainly by ferns and forbs. This understory has low wildfire occurrence probability (Narayanaraj and Wimberly 2012). By contrast, forests in *Temperate grasslands, savannas and shrublands, Mediterranean forests, woodlands and scrub* or *Deserts and xeric shrublands* have an understory of shrubs with low moisture content under warm and dry conditions, so shrubs favor wildfires in those MHTs (Badia *et al.* 2011; Verdú *et al.* 2012; Oliveira *et al.* 2014; Mishra *et al.* 2016; Modugno *et al.* 2016). However, specific information on the role of forest components in specific MHTs is often lacking, since few references are enclosed in just one MHT: for example, *Temperate broadleaf and mixed forest* have 5 references completely included within the MHT, and only Narayanaj and Wimberly (2012) included shrubs in the model (with negative sign). The combined influence of neighboring MHTs in a study may mask particular vegetation patterns of fire occurrence.

4.6.4. Human factors

HCFs are, directly or indirectly, caused by human activities linked to socioeconomic conditions (Oliveira *et al.* 2014). The location of these activities is highly dependent on site-related variables that determine the number and distribution of human sources of ignition. These parameters vary geographically, placing locations under different fire risk levels (Vega-Garcia *et al.* 1995), so human presence can be analysed from explicit spatial factors, such as accessibility. In this way, proximity to, or density of, infrastructures such as roads (Dickson *et al.* 2006; Gralewicz *et al.* 2012b; Yang *et al.* 2015; Zhang *et al.* 2016; Mhawej *et al.* 2016), tracks (Pew and Larsen 2001; Romero-Calcerrada *et al.* 2008, 2010; Rodrigues *et al.* 2014), trails (Syphard *et al.* 2008; Vilar del Hoyo *et al.* 2011; Arndt *et al.* 2013) and railways (Sturtevant and Cleland 2007; Guo *et al.* 2015) are associated with an increase in fire occurrence. For example, in Spain (MAGRAMA 2015) and US (Morrison 2007) more than half of HCFs start along road systems. They act as conveyers for arsonists, careless drivers and campers (Morrison 2007).

Regarding socio-economic indicators, population density is the most important factor related to the occurrence of HCFs (*i.e.* Prasad *et al.* 2008; Kwak *et al.* 2012; Dondo Bühler *et al.* 2013; Knorr *et al.* 2014; Nunes *et al.* 2016), being present in all MHTs in Table 4.2. High population densities are related to high wildfire occurrence, in general. However, studies in which high population density aggregates in large urban areas, such as Gonzalez-Olabarria *et al.* (2011) in NE Spain, Penman *et al.* (2013) in SW Australia, Argañaraz *et al*. (2015) in Argentina or Beccari *et al*. (2015) in North Italy, found low fire occurrence. This may have been caused by the lower availability of fuels to support HCFs. Donoghue and Main (1985) observed an increase of HCF occurrence related only to non-metropolitan population density. In intensive agricultural areas, usually the highest number of farmers (Martínez *et al.* 2009; Koutsias *et al.* 2010) and small holders (Stolle *et al.* 2003), the highest HCF occurrence.

Related to population density, HCFs occur most often near settlements (*i.e.* Pew and Larsen 2001; Romero-Calcerrada *et al.* 2008; Yang *et al.* 2008; Liu *et al.*

2012; Wu *et al.* 2014) or highly built-up areas (Sturtevant and Cleland 2007; Chas-Amil *et al.* 2015). Gonzalez-Olabarria *et al*. (2015) have found that the distribution of arson, smokers, powerlines and camp fires in NE Spain occur near coastal areas, where the population density is higher.

Productive activities on the land, especially agriculture, seem related to wildfire occurrence. Croplands (Catry *et al.* 2009; Vasilakos *et al.* 2009), or proximity to agricultural plots (Vasconcelos *et al.* 2001) are risk factors. Martinez *et al.* (2009), Rodrigues and de la Riva (2014) and Rodrigues *et al.* found that the density of agricultural machinery in Spain, as a proxy for intensive land use, is related to HCF occurrence. When considering livestock production, also livestock density is often directly associated with HCF occurrence (Martínez *et al.* 2009; Oliveira *et al.* 2012; Boubeta *et al.* 2015) but relations are not linear. Dlamini (2010) and Romero-Calcerrada *et al.* (2008) concluded in Swaziland and Central Spain, respectively, that intermediate livestock densities were associated with an increased occurrence of HCFs. Shrub removal for regenerating pastures and feeding livestock tend to locate in areas with lower population density and further from metropolitan areas (Cardille *et al.* 2001; Stolle *et al.* 2003; Zhang *et al.* 2010, 2013; Sitanggang *et al.* 2013).

Outdoor recreational activities (Romero-Calcerrada *et al.* 2008, 2010; Vilar del Hoyo *et al.* 2011) are risky activities related to HCFs in most MHTs. Proximity to campgrounds (Pew and Larsen 2001; Gonzalez-Olabarria *et al.* 2011; Mann *et al.* 2016) or fishing areas (Chang *et al.* 2013; Sitanggang *et al.* 2013) are often related to negligent or careless fires. These activities are mainly carried out during bank holidays (Albertson *et al.* 2009; Plucinski *et al.* 2014), weekends (Prestemon and Butry 2005; Albertson *et al.* 2009; Vasilakos *et al.* 2009; Plucinski *et al.* 2014) and holidays (Mandallaz and Ye 1997; Prestemon and Butry 2005). The fact that they are especially popular in spring (Martell *et al.* 1989; Preisler and Westerling 2007; Albertson *et al.* 2009) and summer (Martell *et al.* 1989; Preisler *et al.* 2004; Vilar *et al.* 2010; Ager *et al.* 2014), matches human risk with the most favorable seasons for ignition. Considering only specific activities may change general patterns, for instance, Narayanaj and Wimberly (2012) concluded that fire ignitions occurred in low population density areas because their fires were linked to hiking, camping and hunting in public forests, which are located far from highly populated areas.

Additionally, HCFs have been modelled including other variables related to economic and educational levels in the population. Wildfires have been found to relate to social level (Mercer and Prestemon 2005; Vadrevu *et al.* 2006; Oliveira *et al.* 2012; Dondo Bühler *et al.* 2013; Chas-Amil *et al.* 2015), poverty levels (Dondo Bühler *et al.* 2013), gross domestic product per capita (Chuvieco *et al.* 2008; Guo, Su, *et al.* 2016; Guo, Wang, *et al.* 2016; Guo, Selvalakshmi, *et al.* 2016), unemployment (Mercer and Prestemon 2005; Prestemon and Butry 2005; Martínez *et al.* 2009; Oliveira *et al.* 2012; Dondo Bühler *et al.* 2013; Chas-Amil *et al.* 2015; Nunes *et al.* 2016), age (Koutsias *et al.* 2010; Martínez-Fernández *et al.* 2013; Nunes *et al.* 2016) or literacy level (Vadrevu *et al.* 2006). Enforcement, measured as police presence was found significant by Donoghue and Main (1985).

4.4. Conclusions

The large quantity of HCF occurrence models found indicates this fire science topic has reached a good level of development. First wildfire occurrence models were simple and did not predict well, then, logistic regression models were introduced and became commonly used, and over the years, they have been joined by more complex methodologies such as CARTs, ANNs, SVMs, GAMs and other parametric and non-parametric models with good accuracies. The majority of studies are located in Europe and North America, mainly focused on MHTs *Temperate broadleaf and mixed forests* and *Mediterranean forests, woodlands and scrubs*. In recent years, People's Republic of China has become the second country with the highest number of studies, behind Spain.

As HCFs are human artefacts, study areas tend to follow political or administrative boundaries that often combine neighboring MHTs, so patterns specific to some vegetation types are not well known. We used MHTs to classify research work over the world, and at the broad scale of the MHT delimitation of Olson *et al*. (2001) we found that few studies have focused on the most active fire regions (Chuvieco *et al.* 2008; Krawchuk *et al.* 2009; Knorr *et al.* 2014; Bedia *et al.* 2015), where wildfire databases are not even available (FAO 2010). *Tropical and subtropical grasslands, savannas and shrublands* of Zambia, Central African Republic, Guinea, Togo, Benin, Guinea Bissau, Angola and Ghana, *Flooded Grasslands and savannas* in Zambia, Botswana, Namibia, Sudan and Bolivia, and *Tropical and subtropical dry broadleaf forests* in Madagascar and Indochinese Peninsula have largely been ignored by research, so far.

A variety of modelling techniques have been applied, but HCF occurrence present similar spatial and temporal patterns across MHTs. HCFs tend to occur in accessible and populated areas, close to humans and their socio-economic activities (both productive and leisure locations), interfaces and fragmented landscapes. Risk factors depend on causative agent, but studies stratified by cause or fire-prone activities are not abundant.

Fire danger rating indices have proved optimal to characterize the weather conditions conducive to fires, particularly FFMC, DC, DMC and FWI, present in the majority of studies conducted.

Modelling HCF occurrence has the potential to improve territorial planning for prevention and suppression management, but regardless of research advances, the current level of operational application of models is very low. Model complexity and model perception as a black box (*i.e.* for ANN) with lack of adequate technical transference may explain partly this issue. Also, policies about total control of fire in most countries, often force managers to consider risk as high and homogeneous all over the territory, all the time, decreasing their need for better predictions (Boulanger *et al.* 2012, 2014).

Future research to inform better wildfire management seems to revolve around deeper knowledge on causality, better stratification of the landscape risk beyond political boundaries and improved technology transfer to managers, but mainly, future research needs to consider the most active fire regions in the world. Improving global wildfire databases (location and causality of ignition sources), either through fieldwork or remote sensing imagery is necessary to have a complete diagnosis of human caused fire occurrence in the world.

Chapter 5.

Fire occurrence and landscape in Spain

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5. The relationship between landscape patterns and human-caused fire occurrence in Spain

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ABSTRACT: Human settlements and activities have completely modified landscape structure in the Mediterranean region. Vegetation patterns show the interactions between human activities and natural processes on the territory, and allow understanding historical ecological processes and socioeconomic factors. The arrangement of land uses in the rural landscape can be perceived as a proxy for human activities that often lead to the use, and escape, of fire, the most important disturbance in our forest landscapes. In this context, we tried to predict human-caused fire occurrence in a 5-year period by quantifying landscape patterns. This study analyses the Spanish territory included in the Iberian Peninsula and Balearic Islands (497,166 km^2). We evaluated spatial pattern applying a set of commonly used landscape ecology metrics to landscape windows of 10 km x 10 km (4751 units in the UTM grid) overlaid on the Forest Map of Spain, MFE200. The best logistic regression model obtained included Shannon's Diversity Index, Mean Patch Edge and Mean Shape Index as explicative variables and the global percentage of correct predictions was 66.3 %. Our results suggested that the highest probability of fire occurrence at that time was associated with areas with a greater diversity of land uses and with more compact patches and fewer edges.

5.1. Introduction

Landscape structure is the result of past and present interactions between human activities and natural processes (Naveh and Lieberman 1994; Löfman and Kouki 2003; Echeverría *et al.* 2007; De Aranzabal *et al.* 2008; Serra *et al.* 2008). Variations in frequency, magnitude and extension of disturbances produce complex patterns in vegetation composition, age structure and patch size distribution over the landscape (Regato *et al.* 1999; Farina 2006; Saura 2010). Thus, the spatial pattern of vegetation, usually assessed by different metrics, allows understanding historical ecological processes and socio-economic factors. Landscape composition and configuration metrics have been proved to be influenced by climate (Pickett and White 1985), forest pests and diseases (Romero *et al.* 2007; Hatala *et al.* 2010), land use changes (Gallant *et al.* 2003; Serra *et al.* 2008; Ferraz *et al.* 2009), human settlements (Fuller 2001), deforestation (Löfman and Kouki 2003; Zhang and Guindon 2005), the abandonment of traditional agrarian tasks (plowing, grazing and cutting) (De Aranzabal *et al.* 2008) and fires: burned area and frequency (Pickett and White 1985; Naveh and Lieberman 1994; Chang *et al.* 2007; Moreno 2007).

In the Mediterranean environment, the landscape has long been modified by human influence (Pausas 2006), becoming what we call a cultural landscape (Farina 2006). Landscape patterns are created by direct human action through the design of boundaries between crops and natural vegetation, wildland-urban interfaces, presence of infrastructures, or indirectly by allowing the spread of disturbances, for instance. Hence, landscape metrics may be proposed as surrogate variables for human activities in our Mediterranean environment.

In the past, fire was the main tool used in cleaning and removal of forest residues, along with grazing and firewood extraction (Pausas 1999; Torre Antón 2010). In current times, fires are still linked to the persistence of traditional agrarian activities (Martínez *et al.* 2009). Approximately 18,600 fires occur per year in Spain, and 96.2 % are caused by people (MAGRAMA 2010). About 75 % of human-caused fires in Spain are related to the rural use of fire for vegetation management (MAGRAMA 2010; Torre Antón 2010). Fires are a human artefact emanating from the rural activities that shape the Mediterranean landscapes.

Consequently, the quantitative analysis of landscape structure becomes a relevant tool to make inferences on future fire occurrence. Among the studies that have dealt with fire occurrence in the literature, many have included geographic or spatial variables (*i.e.* Padilla and Vega-Garcia 2011) but only Henry and Yool (2004), Martínez *et al.* (2009) and Ortega *et al.* (2012) have included independent variables measuring landscape pattern. Henry and Yool (2004) calculated landscape metrics (area, shape and diversity indices) in remote sensing images (Landsat TM and SIR-C data) to relate landscape pattern with historical fire occurrence in National Saguaro Park (Arizona). Martínez *et al.* (2009) considered area, density and fragmentation indices (landscape and cropland fragmentation) with socio-economical and geographical variables to predict human-caused fire occurrence at the municipal scale in Spain. A recent study by Ortega *et al.* (2012) did analyze landscape structural factors (11 metrics) related to increased wildfire incidence in forest-agriculture interfaces within the SISPARES monitoring network (observation size 16 km^2), finding that certain landscape configurations were more vulnerable (fire-prone) than others.

Building on these findings, we propose that some metrics may be more appropriate than others to characterize and identify fire-prone landscape traits at the national level. Thus, the aim of this paper is to evaluate specifically the relationship between landscape patterns and human-caused fire occurrence with a comprehensive array of landscape metrics, encompassing the wide range of compositions and configurations that can be found in Spain.

5.2. Materials and methods

5.2.1. Study area

This study analyzes the Spanish territory included in the Iberian Peninsula and Balearic Islands (497,166 km^2). Most of the study area is dominated by a Mediterranean climate, and only the Northern third has an Atlantic climate. These climatic zones and the complex topography combined with human socio-economical development over millennia have given way to a very uneven spatial distribution of the vegetation, combining the presence of medium-scale farming areas, areas with scarce natural vegetation cover (grasses, rangelands), extensive shrublands, park-like open forest structures (*dehesas*) with undergrowth and high forests of variable densities (EEA 2006).

The main reference for the study of vegetation cover in Spain is the Forest Map of Spain by Ruiz de la Torre (1990) at 1:200,000 scale (digitized 1:50,000). It locates more than 5,500 species of trees, shrubs and grasses, collecting information about other land uses.

In order to fulfill the goals of this study and work at the considered scale (Peninsular Spain and Balearic Islands) it was necessary to reclassify the different plant species and land uses in manageable categories meaningful for risk analysis. The classification was designed according to the fuel models of Rothermel (1972) and species response to fire (Rothermel 1972; Riano *et al.* 2001; Sturtevant and Cleland 2007). Figure 5.1 displays the vegetation classes used, defined in Table 5.1.

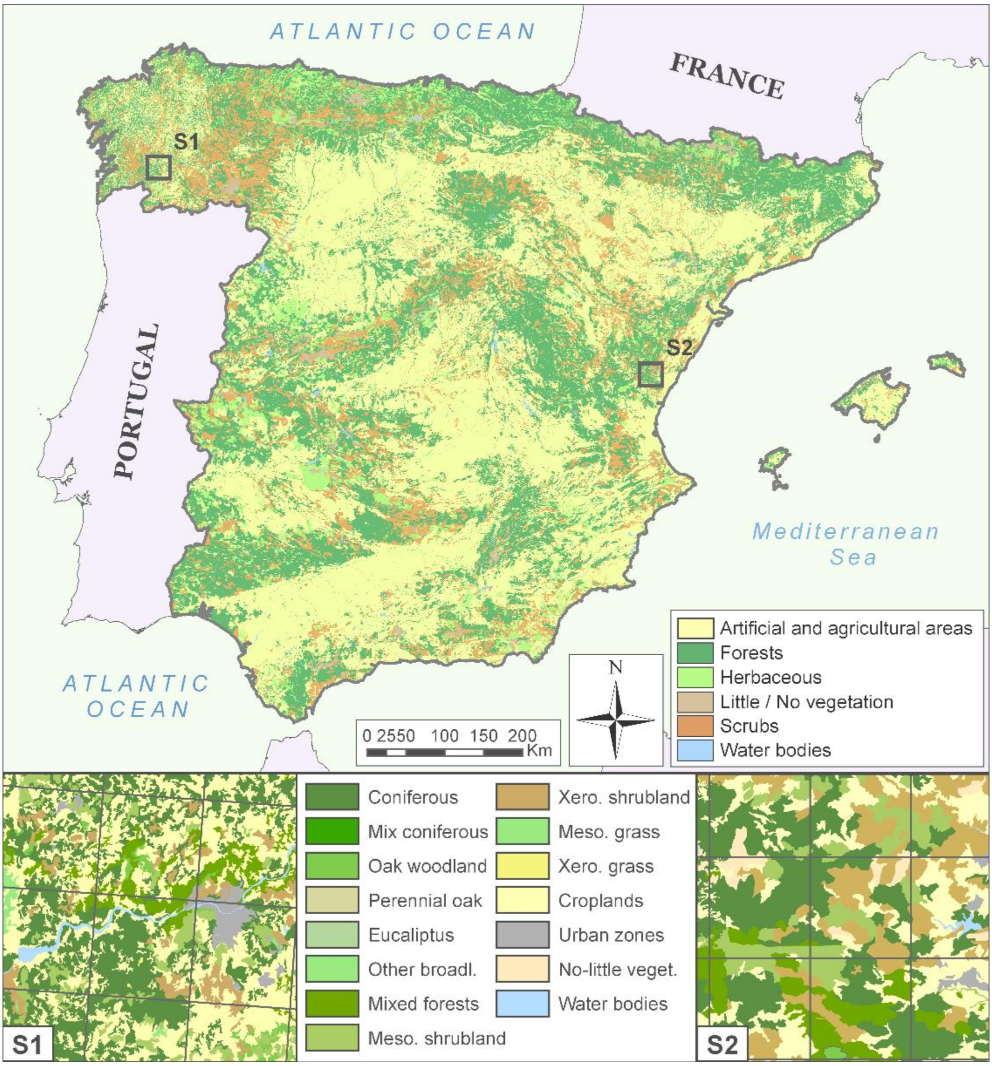

Figure 5.1. Forest Map of Spain with the classes used in the study grouped in six land uses. Zoom windows of 900 km^2, as examples of two forest landscapes in Atlantic (S1) and Mediterranean Spain (S2).

5.2.2. Independent variables: Landscape metrics

To characterize the vegetal landscape pattern we selected 13 metrics related to the area, shape, fragmentation and diversity of the vegetation patches. All of them were indices commonly used in the scientific literature of fire landscape ecology (Forman 1995; Frohn 1997; Lloret *et al.* 2002; Henry and Yool 2004; Hernandez-Stefanoni 2005; Romero-Calcerrada *et al.* 2008; Martínez *et al.* 2009; McGarigal *et al.* 2012; Ortega *et al.* 2012). Table 5.2 shows the selected indices, the group they belong to and a brief description about the information they convey (McGarigal *et al.* 2012).

Table 5.1. Land use classes and fuel description. Classes for landscape metrics calculation.

Forest soil layer-driven fuels Formations with woody plants taller than 7 m and corresponding to fuel models 7, 8, 9 and 10.	Conifers-FC (pinaceous, cupressaceous, mix of conifers and other conifers) Broadleaves-FB (oak woodland, perennial oak, beech forest, riparian forest, eucalypt forest, poplar stand, mix of broadleaves, other broadleaves) Mixed forest-FM
Shrub-driven fuels This group is composed by formations with woody plants shorter than 7 m, alone or under tree cover less than 30% fraction cover that correspond to Rothermel fuel models 4, 5 and 6	Xerophylous shrubland-XS Mesophylous shrubland-MS
Grass-driven fuels This group includes vegetal formations with natural herbaceous habitats (fuel models 1, 2 and 3) and ferns for their shade-tolerance preference and low height	Xerophylous grassland-XG Mesophylous grassland-MG
Little/No-vegetation Composed by open spaces with little or no vegetation such as beaches, dunes, sandy areas, nude land, bare rocks and sparsely vegetated and burned areas	Little/No-vegetation-NV
Anthrophic surface High human influence areas. We separate urban fabric, industrial units, mines dumps and construction sites from herbaceous and woody agricultural plants	Artificial surface-AS Agricultural areas-AA
Continental water Contains any surface covered by water bodies or stream courses. It also includes those herbaceous or woody plants that grow in water	Continental Water-W

Table 5.2. Table of all landscape metrics considered in the study

Group	Abrev.	Description	Mean	Std. Dev.	References where the variable or a similar factor were used
Density	*PD*	Patch Density	0.327	0.199	Lloret *et al.* 2002; Henry and Yool 2004*; Ortega *et al.* 2008, 2012*; Martínez *et al.* 2009*
Area	*MPS*	Mean Patch Size	5.188	7.721	Lloret *et al.* 2002; Henry and Yool 2004*; Romero-Calcerrada and Perry 2004; Hernandez-Stefanoni 2005; Ortega *et al.* 2012*
	MedPS	Median Patch Size	1.341	6.804	Martínez *et al.* 2009*
Shape	*ED*	Edge density	0.036	0.040	Ortega *et al.* 2012*
	MPE	Mean Patch Edge	10.682	3.839	Ortega *et al.* 2012*
	MSI	Mean Shape Index	1.967	0.276	Henry and Yool 2004*; Ortega *et al.* 2012*
	AWMSI	Area-Weighted Mean Shape Index	2.846	0.993	Henry and Yool 2004*
	MPAR	Mean Perimeter-Area Ratio	0.162	1.314	Henry and Yool 2004*; Hernandez-Stefanoni 2005; Ortega *et al.* 2008
Diversity	*PR*	Patch Richness	7.102	2.335	Ortega *et al.* 2012*
	SHDI	Shannon's Diversity Index	1.114	0.502	Lloret *et al.* 2002; Henry and Yool 2004*; Romero-Calcerrada and Perry 2004; Ortega *et al.* 2012*
	SHEI	Shannon's Evenness Index	0.565	0.217	Henry and Yool 2004*
	SIDI	Simpson's Diversity Index	0.534	0.231	
	SIEI	Simpson's Evenness Index	0.624	0.258	

* References which have used landscape metrics to predict forest fire occurrence

These metrics were computed for the landscape units in Spain using Patch Analyst 4 (Elkie *et al.* 1999) and ArcGis 9.3 (ESRI Inc 2009). The landscape units corresponded to 10 km x 10 km UTM grid cells used by the Ministry of Environment in Spain to record locations of fires in the reports (Figure 5.2). Because these landscape units were not constant in area, it was not possible in principle to compare the values for each grid, since some metrics are sensitive to the size of the landscape unit (Saura 2002). The original grid consisted of 5,278 cells, but some irregular cells on the coastline and in the boundaries between UTM zones 29, 30 and 31 were excluded to obtain comparable landscape units (100 ± 25 km^2). The resulting grid of 4,751 cells was set as the spatial base for calculation of the explanatory variables and for the analyses of the present study.

5.2.3. Dependent variable: Fire occurrence

The fire history registry from 1983 to 2008 was provided by the Ministry of the Environment and Rural and Marine Affairs (MAGRAMA) in Spain. The fire reports routinely included information about the causes of the fires, dividing these into natural (lightning) and human-caused fires. This information could be easily summarized in number of fires per year for each 10 km x 10 km UTM grid used by the Ministry to locate fires. According to our stated goal, only anthropogenic fires were selected for this study.

The dependent variable was the probability that at least one fire happened in the 5-year period between 1989 and 1993. Fire occurrence data in the historical reports (Figure 5.2) was summed up for each 10 km x 10 km UTM cell or landscape unit and coded as Y=1 if at least one fire took place in the period and cell, or Y=0 if otherwise.

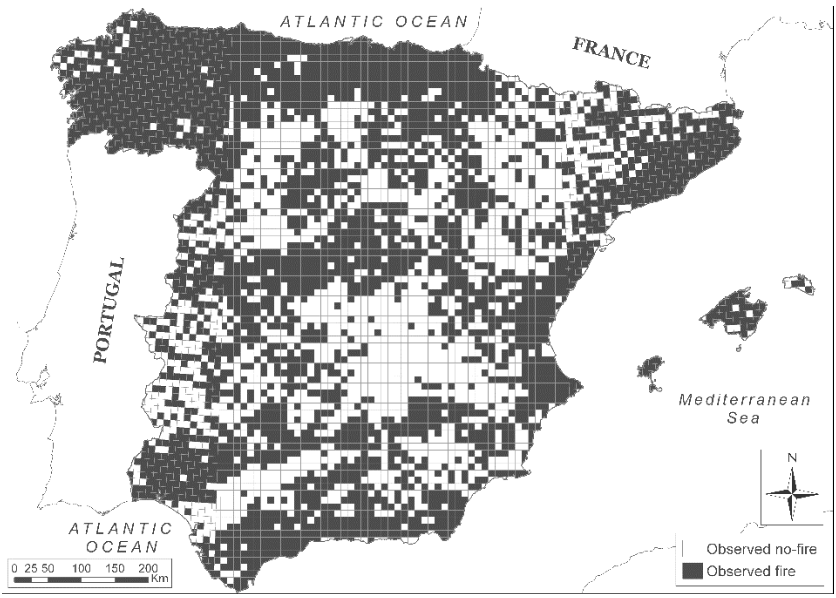

Figure 5.2. Human-caused fire occurrence in Spain, 1989-1993

This study period of 5 years was carefully chosen so that it chronologically followed the time span between the acquisitions of the ortophotos (1982 - 1986), the field work (up to 1989) and the date of creation of the Forest Map of Spain (MFE200, 1990). According to Chuvieco (1996), Viegas *et al.* (1999) and Vega-Garcia and Chuvieco (2006), the reasonable period for updating dynamics in vegetation maps is around 4 or 5 years. More importantly, the years 1989 and 1994 were severe fire-years; a number of large fires occurred in those years (burning 426,468 and 437,635 ha respectively), and in between, fires burned slightly more (90,000-260,000) hectares than are burned nowadays (50,000-190,000 ha, MAGRAMA 2010), reflecting worse conditions than at present, but conditions that could develop again in the future (Vega-García and Chuvieco 2006). The number of occurrences, though, was very similar (12,913-20,811 in 1989-1993) to present numbers (10,932-25,492 in 2004-2008).

During this study period (1989 to 1993), at least one human-caused forest fire occurred in 60.5 % (2,876 cells) of the 4,751 observations in Spain, and no fire took place in 39.5 % (1,875) of the landscape units. The landscapes for analysis were sufficiently large (100 km^2) and diverse to include all Table 5.1 classes under different spatial arrangements. Composition seemed influential but not determinant: For instance, out of 772 cells with >90% forest cover, 544 had fires (71%), 228 had not (29%). Out of 667 cells with >90% no-forest classes, there were 213 with fires (31%) vs 454 without fires (69%). 140 cells >90% agriculture had fires. The only landscape with 40% water had experienced fire. The only two landscapes >90% urban (Madrid) had fires in the study period.

5.2.4. Statistical analysis: logistic regression

Logistic regression has been frequently used to predict fire occurrence (Martell *et al.* 1987; Vega-Garcia *et al.* 1995; Stolle *et al.* 2003; Henry and Yool 2004; Vilar del Hoyo *et al.* 2008; Chuvieco *et al.* 2009; Martínez *et al.* 2009; Padilla and Vega-Garcia 2011), and it was also chosen for this work.

Logistic regression models can estimate or predict the probability P that a dichotomous or binomial variable occurs or not, based on a more or less extensive list of independent variables related to the event studied (Equation 5.1). Logistic regression requires fewer statistical assumptions than linear, being the main that independent variables are uncorrelated with each other.

$$\mathrm{P}(Y=1)=\frac{1}{1+\exp^{-(\beta_0+\sum\beta_i X_i)}} \qquad (5.1)$$

where P is the probability of an event happening (wildfire), and *Xi* and *Bi* are the independent variables (the metrics computed in the landscape units) and the estimated coefficients of the model, respectively.

The cut-off point of the logistic function is usually set by default to 0.5 (the midpoint of the distribution). However, this value is arbitrary and depends on the model goals or the user interests (Jamnick and Beckett 1988). The decision on the level of maximum likelihood involves usually predicting correctly both (Vega-Garcia *et al.* 1995; Stolle *et al.* 2003).

The number of variables is important when dealing with logistic regression. A small number of variables introduced in any model make it simpler, and the appearance of high errors in the formulation or non-significant values is more likely. On the contrary, an excessive amount of variables reduces the residual errors but makes fitting the equation more difficult (Martínez *et al.* 2009). A variable selection process was carried out before modeling the relationship between fires and landscape metrics, based on a Spearman's correlation analysis between all independent variables, most not-normally distributed. We grouped the variables according to their landscape feature typology (size, density, shape, diversity) and their Spearman correlation, calculated using SPSS 15 (SPSS Inc 2006). Also, their individual capability to predict human-caused fires occurrence was tested by building one-variable models. Only uncorrelated variables from every metric group and with significant relationship to fire occurrence entered the model building process.

Model fit and validation

The database for analysis was divided randomly in two groups: 60 % of cases were used to adjust the logistic regression function and the remaining 40 % were reserved for validation. The overall fit of the model was evaluated by the -2LL value, the Nagelkerke R^2, the Hosmer-Lemeshow test and the percentage correctly predicted in the classification table. In addition, the significance of the dependent variables was assessed using the Wald statistic and its statistical significance (p-value less than 0.05) (Hair *et al.* 1998; Silva and Barroso 2004). The validation results were evaluated using the classification table and the Kappa statistic (Congalton and Green 1999).

The adjustment method for the logistic regression model was the forward stepwise approach, more demanding than the backward stepwise approach, which proceeds by adding variables with statistical significance (p-value less than 0.05) one by one (Hair *et al.* 1998; Silva and Barroso 2004).

In order to evaluate the spatial distribution of errors, we tested clustered or dispersed conditions of the over and underestimated errors (false alarms and missed fires) with the Average Nearest Neighbor Distance Index (ANND) (Martínez *et al.* 2009). This index examines the distances between the centroid points of the closest misclassified quadrants, and compares their distance mean with the expected mean distance that would occur for a random distribution. Expected R values for randomness should be close to one, within an interval ranging from 0 to 2.14.

5.3. Results

5.3.1. Results of the variable selection

The Spearman correlation values between variables are presented in the Appendix.

As should be expected, Mean Patch Size (*MPS*), Patch Density (*PD*) and Edge Density (*ED*) were strongly correlated. *MPS* was inversely correlated to *ED* and *PD*. Median Patch Size (*MedPS*) had a moderate correlation to MPE, but not to MPS and PD.

Regarding shape, the correlation between the Mean Shape Index (*MSI*) and the Area-Weighted Mean Shape Index (*AWMSI*) was moderate. Both have a similar behaviour, although *MSI* is more influenced by the area of the observation unit.

The low correlations of *MedPS* and Mean Perimeter-Area Ratio (*MPAR*) with the other metrics discouraged their grouping with any other landscape metrics.

All diversity metrics were highly correlated (r-values over 0.427 with Patch Richness and over 0.939 between Shannon and Simpson's Indices). Correlation between *PR* and *SHEI* and *SIEI* was low, but these indices showed good correlation with other diversity metrics. We included the five variables (*PR*, *SHDI*, *SHEI*, *SIDI* and *SIEI*) in the same group, and selected only one at a time for model building trials.

Thus, all metrics considered were classified into six groups (Table 5.3) depicting landscape patch size, patch density (fragmentation) and vegetation diversity, plus shape characteristics split into three groups.

Within each group, we selected the most significant variable in terms of individual prediction of the human-caused fire occurrence, if any. We also regarded previous use in the literature. The Shannon's Diversity Index had been the most widely used metric in studies of landscape diversity (Henry and Yool, 2004, Lloret *et al.*, 2002, Ortega *et al.*, 2012, Romero-Calcerrada and Perry, 2004) and we wanted the results of this study to be comparable. In addition, Shannon's Diversity Index predictive capability in the one-variable models was the highest among all variables (Nagelkerke $R^2_{SHDI} = 0.141$). The selected metrics were four: Mean Patch Edge (*MPE*), Patch Density (*PD*), Mean Shape Index (*MSI*) and Shannon's Diversity Index (*SHDI*).

Table 5.3. Uncorrelated groups of correlated metrics.

Size	**Density**	**Shape**			**Diversity**
Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
MPS	*PD*	*AWMSI*	*ED*	*MPAR*	*SIDI*
MedPS		*MSI*			*SIEI*
MPE					*SHEI*
					SHDI
					PR

These uncorrelated metrics best explained fire occurrence within their groups in the one-variable models built (Nagelkerke $R^2_{MPE} = 0.023$, $R^2_{PD} = 0.121$, $R^2_{MSI} = 0.052$, $R^2_{ED} = 0.111$, $R^2_{SHDI} = 0.154$). *MPS*, *MedPS*, *MPAR* and *AWMSI* showed low human-caused fire occurrence predictability in the univariate logistic regression analysis (Nagelkerke R^2 less than 0.007).

5.3.2. Results of the logistic regression

The best model included three variables: Shannon's Diversity Index (*SHDI*), Mean Patch Edge (*MPE*) and Mean Shape Index (*MSI*), all significant with p-value less than 0.016. The p-value of the Hosmer-Lemeshow test was significant (p-value < 0.001), and the Nagelkerke R^2 was 0.224. Table 5.4 lists the estimated coefficients and variables of this model.

Table 5.4. Estimated coefficients and significance values of the best logistic regression model (p-values for the three variables < 0.001)

Variables	β	E.T.	Wald	Exp(β)
SHDI	1.431	0.085	280.966	4.181
MPE	-0.065	0.013	24.665	0.937
MSI	-0.221	0.092	5.796	0.801

Interpretation of the Wald statistic indicated that *SHDI* was the variable with greater weight in the adjusted model (Wald = 280.97), followed by *MPE* (Wald = 24.67) and *MSI* (Wald = 5.80). The analysis of exp(β) confirmed this since a unit increase of the Shannon Diversity Index increased by 418.1 % the probability of forest fire occurrence, while the unit chance of the MPE meant a decrease of 93.7 % and only 80.1 % for the *MSI*. The analysis of signs of the β coefficients indicated that the highest probability of human-caused fire occurrence occurs with high values of the SHDI and with low values of *MPE* or *MSI*.

A classification table (Table 5.5) was used for evaluating the predictability of the model, comparing predicted and observed fire occurrence. The cut-off point applied was 0.61, which balanced the percentages of correct matches of the landscape units with fire (Y = 1) and no fire (Y = 0) occurrences. The overall percentage of correct predictions was 66.3 %, 65.1 % for no-fire and 67 % for fire observations.

Table 5.5. Classification table of logistic regression (cut-off point = 0.61)

Model building data				**Validation data**			
Observed	*Predicted*			*Observed*	*Predicted*		
	no-fire	fire	TOTAL		no-fire	fire	TOTAL
no-fire	742	397	1139	no-fire	462	275	737
fire	565	1147	1712	fire	365	798	1163
TOTAL	1307	1544	**2851**	TOTAL	827	1073	**1900**

Results in the classification table for the validation data (40 % of the initial data) were similar to those obtained with the model building dataset. The percentage of correctly predicted no-fire observations was 62.7 % and the percentage of correctly predicted and observed fires was 68.6 % (with an overall percentage of correct predictions of 66.3 %).

Lastly, the fitted equation was used to map the correct human-caused fire occurrence predictions for the 10 km x 10 km landscape units in the period 1989 to 1993 (Figure 5.3A).

In general, the model identified landscape units with higher fire occurrence probability in Northwest areas and in the Mediterranean coast. Agricultural inland valleys with scarcer presence of natural vegetation presented a lesser likelihood of fire (Ebro, Guadalquivir). Both general spatial trends agreed with historical forest fire records from the Ministry of Environment in Spain (MAGRAMA). The spatial representation (Figure 5.3B) of misclassified predictions did not show a clear pattern indicative of a specific geographic trend (North/South, Atlantic/Mediterranean), but the $ANND_{OMISSION}$ z-score value was -9.647 and the $ANND_{COMMISSION}$ z-score value was -14.570, both significant (p-value < 0.001). Overestimation errors (false alarms) were aggregated in locations with high diversity (mean *SHDI* 1.47), but lower than in the fire-prone areas correctly classified (1.50) and underestimation errors (missing fires) were aggregated in areas with greater diversity (0.76) than in the identified as no-fire-prone (0.58).

5.4. Discussion

The probabilistic relationship between landscape metrics and human-caused fire occurrence could be modelled and was found to be significant in Spain. These results agreed with previous studies that made use of landscape metrics as proxies for the impact of human activities on the territory (Fuller 2001; Löfman and Kouki 2003; Echeverría *et al.* 2007; Serra *et al.* 2008; Ruiz-Mirazo *et al.* 2012).

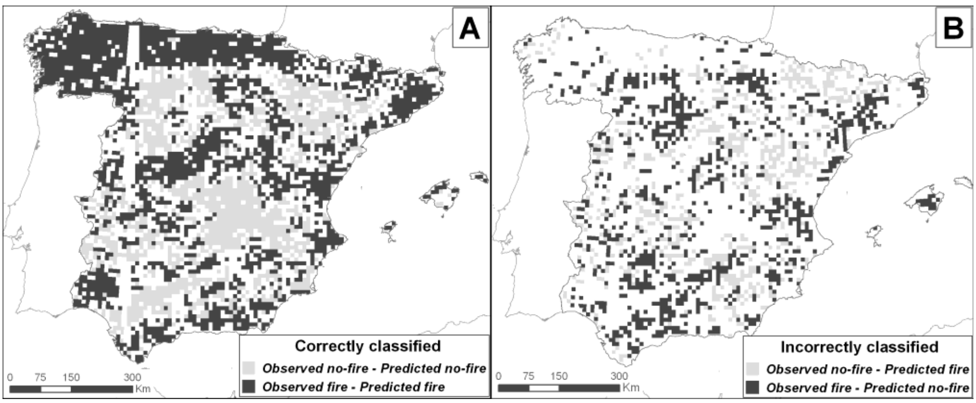

Figure 5.3. Correctly (A) and incorrectly (B) classified landscape units of human-caused fire occurrence.

The results of the classification table suggested a moderate predictive capability of the best model, with overall percentage correctly predicted of 66.3 %. This value was almost identical to that obtained with the validation sample (66.3 %), which indicated the model robustness. However, the low value of Nagelkerke R^2 (0.224) pointed at the fact that a large portion of the dependent variable variance was not explained by the fitted model. This should be expected. We knew other environmental or socioeconomic factors affected human-caused fire occurrence (Díaz-Delgado *et al.* 2004; Sturtevant and Cleland 2007; Romero-Calcerrada *et al.*

2008; Padilla and Vega-Garcia 2011), but it was not our purpose to evaluate those factors in this study.

The reduction in the number of variables to include in the fitting of the logistic regression allowed to respect the non-collinearity assumption and made the model more parsimonious. There were three significant variables in the model: Shannon's Diversity Index (*SHDI*), Mean Patch Edge (*MPE*) and Mean Shape Index (*MSI*), in line with the statement by Forman (1995) that two or three well-selected landscape metrics should be sufficient to answer specific questions on landscape processes.

These selected variables were also found significant in other studies. Henry and Yool (2004) determined that *SHDI* and *MSI* explained some of the variability of fire occurrence in Arizona from remote sensing images in a fusion of SIR-C and Landsat TM images. Other variables, such as *MPAR* and *AWMSI*, were significant in the analysis with Landsat TM images. *SHDI* and *MPS* were found to have significant effects on wildfire occurrence in the period 1985-1998 by Ortega *et al.* (2012). Fine-grained forest-agriculture mixtures and road density had significant effects in all periods (1974-2008) in their forest-agriculture interface landscapes. The study by Martínez *et al.* (2009) tested only three landscape metrics (Fragmentation using a 7x7 kernel on the Corine Land Cover 1990 grid reclassified into four classes, Patch Density and *MedPS*) but only agricultural land fragmentation was selected for their model.

Landscape diversity was the main factor in predicting human-caused fires in this study. Our analysis concluded that in the 10 km x 10 km units with greater landscape diversity the probability of human-caused fire occurrence was generally higher. Also, this likelihood of occurrence was greater in landscape units with fewer edges and with more compact patches. These characteristics are common in humanized environments (Badia-Perpinyà and Pallares-Barbera 2006) because, for example, the sharing of edges between roads and agricultural areas (Martínez *et al.* 2009).

The map obtained by applying the fitted equation (Figure 5.3A) agreed with that of Martínez *et al.* (2009) at the municipal level. The areas with greater agreement between observed and predicted values in the model are given in the Atlantic North of Spain. Is in these areas where most of the human-caused fires occur in Spain, and consequently, there it is greater the consistency in the relationship of the fitted model between landscape structure and fire occurrence. The landscape configuration of the Atlantic zone is characterized by small and highly fragmented patches with high diversity of species, due mainly to a fractured topography, high rainfall and humidity (Figure 5.1, S1). In the Northwest these landscape characteristics are associated with risk factors such as a traditional use of fire to obtain open areas for increasing pasture land and the low profit from forests by local people (Torre Antón 2010). There is also agreement in the Mediterranean coast (Coastal Catalonia and the Baetic Ranges), a scenario of significant urban development linked to tourism and the influx of population in the summer overlaps with dry weather to increase fire risk levels (Vilar del Hoyo *et al.* 2008). Most of the landscape units without fire occurrence in the period are plains with fertile deep soils where intensive agriculture is the most profitable economic activity: the Ebro and Guadalquivir river basins and the Meseta Central, where large extensions of croplands exist and natural vegetation is scarce.

Misclassified units (errors) were found scattered throughout the Spanish territory (Figure 5.3B), but their distribution was locally aggregated. These clusters respond to the presence of local conditions that influence the occurrence or absence of fire, according to Martínez *et al.* (2009) and Padilla and Vega-Garcia (2011). Martínez *et al.* (2009) found that landscape metrics showed comparatively lower significance compared to socio-economic changes in rural and urban areas and traditional activities associated with fire, and the authors obtained better results in predicting overall fire occurrence in Spain (model building data: 85.4 %, and validation: 76.2 %) by including socio-economic factors in their model.

Results in previous studies indicate that it is not possible to have good wildfire predictions taking into account only landscape structure, but landscape pattern variables, and specifically diversity and shape, must be considered in fire occurrence models in Spain. It would be highly convenient to test these results at different scales, and with more recent fire data, once the Forest Map of Spain MFE50 (Andalucía not available yet) and MFE25 (expected 2017) are published.

5.5. Acknowledgements

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Appendix. Spearman's correlation matrix of all landscape metrics

	PD	***MPS***	***MedPS***	***ED***	***MPE***	***MSI***	***AWMSI***	***MPAR***	***SHDI***	***SHEI***	***SIDI***	***SIEI***	***PR***
PD	1												
MPS	-0.5	1											
MedPS	-0.18	0.849	1										
ED	0.415	-0.204	-0.077	1									
MPE	-0.569	0.728	0.583	-0.162	1								
MSI	0.114	-0.205	-0.189	0.176	0.253	1							
AWMSI	0.499	-0.353	-0.179	0.276	-0.112	0.493	1						
MPAR	0.005	-0.017	-0.014	0.003	-0.017	0.014	0.01	1					
SHDI	0.553	-0.481	-0.173	0.269	-0.333	-0.051	0.102	0.002	1				
SHEI	0.463	-0.479	-0.19	0.246	-0.245	-0.037	0.134	0.002	0.931	1			
SIDI	0.527	-0.49	-0.18	0.271	-0.293	-0.036	0.149	0.003	0.976	0.966	1		
SIEI	0.495	-0.485	-0.184	0.262	-0.258	-0.03	0.162	0.003	0.947	0.985	0.991	1	
PR	0.54	-0.476	-0.22	0.227	-0.456	0.007	0.122	0.006	0.735	0.473	0.633	0.541	1

Chapter 6.

Space-time aggregations of human-caused fires

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6. Spatio-temporal configurations of human-caused fires in Spain through point pattern processes

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ABSTRACT: Human-caused wildfires are often regarded as unpredictable, but usually occur in patterns aggregated over space and time. We analysed the spatio-temporal configuration of 7790 anthropogenic wildfires (2007–2013) in nine study areas distributed throughout Peninsular Spain by using the Ripley's K-function. We also related these aggregation patterns to weather, population density, and landscape structure descriptors of each study area. Our results provide statistical evidence for spatio-temporal structures around a maximum of 4 km and six months. These aggregations lose strength when the spatial and temporal distances increase. At short time lags after a wildfire (<1 month), the probability of another fire occurrence is high at any distance in the range of 0–16 km. When considering larger time lags (up to two years), the probability of fire occurrence is high only at short distances (>3 km). These aggregated patterns vary depending on location in Spain. Wildfires seem to aggregate within fewer days (heat waves) in warm and dry Mediterranean regions than in milder Atlantic areas (bimodal fire season). Wildfires aggregate spatially over shorter distances in diverse, fragmented landscapes with many small and complex patches. Urban interfaces seem to spatially concentrate fire occurrence, while wildland-agriculture interfaces correlate with larger aggregates.

6.1. Introduction

Human-caused fires (HCFs) do not occur randomly, they follow spatio-temporal patterns that change depending on the socioeconomic activity linked to the use or misuse of fire triggering ignitions (González-Olabarria *et al.* 2015). Ignition points have been proved to show broadly identifiable spatial and temporal patterns (Juan *et al.* 2012). For instance, fire starts have occurred most often near roads (Badia-Perpinyà and Pallares-Barbera 2006), near urban- and cropland-forest interfaces (Martínez *et al.* 2009) and in areas with an extensive presence of shrubs or conifers (Verdú *et al.* 2012). Fire starts also showed clustered temporal structures due to the seasonal distribution of the risk of ignitions (Prestemon *et al.* 2012).

The number of HCFs can vary widely between locations and time spans. Thus, the characterization of spatio-temporal patterns of fire ignition can provide important information for optimizing resource allocation in strategic firefighting (Genton *et al.* 2006). Fire management strategies usually focus on the control of potential multiple-fire situations in areas and periods with high risk of fire (Gonzalez-Olabarria *et al.* 2012). Because of budgetary restrictions and rising firefighting costs, it is usually impossible to maintain sufficient resources to cope with all potential multiple-fire occurrences. In fact, under extreme weather conditions, available firefighting resources may be overloaded beyond suppression capacity. In these cases, the ability to anticipate high-risk wildfire conditions and take preventive actions, or to pre-position firefighting resources in advance, can reduce the damages and optimize the use of the suppression resources (Boychuk and Martell 1988; Genton *et al.* 2006).

A number of previous studies have focused on the spatial and/or temporal distribution of wildland fires. For instance, Padilla and Vega-Garcia (2011) identified the most significant spatial variables for analysing human-caused wildfire occurrences using non-spatially explicit models (autoregressive Poisson and logit processes). Other studies have used spatially explicit models to explain patterns of fire occurrence, for instance, geographically weighted regression models (de la Riva *et al.* 2004), ignition density estimates (Amatulli *et al.* 2007), log-Gaussian Cox processes (Serra *et al.* 2014; Najafabadi *et al.* 2015), scan statistics permutation (Vega Orozco *et al.* 2012), or Ripley's K-function (Turner 2009; Fuentes-Santos *et al.* 2013; Serra *et al.* 2013). A few studies have focused on the temporal pattern of fire ignitions; Tanskanen and Venäläinen (2008) found temporal aggregations using temporal trajectory metrics of wildfire ignition densities, while Hering *et al.* (2009) found temporal aggregations when analysing the fire weather indices of summer fire ignitions in Finland. In addition, time series of the fire occurrence models of Prestemon *et al.* (2012) included temporal and spatio-temporal lags lasting up to 2-3 days.

Wildfire occurrences have also been analyzed as points placed within a spatio-temporal region using point process statistical tools. These tools include, for instance, analysis of inhomogeneous spatio-temporal structures of wildfire ignitions (Hering *et al.* 2009), cluster analysis (Vega Orozco *et al.* 2012; Pereira *et al.* 2015), modelling of fire locations by spatio-temporal Cox point processes (Møller and Díaz-Avalos 2010), and spatio-temporal analysis of fire ignition points combined with geographical and environmental variables (Juan *et al.* 2012). For instance, (Hering *et al.* 2009) analyzed space-time configuration of wildfires assuming spatial tools for each year of study separately, and they did not consider a continuous space-time approach for the fire occurrence.

Here we consider inhomogeneous spatio-temporal point processes to analyze the point pattern configuration of human-caused wildfire ignition points of several data sets in Spain. We applied the inhomogeneous spatio-temporal counterpart version of Ripley's K-function proposed by Gabriel and Diggle (2009). This approach was adopted because of the apparent inhomogeneous structure of the spatio-temporal point patterns suggested by the analysis of available official fire reports from the Spanish Ministry of Environment. The analysis of these point configurations would be valuable for interpreting the space-time dependencies of fire ignition points in order to understand wildfire dynamics.

The expected spatial and temporal aggregation patterns of HCFs should be related to the underlying fire risk factors (Padilla and Vega-Garcia 2011) found in previous work such as weather or population. Land use has been used often as a proxy variable for distribution of vegetation/fuels and the presence and activity of human sources of ignition (Henry and Yool 2004; Costafreda-Aumedes *et al.* 2013). However, the spatial structure of the land mosaic is rarely considered (Costafreda-Aumedes *et al.* 2013), although its composition, configuration, and length of land use interfaces should be of special interest in spatial processes like this. Advances in landscape ecology provide abundant indices to measure mosaic characteristics (McGarigal *et al.* 2012). Consequently, we also test linear correlations between spatial and temporal parameters derived from the fire patterns and relevant spatial variables linked to the structure of the fire environment with the Pearson product-moment correlation coefficient (Pearson 1920).

6.2. Materials and Methods

6.2.1. *Study area*

This study analysed nine regions in windows of 40 km × 40 km distributed over forested areas (at least >20% forest area) in Peninsular Spain (Figure 6.1). These study areas comprise a wide range of forest environments with different landscape structures, but all have fire use levels conducive to significant fire occurrence (at least 100 fires over the study period).

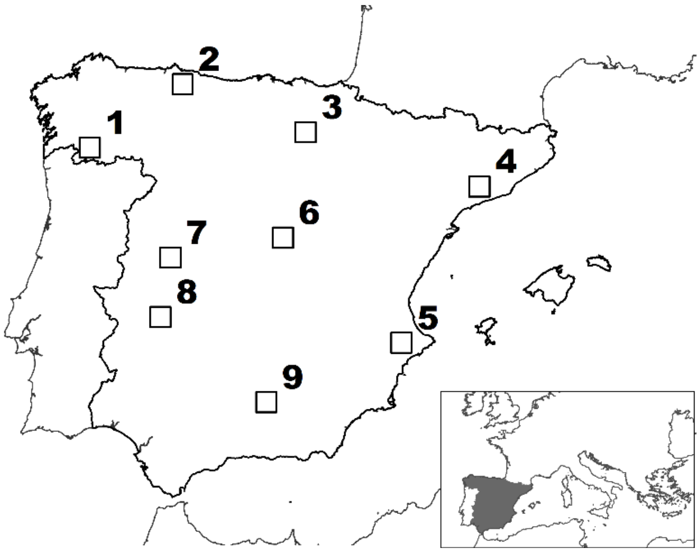


Figure 6.1. Location of the 9 study areas in the Spanish peninsula. 1. Ourense, 2. Asturias, 3. La Rioja, 4. Tarragona, 5. Alicante, 6. Guadalajara, 7. Caceres, 8. Badajoz, 9. Jaen.

Most of peninsular Spain is dominated by a Mediterranean climate, and only 15% of the land area, located in the north, has an Atlantic climate. These climatic zones and the complex topography combined with human socio-economic development over millennia have given way to a very uneven spatial distribution of the vegetation, combining the presence of medium-scale farming areas, areas with scarce natural vegetation cover (grasses, rangelands), extensive shrub-lands, park-like open forest structures (*dehesas*) with undergrowth, and high forests of variable densities (EEA 2006). Tables 6.1 and 6.2 include a subset of the total number of independent variables that were generated to capture weather, socioeconomic, and landscape composition and configuration traits of the nine study areas; these variables were selected for their potential relation to the spatio-temporal aggregation of fires. Population density was derived from the municipal registry of 2014 available on the website of the National Institute of Statistics of Spain (http://www.ine.es) and is weighted by the township area included in each study area. Annual climate data was derived from the Digital Climate Atlas of the Iberian Peninsula (1971–2000) (http://www.opengis.uab.es). Landscape ecology indices (landscape and class levels) (McGarigal *et al.* 2012) were calculated with Patch Analyst 5.2 (Rempel *et al.* 2012) extension of ArcGis 10.3 over a land use reclassification (Figure 6.2) of the Forest Map of Spain (digitized at 1:50,000 from 1997 to 2006) from Ruiz de la Torre and available on the website of the Spanish Nature Databank of the Ministry of Agriculture, Food and Environment (http://www.magrama.gob.es). Woodland-urban interfaces (WUI), woodland-agriculture interfaces (WAI), and urban-agriculture interfaces (UAI) were evaluated, firstly, calculating a 100 m-buffer of each land use (Ruiz Cejudo and Madrigal Olmo 2013) and intersecting them, and secondly, by dividing the area of each interface by all interface areas.

Table 6.1. A subset of independent variables for general characterization of each study area

	Weather		Landuse			Interfaces			Landscape metrics				
Pp	Tx	P	W	A	U	WUI	WAI	UAI	NP	MdPS	MPE	PAR	SDI
37.1	17.8	1076	67.0	31.5	1.0	4.3	90.4	2.9	493	21.7	16.1	0.4	0.71
275.4	16.9	1169	56.1	39.4	4.3	4.7	82.8	10.9	1516	8.8	10.5	0.7	0.84
112.7	17.4	606	36.9	59.9	2.9	4.2	81.9	10.6	4469	0.6	3.1	1.5	0.80
89.9	18.9	583	45.3	50.9	3.7	3	86.6	4.8	1542	6.3	9.2	0.8	0.83
135.9	20.3	541	53.6	42.0	4.0	7.5	65.7	12.2	1401	5.3	8.2	0.6	0.85
298.3	19.6	478	24.5	68.7	6.6	3.8	85.1	9.8	1023	8.2	10.8	0.5	0.79
32.7	18.4	1073	81.0	17.5	0.9	3.9	88.7	6.9	782	7.6	8.4	0.4	0.55
29.6	22.3	580	49.1	49.0	1.3	4.4	80	12.3	441	12.7	12	0.3	0.79
78.9	20.4	568	40.9	57.2	1.8	3.4	86.2	8.8	966	5.2	7.5	0.5	0.77

Pp: Population density (inhab/km^2); *Tx*: Annual maximum temperature (ºC); *P*: Annual precipitation (mm); *W*: Forest, shrubs and pastures (%); *A*: Croplands (%); *U*: Urban (%); *WUI*: Wildand-Urban interface (%); *WAI*: Wildland-Agriculture interface (%); *UAI*: Urban-Agriculture interface (%); *NP*: Number of patches; *MdPS*: Median patch size (ha); *MPE*: Mean patch edge (km); *PAR*: Perimeter-Area ratio (km/ha); *SDI*: Shannon’s diversity index

Table 6.2. Class metrics by land use and study area

Location	Class	CA	NP	MPS	MdPS	PSSD	MPE	ED	PAR	MSI
Ourense	Agriculture	31.5	316	159.6	28.7	0.705	11.6	23	324.7	2.896
	Wildland	67	127	843.9	11.2	7.136	30.4	24.2	508.3	2.386
	Urban	1	44	37.7	10.6	0.086	6.5	1.8	284.1	2.434
	Water	0.5	6	124.1	25.2	0.207	16	0.6	438.2	4.157
Asturias	Agriculture	39.4	793	79.5	11.2	0.795	9.4	46.8	773.8	3.015
	Wildland	56.1	422	212.6	9.5	2.594	16.7	44	569.9	2.904
	Urban	4.3	289	23.7	3.8	0.216	4.5	8.1	472.3	2.445
	Water	0.2	12	31.8	19.3	0.030	10.6	0.8	412.0	5.084
La Rioja	Agriculture	59.9	1494	64.1	0.8	0.952	4.3	40.2	916.4	1.814
	Wildland	36.9	2302	25.7	0.4	0.668	2.7	38.9	2198.3	2.047
	Urban	2.9	621	7.4	0.9	0.044	16.4	6.4	679.3	1.860
	Water	0.4	52	11.1	1.5	0.030	4.5	1.5	543.8	2.470
Catalonia	Agriculture	50.9	722	112.8	6.4	0.123	9.4	42.6	580.8	2.565
	Wildland	45.3	616	117.7	5.5	2.206	10.6	40.7	1290.5	2.920
	Urban	3.7	199	30.1	9.4	0.079	3.8	4.8	340.1	2.184
	Water	0.1	5	21.0	20	0.012	7.8	0.2	376.6	4.676
Alicante	Agriculture	42	804	83.6	6.5	0.342	6.7	33.9	487.1	2.369
	Wildland	53.6	352	243.8	3.1	4.228	14	30.7	810.5	2.255
	Urban	4	226	28.5	7.1	0.115	4.3	6	345.3	2.219
	Water	0.3	19	29.0	9.8	0.042	9.6	1.2	620.1	5.406
Guadalaj.	Agriculture	68.7	388	283.4	8.3	2.251	13.7	33.2	726.3	2.323
	Wildland	24.5	460	85.4	7.1	0.468	10.7	30.8	501.5	2.833
	Urban	6.6	165	64.4	12.1	0.401	4.6	4.7	195.9	1.861
	Water	0.1	10	13.4	11.6	0.009	7.3	0.5	473.7	5.040
Caceres	Agriculture	17.5	493	56.7	9.5	0.201	6.1	18.7	381.4	2.407
	Wildland	81	138	939.2	4.5	10.875	22.9	19.7	745.2	2.153
	Urban	0.9	110	13.1	6.2	0.022	2.4	1.6	268.5	1.962
	Water	0.6	41	24.7	6.6	0.066	4.3	1.1	354.2	2.846
Badajoz	Agriculture	49	202	387.9	13.4	1.409	11.2	14.1	243.8	2.014
	Wildland	49.1	135	582.0	10.9	4.315	15.8	13.4	421.2	2.507
	Urban	1.3	62	34.3	16.4	0.077	8.3	3.2	239.4	2.911
	Water	0.6	42	22.7	12.3	0.042	8.9	2.3	420.7	4.471
Jaen	Agriculture	57.2	298	306.9	5.1	2.659	11.8	21.9	686.2	2.093
	Wildland	40.9	524	124.8	5.3	2.353	6.2	20.3	513.5	2.273
	Urban	1.8	123	23.8	5.5	0.086	3.6	2.7	323.5	2.043
	Water	0.1	21	9.4	4.7	0.025	2.6	0.3	487.3	2.658

CA: Classes (%); *NP*: Number of patches; *MPS*: Mean patch size (ha); *MdPS*: Median patch size (ha); *PSSD*: Patch size standard deviation (ha); *MPE*: Mean patch edge (km); *ED*: Edge density (km/ha); *PAR*: Perimeter-Area ratio (km/ha); *MSI*: Mean shape index (km/ha); *PAR*: Perimeter-Area ratio (km/ha); *MSI*: Mean shape index

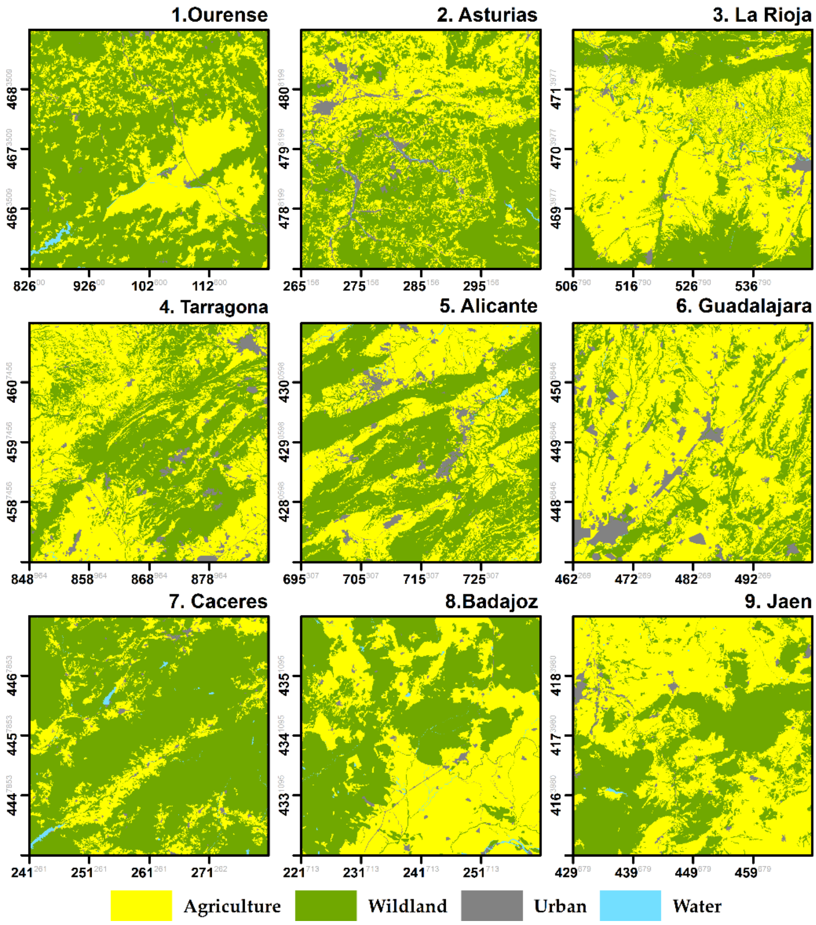


Figure 6.2. Land use map of the study areas

6.2.2. Fire data

The Spanish Forest Service of the Ministry of Environment and Rural and Marine Affairs (MAGRAMA) provided the fire records for the study. The nine study areas held a sufficient number of fire ignition points to study the spatio-temporal dynamics of fire ignition: at least 100 fires over the study period. Our data sets involved historical records of daily human-caused fire occurrences during the period 2007–2013. The period of study was restricted to seven years due to data availability (precise GPS locations available), but this period was considered appropriate because it surpassed the usual time framework for fire prevention planning in Spain (Generalitat Valenciana 2012). This period included a variety of weather conditions, with mild years but also years with high risk weather conditions, *i.e.*, 2006 in NW Spain (1900 fires set in just 12 days in August) (Chas-Amil *et al.* 2010).

The spatio-temporal point pattern analyzed consisted of 7790 fire ignition points located in 9 square areas of 40 x 40 km^2 for the seven years, with 877 ignitions in 2007, 1060 in 2008, 1298 in 2009, 1032 in 2010, 1308 in 2011, 1478 in 2012 and 903 in 2013. Figure 6.3 displays their distribution by study area, monthly.

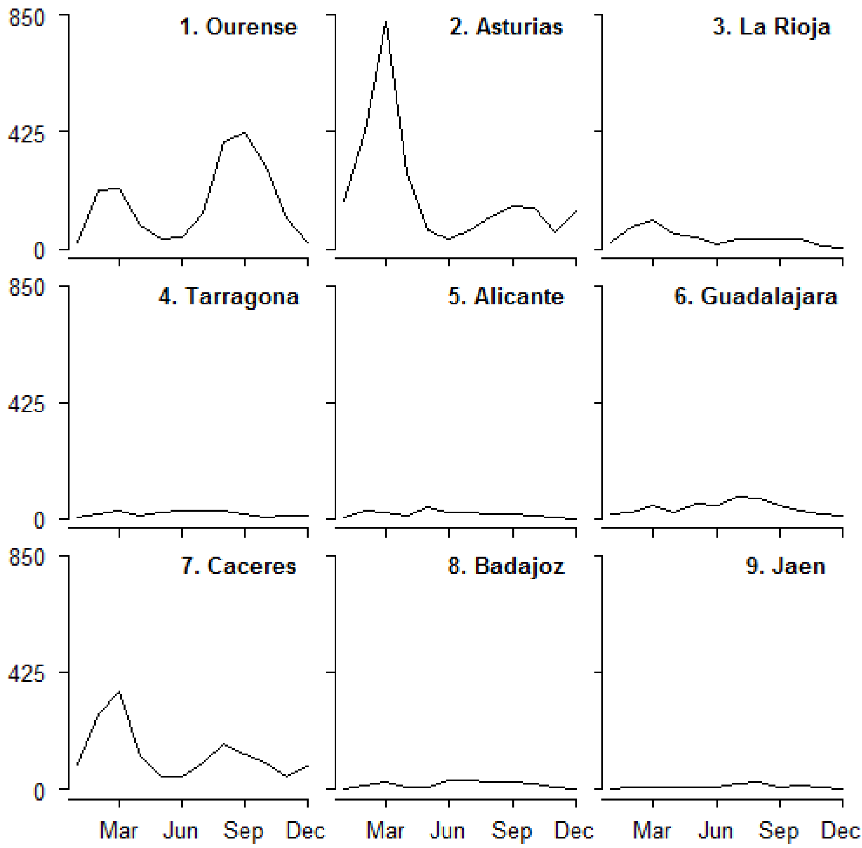


Figure 6.3. Human-caused wildfire frequency for the period 2007 - 2013 given by study area and month.

Figure 6.4 shows the HCFs spatial pattern of the 9 selected study regions. Visual inspection of the point pattern in the 9 plots suggests that the point structures are inhomogeneous, with areas of high point intensity juxtaposed to areas of low point intensity. This figure also highlights the presence of point clusters, suggesting that fire events aggregate in space and in time.

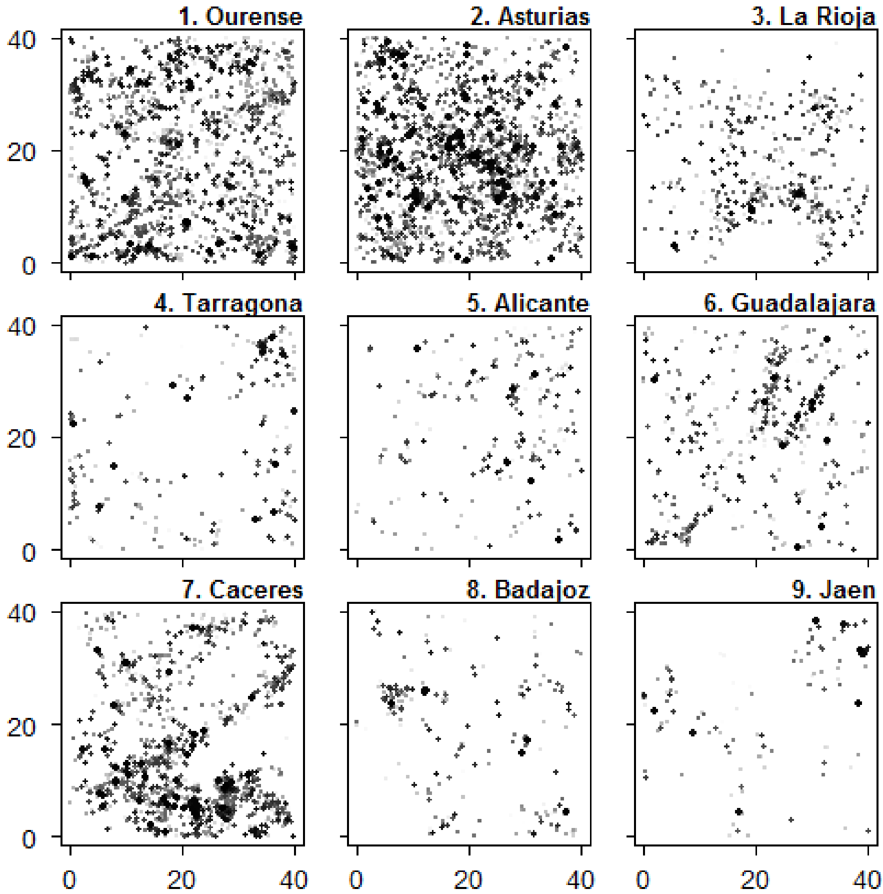


Figure 6.4. Spatial positions of the 7790 HCFs in the study. The biggest and darkest points correspond to recent fires while the lightest points occurred earlier.

6.2.3. Spatio-temporal statistics

To analyze the spatio-temporal structure of inhomogeneous point patterns representing ignition point fires, we used the spatio-temporal counterpart version of Ripley's K function proposed by Gabriel and Diggle (2009). For a review about space-time point processes see Illian *et al.* (2008). Considering a stationary and anisotropic spatio-temporal point process Φ on whose elements form a countable set $S_i = (X_i, t_i)$, for $i = 1, \ldots, n$ and $X_i = (x_i, y_i) \in \Re^2$ and $t_i \in \Re$ in a bounded region $M = W \times T$. This M region contains all the ignition fires for a given planar region W for a time interval $T \in [T_0, T_1]$. Now, the point pattern should be assumed as a set of points in a continuous tridimensional space. The inhomogeneous spatio-temporal Ripley's K-function proposed by Gabriel and Diggle (2009) assumes that the point pattern under analysis is second-order intensity reweighted stationary and isotropic or, in other words, it assumes a weaker form of stationarity and therefore relaxes the hypothesis of homogeneity. A point process is stationary and isotropic if its statistical properties do not change under translation and rotation, respectively. Informally, stationarity implies that one can estimate properties of the process from a single realization on W x T, by exploiting the fact that these properties are the same in different, but geometrically similar, subregions of W x T; isotropy means that there are no directional effects.

Function $K_{st}(u, v)$ is the expected number of further points in a spatio-temporal region delimited by a cylinder whose bottom surface area is centered at an arbitrary point of Φ (a point process) with radius u (a spatial distance) and height $2v$ (a time interval). For any inhomogeneous Poisson process (*i.e.* the a Poisson process where the constant intensity is replaced by a spatially varying intensity function) with spatio-temporal intensity function bounded away from zero, $K_{st}(u, v) = 2\pi u^2 v$, and hence $K_{st}(u, v) - 2\pi u^2 v$ (*i.e.* the empirical spatio-temporal Ripley's K function minus this function under the hypothesis of no spatio-temporal structure, fire ignitions are independently distributed) can be considered a measure for detecting spatio-temporal point dependences (Gabriel and Diggle 2009). Values of $K_{st}(u, v) - 2\pi u^2 v < 0$ will indicate regularity, while $K_{st}(u, v) - 2\pi u^2 v > 0$ will suggest spatio-temporal clustering. Moreover, $K_{st}(u, v)$ can also be used to detect absence of spatio-temporal interaction. In particular, separability of $K_{st}(u, v)$ into purely spatial and temporal components, $K_{st}(u, v) = K_s(u) K_t(v)$, suggests absence of spatio-temporal dependency (Diggle *et al.* 1995). The lack of spatio-temporal interaction indicates that ignition point locations and ignition times are independent, *i.e.* there is no correlation between where a fire happens and when it happens. However, in real life one may expect these two components to be correlated, so the time occurrence of a fire will depend on the spatial location. An edge-corrected estimator of $K_{st}(u, v)$ can be defined via Gabriel *et al.* (2013)

$$\hat{K}_{st}(u,v) = \frac{1}{|W \times T|} \sum_{i=1}^{n} \sum_{j \neq i}^{n} \frac{1}{\omega_{ij} v_{ij}} \frac{I(u_{ij} \le u) I(|t_j - t_i| \le v)}{\hat{\lambda}(S_i)\hat{\lambda}(S_j)} \qquad (6.1)$$

where n is the total number of points in M, $u_{ij} = \|X_i - X_j\|$, $I(\cdot)$ is the indicator function where $I(F) = 1$ if F is true and $I(F) = 0$ otherwise, $|W \times T|$ denotes the volume of this region and $\hat{\lambda}(\cdot)$ is an estimator of the spatio-temporal intensity function at the location S_i or, in other words, an estimator of expected number of points per unit volume at this exact location. To correct spatial edge effects we use Ripley's factor ω_{ij} (Ripley 1976) and to deal with time-edge effects we consider v_{ij}. This v_{ij} equals to 1 if both ends of the interval of length $2|t_j - t_i|$ centered at t_j lie between T and it equals to 1/2 otherwise (Gabriel *et al.* 2013). Note that correctors for edge-effects are necessary to deal with window sampling where information outside this space-time window (unobserved points) is lost, introducing, usually, a negative bias for $\hat{K}_{st}(u,v)$. Edge-effect correctors such as the Ripley's factor and the time correction considered here are standard approximations to reduce these biass effects based on mathematical arguments. Usually these arguments consider that the unobserved numbers of points outside the observation windows are proportional to those inside these windows.

In order to obtain Equation 6.1, we need to obtain an estimator of the spatio-temporal intensity function. Here we adopted a kernel-based estimator for this space-time function. First we need to assume that first-order effects (*i.e.* the intensity function) are separable from the space and the time domain, as suggested by Gabriel and Diggle (2009), *i.e.*

$$\lambda(X,t) = m(X)\mu(t) \qquad (6.2)$$

and thus any non-separable effects can be considered as second-order effects (*i.e.* related to the variance of the process) rather than first-order effects. Then from Equation 6.2 we can estimate $\lambda(\cdot)$ (Ghorbani 2013) as

$$\hat{\lambda}(X,t) = \hat{m}(X)\hat{\mu}(t)/n \qquad (6.3)$$

as

$$\int_W \hat{m}(X)d(X) = \int_T \hat{\mu}(t)d(t) = n \qquad (6.4)$$

Now, we can estimate both the space and the time intensity function separately. For the space point intensity $m(X)$, we used a Gaussian kernel-based estimator, with bandwidth initially chosen to minimize the estimated mean-square error of $\hat{m}(X)$, as suggested in Berman and Diggle (1989). In some cases, this optimal bandwidth was slightly increased to provide a good visual fitting to the point patterns. Moreover, for time point intensity, we adopted a Gaussian kernel estimator since we do not consider covariate information related the fire locations.

Note that a kernel-based estimator for the time intensity does not assume any previous knowledge of the time series, while providing a reasonable approximation for the intensity function. After some experimentation, we considered $\sigma_\mu = 10.0$ as it provides a good visual fitting to the data while reproducing quite well some of the outliers observed in the time series.

To test for evidence of spatio-temporal clustering or regular structures, we compare the estimator $\hat{K}_{st}(u,v)$ with estimates obtained for simulations under a suitable null hypothesis. Here the null hypothesis is that the underlying point process is an inhomogeneous Poisson process, and therefore the empirical spatio-temporal pattern is compared with a spatio-temporal Poisson process with point intensity (Equation 6.3), based on a Monte Carlo test. This is a space-time Poisson process where the constant intensity is replaced by a spatially varying intensity function estimated by Equation 6.3.

We simulate 1000 spatio-temporal point patterns under this null hypothesis and for each one an estimator of Equation 6.1 is obtained. This set of functions is then compared with the resulting estimator for the empirical data under analysis. Under this test, we reject the null hypothesis (spatio-temporal point independence) if the resulting estimator of this function lies above the 95th percentile of estimates calculated from the 1000 simulations of inhomogeneous Poisson point process with intensity (Equation 6.3). This 95th percentile of estimate values form the tolerance envelops for our test. In this case, we should accept spatio-temporal clustering of fire locations.

All the spatio-temporal statistical analyses were computed using the stpp statistical package (Gabriel *et al.* 2013) for the R statistical environment (R Development Core Team 2005).

6.2.4. Spatio-temporal aggregation trends

In order to explain possible spatio-temporal HCFs aggregations, the Pearson product-moment correlation coefficient was selected to measure the strength of the linear dependence between the spatial and temporal aggregation patterns of HCFs and the independent weather, socioeconomic and landscape composition and configuration variables (Tables 6.1 and 6.2). This estimator ranges from +1 to -1, where the positive and negative values indicate, respectively, positive and negative correlation (data-pairs best regression fit), and 0 indicates no significant correlation between variables (Amatulli *et al.* 2007).

6.3. Results

6.3.1. Spatio-temporal aggregation of HCFs

In Figure 6.5, we compare $\hat{K}_{st}(u,v) - 2\pi u^2 v$ and tolerance envelopes suggesting the presence of different spatio-temporal structures for time lags of less than two years and ignition point distances in the range of 0-16 km. In particular, this figure provides results on clustering patterns in the 9 regions under analysis; black values indicate spatio-temporal clustering for these space-time scales. We used these maximum time and space intervals to avoid edge effects that may not be corrected by the mathematical assumptions made here. The maximum scale of the spatio-temporal aggregation of HCFs was found to be around 4-4.5 km and 5.5-6 months in Tarragona, and the minimum, less than one month and one km, in La Rioja. The spatio-temporal structures generally lose strength as the time lag increases; at the time lag of 6 months, or higher, these dependencies are only observable for short inter-ignition point distances of less than 3 km.

However, in the NW of Spain with Atlantic climate (Ourense and Asturias), the spatial pattern shows a cyclical aggregation trend of around one year (a hump in the plot around the 12-month value). These Atlantic areas also display aggregation up to the maximum spatial distance considered (16 km) for all time lags under three months. This means that once a fire happens, the probability that another takes place within a wide area around the first one (up to 16 km in radius) persists for a period close to 3 months. In the other study areas, the probability that an additional fire occurs once one takes place, only persist for the maximum distance (up to 16 km in radius) for short time lags (under 1-2 months).

6.3.2. Trends of the spatio-temporal HCFs pattern

The values found in each plot at the limits of the maximum intervals considered or axis—the *x* for 24 months, *x*24; the *y* for 16 km, *y*16- were taken as descriptors of spatial and temporal aggregation. *x*24 is the spatial lag for aggregation at any time lag (spatial lag of aggregation independent of the time lag). $y16$ is the time lag for aggregation at any spatial lag considered (time lag of aggregation independent of the space lag). Table 6.3 shows the Pearson's correlation between those aggregation parameters, the number of fires of Figure 6.3 and the descriptive variables of Table 6.1 at the landscape level. The number of HCFs shows a positive correlation with the time-independent spatial aggregation values $x24$, even higher with the distance-independent temporal aggregation values $y16$. Therefore, the higher the fire occurrence caused by humans, the more likely fires aggregate over longer distances and longer time frames, and vice versa.

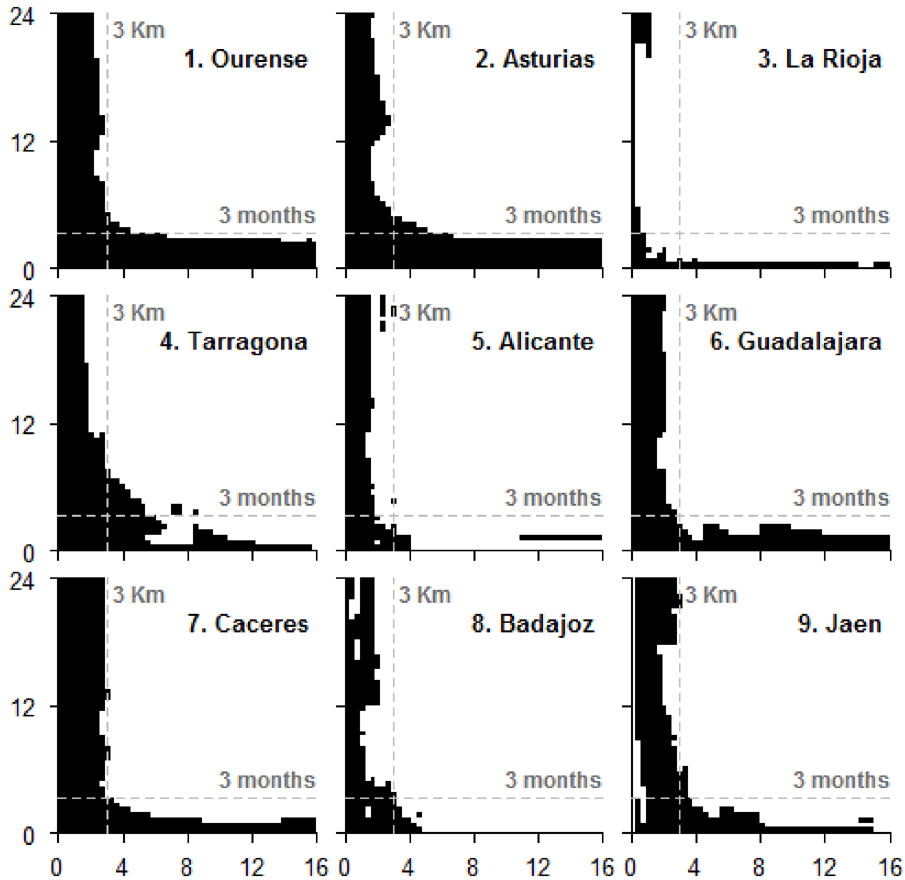


Figure 6.5. Comparison between $\hat{K}_{st}(u,v) - 2\pi u^2 v$ and tolerance envelopes indicating spatio-temporal clustering (black values) for each study area.

According to the results, higher population density causes distance-aggregation or spatially closer fires and dilates the time lag for wildfire occurrence, but the correlation is not high. Drought weather conditions (higher *Tmax* and lower *P*) influence wildfire aggregates by decreasing the distance and time lags. Weather, mean patch edge (*MPE*) and fire frequency (*FF*, the occurrence of other fires) seem to be the variables mainly related to temporal aggregation of fires.

Table 6.3. Pearson product-moment correlation coefficient between each variable of Table 1 and the descriptors of spatial and temporal aggregation. In bold, values over 0.5.

Variable	Spatial $x24$	Temporal $y16$	Variable	Spatial $x24$	Temporal $y16$
FF	**0.609**	**0.813**	*WAI*	**0.539**	0.192
Pp	-0.218	0.391	*UAI*	**-0.562**	-0.418
Tmax	-0.123	**-0.688**	*NP*	**-0.768**	-0.162
P	**0.696**	**0.693**	*MdPS*	**0.648**	0.488
Wil	**0.683**	0.327	*MPE*	**0.649**	**0.514**
Agr	**-0.681**	-0.371	*PAR*	**-0.744**	-0.157
Urb	-0.422	0.198	*SDI*	**-0.627**	0.035
WUI	-0.221	0.154			

FF: Fire frequency; *Pp*: Population density (inhab/km^2); *Tmax*: Annual maximum temperature (ºC); *P*: Annual precipitation (mm); *Wil*: Forest, shrubs and pastures (%); *Agr*: Croplands (%); *Urb*: Urban (%); *WUI*: Wildand-Urban interface (%); *WAI*: Wildland-Agriculture interface (%); *UAI*: Urban-Agriculture interface (%); *NP*: Number of patches; *MdPS*: Median patch size (ha); *MPE*: Mean patch edge (km); *PAR*: Perimeter-Area ratio (km/ha); *SDI*: Shannon's diversity index

Proportions of land covers (*Wil*, *Agr*, *Urb*) indicate an effect on spatial aggregation of fires, linked by larger distances in landscapes with higher wildland cover and closer distances in landscapes with a higher relative proportion of agriculture and urban areas. Interfaces between land covers are correlated to the time-independent spatial aggregation of fires, particularly, urban interfaces (*WUI* and *UAI*) seem to spatially concentrate fire occurrence, while *WAI* correlates with larger aggregates.

The time-independent spatial lag for aggregation $x24$ is clearly influenced by landscape composition and configuration, being negatively correlated to *SDI*, *NP* and *PAR* and positively to *MPE* and *MdPS*. In other words, wildfires aggregate over closer distances in diverse, fragmented landscapes with many patches, where patches are small and with complex shapes.

Table 6.4 shows the Pearson's correlation between the descriptors of spatial and temporal aggregation and the variables in Table 6.2 for landscape structure analyzed at the land use class level. Higher relative proportion of wildland organized in larger patches (*MPS*, *MdPS*), with more edges (*MPE*), and lower complexity (*PAR*) and number of patches (*NP*) favor larger spatial aggregation distances. In general, fire spatial aggregates grow in coarse-grained landscapes, with decreasing number of patches (*NP*) and compact shapes (*PAR*) in all land use classes. The temporal lag for aggregation of fires seems to be positively related to the presence of larger and complex agriculture patches (*MdPS*, *MSI*), and wildland edges (*MPE*).

Table 6.4. Pearson product-moment correlation coefficient between each variable in Table 6.2 with the descriptors of spatial and temporal aggregation. In bold, values over 0.5.

	Class	NP	MPS	MdPS	PSSD	MPE	ED	PAR	MSI
Spatial x24	*Agr*	**-0.696**	0.042	**0.659**	-0.108	0.378	-0.444	**-0.521**	**0.635**
	Wil	**-0.769**	**0.711**	**0.580**	**0.709**	**0.777**	-0.403	**-0.712**	0.109
	Urb	**-0.761**	0.107	0.200	-0.054	0.245	**-0.597**	**-0.575**	0.204
Temporal y16	*Agr*	0.009	-0.459	**0.572**	-0.344	0.161	0.421	0.073	**0.915**
	Wil	-0.257	0.163	0.389	0.145	**0.569**	0.459	-0.241	0.364
	Urb	-0.089	0.174	-0.200	0.304	0.062	0.227	0.040	0.044

Wil: Forest, shrubs and pastures (%); *Agr*: Croplands (%); *Urb*: Urban (%);*NP*: Number of patches; *MPS*: Mean patch size (ha); *MdPS*: Median patch size (ha); *PSSD*: Patch size standard deviation (ha); *MPE*: Mean patch edge (km); *ED*: Edge density (km/ha); *PAR*: Perimeter-Area ratio (km/ha); *MSI*: Mean shape index

6.4. Discussion

The methodology used appears to be suitable for identifying differentiated patterns of spatio-temporal aggregation for HCFs in environments with different fire incidence, such as Peninsular Spain, even though the influence of window size (40 km x 40 km) and study period remains to be explored in future research. This method is especially useful in regions with enough observations because its negative simulations' bias decreases as the number of observations increases (Gabriel and Diggle 2009). The largest spatial and temporal distances for wildfire aggregation were found with increased fire occurrence, which is coherent with higher risk levels that cause more fires over longer time spans and greater distances (*i.e.* Galicia, Asturias).

Our results provide statistical evidence for spatio-temporal structures around a maximum of 4 km and three months, but these aggregated structures lose strength when the spatial and temporal distances increase. These results agree with previous work (Alonso-Betanzos *et al.* 2003; Telesca and Pereira 2010; Juan *et al.* 2012; Fuentes-Santos *et al.* 2013; Chas-Amil *et al.* 2015; Pereira *et al.* 2015) which detected spatial and temporal structures in wildfire occurrence in Portugal and Spain, and the general state-of-knowledge on fire occurrence in Spain; at short time lags after a wildfire (<1 month), the probability of another fire occurrence is high at any distance in the range of 0-16 km. This is in agreement with the fact that in the short term, weather is the main driver of fire occurrence, and its effects are regional. When considering larger time lags (up to two years, or 24 months), the probability of fire occurrence is high only at short distances, closer than 3 km, which is consistent with the presence of local structural risk factors independent of the season or weather condition (*i.e.* arson, Serra *et al.* 2014). These results agree with Vega Orozco *et al.* (2012) and Pereira *et al.* (2015), which mention that aggregations between fires are more often at the local level and are not visible in larger distances (15 or 50 km).

Nevertheless, these aggregated patterns vary depending on location in Spain, suggesting the existence of varied spatio-temporal aggregation patterns of HCFs throughout the country, mainly related to fire frequency, weather and landscape structure variables, and hence, fire regimes.

Patterns in Atlantic (Ourense, Asturias) and Mediterranean Spain (the other areas) differ, which should be expected given their climatic and landscape structure characteristics than determine different fire regimes (Verdú *et al.* 2012). The spatial aggregation found (up to the maximum distance considered, 16 km) for all time lags under three months is likely determined by the duration of the bimodal fire season in the milder Atlantic region (February-April, June-August, three months), but also a consequence of a fragmented landscape and a generally high human risk and occurrence all year round. This pattern has been also identified in Portugal (Telesca and Pereira 2010) linked with the annual cycle of weather and vegetation phenology. Relatively stable conditions with higher rainfall (>1000 mm) and lower maximum temperatures extend risk over longer periods than in the Mediterranean (around 550 mm). Variations of weather events occur gradually in the NW, so the range of variation in temperature and precipitation is low within each Atlantic study area. In areas with higher precipitation there are more rainy days and, therefore, the number of fire-days decreases (Garcia-Gonzalo *et al.* 2012; Boubeta *et al.* 2015), so fires aggregate over longer time lags (Gabriel and Diggle 2009).

Wildfires seem to aggregate within fewer days in warm and dry Mediterranean regions (0-1.5 months). The annual weather cycle (Cardil, Molina, *et al.* 2014) favors multiple fires per day or in a few days in the summer fire season (De Haan and Icove 2011). Fire suppression resources sufficient to manage one fire may be challenged in high temperature days with simultaneous occurrences (Rachaniotis and Pappis 2006), which require exhaustive firefighting personnel management (Haight and Fried 2007). During high temperature-days, the temporal aggregation of HCFs decreases, since the occurrence of new fires is associated to those spells of extreme weather conditions (Padilla and Vega-Garcia 2011; Cardil, Molina, *et al.* 2014; Barreal and Loureiro 2015). Our temporal results are coherent with the occurrence of heat waves (high-temperature days, HTDs, Cardil, Molina, *et al.* 2014) that combine with more uneven human risk levels over coarser landscapes to render a lower fire occurrence, though these fires may have catastrophic results in terms of burned area.

Previous studies done in the Iberian Peninsula (Barreal and Loureiro 2015; Chas-Amil *et al.* 2015), found direct relations between population density and HCF occurrence; we found that higher population density causes distance-aggregation or spatially closer fires and dilates the time lag for wildfire occurrence, though the correlations were not very high. We used a single population density value for each study area (40 km x 40 km), but considering mean distances to towns (Badia-Perpinyà and Pallares-Barbera 2006; Padilla and Vega-Garcia 2011; Serra *et al.* 2014), access by road (Badia-Perpinyà and Pallares-Barbera 2006; Oliveira *et al.* 2014; Rodrigues and De la Riva 2014) and trails (Vasilakos *et al.* 2009; Chas-Amil *et al.* 2015) could also be adequate to account for the combined effect of population and access on HCF spatio-temporal aggregation.

Landscape structure clearly influences spatio-temporal patterns in wildfire occurrence. We found that wildfires aggregate spatially in closer distances in diverse, fragmented landscapes with many patches, where patches are small and with complex shapes. Ignitions have been found before to concentrate in highly fragmented landscapes (Martínez *et al.* 2009; Ruiz-Mirazo *et al.* 2012) or, in other words, in areas with a larger number of small patches (Henry and Yool 2004; Costafreda-Aumedes *et al.* 2013) in anthropic environments where patches are more compact (Henry and Yool 2004; Costafreda-Aumedes *et al.* 2013) with shorter edges (Gralewicz *et al.* 2012a), raising doubts about the role of patch shape on ignition. We propose that patch shape is relevant in combination with landscape composition, depending on the class under consideration and its dominance in the landscape. Landscapes with higher relative proportion of wildland coverage organized in larger patches (*MPS*, *MdPS*), with more edges (*MPE*), and lower complexity (*PAR*) and number of patches (*NP*) favor larger spatial aggregation distances. In general, fire spatial aggregates cover larger distances in coarse-grained landscapes, with decreasing number of patches (*NP*) and compact shapes (*PAR*) in all classes. These forest landscapes are typically created by land abandonment processes (Vega-García and Chuvieco 2006), expanding in all the Southern European Mediterranean countries for the last 60 years.

Landscape composition and patch shapes determine the presence of interfaces between land use classes. Urban interfaces with wildlands and crops (WUI and UAI) seem to spatially decrease the distance for fire clustering, while increasing percentages of wildland-agriculture interfaces correlate with larger aggregates, effectively showing a spatial extension in risk. Previous studies in HCF prediction (Catry *et al.* 2009; Chas-Amil *et al.* 2015) have linked wildfires to agricultural cover over wildland (Garcia-Gonzalo *et al.* 2012; Oliveira *et al.* 2014; Serra *et al.* 2014) and urban covers (Gonzalez-Olabarria *et al.* 2011). Fires in Spain often occur at the wildland-agriculture interface (Rodrigues and De la Riva 2014). The study areas with lower proportion of wildland-agriculture interface have wildfires clustered at shorter distances and they seem to aggregate on patch perimeters between these classes (*WAI*). This finding agrees with Gonzalez-Olabarria *et al.* (2011) and Martínez-Fernández *et al.* (2013) who have associated also higher proportion of wildland-agriculture interface with an increase of fire occurrence in Spain. Interestingly, the temporal lag for aggregation of fires seems to be positively related to the presence of larger and complex agriculture patches (*MdPS*, *MSI*), and wildland edges (*MPE*) pointing again to the importance of WAI interfaces in fire occurrence.

Beyond supporting previous findings in the field of fire occurrence prediction -related to fire frequency, weather and landscape structure variables- we would like to point out that our analysis contributes additional information that is useful for fire management. The descriptors of spatial and temporal aggregation (*x*24, *y*16) have different values in different study areas, and may serve as indicators for diverse applications, for instance, fire regimes classification concerning fire occurrence. A better knowledge of factors related to occurrence is useful for prevention and suppression, but the spatial and temporal dimensions added for each window of analysis have direct operational applications. Wildfire suppression performance in the fire season depends on number and behavior of active fires (Haight and Fried 2007); fire managers must make crucial decisions on the amount, type and allocation of the fire suppression resources required. For instance, risk levels and probability of new fire occurrences remain high in Ourense for up to three months, which allows for less mobility in the positioning of initial attack crews than in Badajoz with no temporal aggregation, or La Rioja (<1 month). Spatial risk at any time lag occurs under 0.75 km distance in La Rioja, but reaches 2.75 km in Caceres or Ourense, with implications for the design of the detection network. This persistent local risk is related to complex socioeconomic factors (Prestemon *et al*. 2012), but can be linked to landscape structure, which can be used to inform also general prevention and land planning to avoid risky structures.

6.5. Conclusions

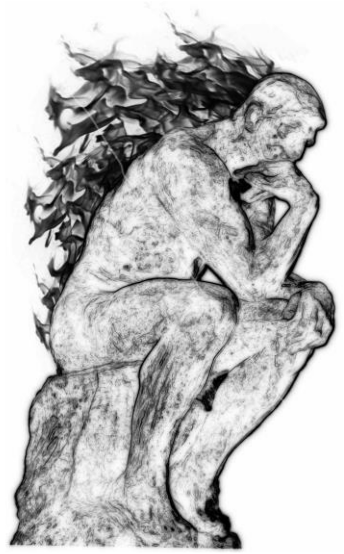
This study demonstrates the existence of spatio-temporal aggregation patterns of human-caused fires in Peninsular Spain. This aggregation reaches maximum values around 4 km and 6 months, but decreases with increasing temporal and spatial distances, and varies in different study areas. The probability of an additional fire is higher at any distance in the range of 0-16 km for short periods after a fire. On the long term, the probability of fire occurrence is higher at distances closer than 3 km from the location of a first fire. Temporal aggregation is mainly related to meteorology (annual rainfall and maximum temperature), while spatial aggregation is mainly linked to the structure and composition of the landscape. Our results suggest that wildfires temporally aggregate in fewer days in warm and dry Mediterranean regions than in milder Atlantic areas; wildfires spatially aggregate in fewer kilometers in highly fragmented wildland and agriculture landscapes with high land use diversity, and spatially disperse comparatively more in forest coarse-grained landscapes resulting from abandonment. Our results also suggest the existence of local risk conditions that persist over time, probably related to land structure and complex socioeconomic factors.

6.6. Acknowledgments

We gratefully acknowledge the Spanish Ministry of Environment, Rural and Marine Affairs (MAGRAMA) for allowing us to use the historical wildfire registry (EGIF).

Chapter 7.

General discussion



7. Discussion

7.1. Factors affecting firefighting resource management

The spatiotemporal pattern of HCF occurrence in Spain can be characterized from different approaches. There is an advanced state of the art in wildfire occurrence modeling around the world, to which this thesis contributes. Consequently, the efficiency of planning for the prevention and control of fires can be improved (Rachaniotis and Pappis 2006) in order to minimize vegetation damage and human losses. Anticipation and planning will be crucial in the future due to climate change forecasts that estimate the increase of temperature and the decrease of the precipitation and the number of precipitation-days (Yang *et al.* 2015). Fuel flammability, number and severity of wildfires are expected to increase (Wotton *et al.* 2003; Lee *et al.* 2012), especially in regions with high HCF occurrence (Turco *et al.* 2014) like Spain. Under drought and heat conditions predicted in the Mediterranean basin, the occurrence of multiple-fire-days will increase (Costafreda-Aumedes and Vega-Garcia 2014), which will in turn increase demands on firefighting resources more and more limited by budgets.

Large wildfire-incidence-related aspects (fire duration, fire type, fire size and fire load in the same province and day) were related to the deployment of suppression resources in Chapter 3. The number of firefighting personnel, terrestrial and aerial units deployed by Autonomous regions reached different response level. Prediction accuracy of human resources sent to fires was the best in all models and, on the contrary, terrestrial units' accuracy was the worst, showing different deployment patterns across Spain. This may be explained by the use of only fire-related factors. Trends in dispatching terrestrial units could be influenced by their proximity and accessibility to the fire. According to Mees and Strauss (1992), distance, access and steepness of forest roads could explain the higher use of terrestrial units in highly-populated and connected regions in the East and South peninsular Spain and the lower use in depopulated Castile and Leon. Also, usually aerial units are only justified when other resources cannot reach the fire site (Ganewatta and Handmer 2009), but are usually restricted by weather conditions, geographic or socio-economic factors (Donovan and Rideout 2003; Gebert *et al.* 2007; Kaval 2009), not included in this analysis.

At the national level, results of Chapter 3 show that the number of firefighting resources deployed in a wildfire increases in large fires, crown fires and long duration fires when the number of fires in the same day and province is low, in agreement with results by Gonzalez-Caban *et al*. (1986) and Donovan and Rideout (2003) in US, and Islam and Martell (1998) in Canada. However, our results contradict Hunter (1981), who found that response time and dispatching decisions were not affected by multiple-fire ignitions in Montana (US). This can be explained considering that this US environment and fire management significantly differ from the Spanish situation.

Regional deployment models show similar trends to the national model, but some differences were found in accuracy and selected variables, suggesting different firefighting resources management trends across Spain. Central and Mediterranean Spain had higher accuracy than other regions. Mediterranean regions, and especially South Mediterranean Spain, present strong relations between fire size and terrestrial and aerial units that can be explained by the high population density and the high availability of local firefighting resources.

On the contrary, NW Spain shows lower accuracy but also low average absolute errors, which are mainly related to the lower number of deployed resources in these regions. This lower accuracy agrees with Padilla and Vega-Garcia (2011) who concluded that NW Spain model accuracy of HCF occurrences was lower and the social and biophysical fire environments and related patterns of suppression resources management are more complex than elsewhere in Spain. However, the pattern of resources deployment also varies within NW Spain. Cantabria and Asturias presented more dispatched firefighting resources in surface fires than crown fires in comparison to Galicia. This difference is likely related to a higher topographic complexity and forest property fragmentation, which does not favor the transmittance of surface fires to tall forests.

Regional differences were also found to be linked to different fire regimes in Atlantic (NW Spain) and Mediterranean Spain, as pointed out by Verdu *et al*. (2012), Cardil and Molina (2013) and Moreno *et al*. (2014). Resource use in large fires in the Mediterranean region was substantially above the Atlantic average. This lowest Atlantic resource use indicates that burning conditions were not as extreme, assuming no budgetary restrictions in any Spanish region. However, some regional models in Galicia showed that the occurrence of multiple fires reduces available resources for large fires.

Management implications for high fire occurrence regions, like Spanish Atlantic and coastal Mediterranean regions, need to be considered in the current scenario of full-suppression policy in Spain. When fire load is high, fewer resources are available and late arrival to fires may happen, hence, fires may escape. Firefighting managers can improve in efficiency by training in advance fire behavior and meteorology (Molina *et al.* 2010) but also by optimizing resources selection and allocation, and pre-attack planning (Martin-Fernandez *et al.* 2002; Rodríguez y Silva 2007), based on fire occurrence prediction models.

Accordingly, understanding which weather-, physiography-, vegetation- and human-related factors favor fires is crucial to improve firefighting resources allocation or to manage efficiently the pre-attack planning process (Donoghue and Main 1985). For this purpose, descriptive models of past events and predictive models of potential future fire ignitions have been developed worldwide.

7.2. HCF occurrence modelling status

According to Finney (2005), the basis for forest fire occurrence modelling usually include the location, date and time, cause and size of each fire. However, fire occurrence data is not available in all countries. According to FAO (2010), only 64 countries (with 60% of the world's forest cover) have compiled national wildfire datasets, but only some of these countries are located in the most active fire areas, in Africa and Latin America. Undetected and/or unreported fires or missing fires are a common problem in many countries, due to lack of managerial resources, peak high fire loads, differing policies on minimum reporting size or occurrence in remote underpopulated regions with low values-at-risk (Lefort *et al.* 2004). When reliable fire accounts are unavailable, fire occurrence can only be estimated from remote sensing sources from burned areas or hotspots (Chuvieco *et al.* 2008), but precise ignition locations and causes are uncertain.

Spain has one of the longest registries in Europe (the second). Fire historical records include a cause field that allows separating natural fires from other human-related sources of ignition. Consequently, this thesis focuses on human-caused fires (HCFs) because the largest proportion of wildfires in Spain are related, directly or indirectly, to humans.

A literature review shows that the first HCF models were done by Donoghue and Main (1985) and Martell *et al*. (1987), which used, respectively, binary logistic regression and Poisson logistic regression for predicting the binary occurrence and the number of fires. The progressive availability of georeferenced data and higher computation capabilities has led to complex techniques such as CARTs, ANNs, SVMs, GAMs or MARS. Contrary to traditional models, these new methods are useful when dealing with large databases (currently known as Big Data), non-linear patterns and not normally distributed or highly correlated variables. However, most recent predictions of HCF occurrence focus on point pattern models (Rodrigues *et al.* 2014; Serra *et al.* 2014) instead of regions (*i.e*. Martell *et al.* 1987; Padilla and Vega-Garcia 2011). Currently, the analysis of the HCFs risk patterns has incorporated non-parametric spatio-temporal models, used to identify space and time aggregation patterns (Pereira *et al.* 2015). It seems that this innovation would continue to be applied and new mathematical methods will be developed.

Model accuracy under any technique seems to increase when the variability of fire characteristics (minimum fire size, study area size, binary/frequency response, and causality range) diminishes. Accordingly, the highest model accuracy occur when the number of ignition causes is low, or just one cause is under study (Costafreda-Aumedes and Vega-Garcia 2014). Consequently, for effectively implementing HCFs occurrence predictive models in any suppression management system, models should aim to minimize the variability of the input data by stratifying the different human-related processes that lead to fires (causes).

Also, the use of dynamic spatial and temporal models is possible as new wildfire records keep being compiled yearly by autonomic forest services.

The methodological evolution in HCF occurrence prediction has also increased models accuracy. The linear regression model of Altobellis (1983) showed low accuracy for all fire causes. When dealing with HCFs, the logistic regression model of Donoghue and Main (1985) had an accuracy of 0.49, while Oliveira *et al*. (2012) presented an accuracy of 0.95 using random forests in Mediterranean Europe. The higher accuracy increases the reliability of HCF occurrence models for operational use by fire managers. In this way, predicting locations and weather conditions is especially important in multiple-fire days or periods and have the potential to aid in detection and initial attack (Simard *et al.* 1978). However, the current level of operational implementation of the majority of these models is scarce, though some fire management systems have made provisions for their use (Chuvieco *et al.* 2010).

7.3. Factors that affect HCFs in Spain

Across the abundant research done until now, many spatial and temporal factors have been found to be related to, or to be able to explain, HCF occurrence behavior. Factors with high temporal variability are mainly based on weather and weather-driven indices related to drought or vegetation moisture. By contrast, the spatial pattern is more often related to physiography, land cover or socioeconomic factors, with inherent low temporal variability or the unavailability of frequently updated data. Worldwide, HCFs have similar spatial and temporal trends, but variations have been found between and within habitats. However, trends depend on the amount and type of the input variables considered by the authors (Plucinski 2012).

A great amount of weather variables has been selected before, being temperature, precipitation and relative humidity the most typical variables in HCF occurrence modelling. The highest wildfire occurrence probability is favored by high temperatures and low precipitation and relative humidity everywhere. In these conditions, vegetation suffers water deficit and cannot absorb enough water from the soil for growing and, subsequently, the moisture content of litter and fine fuels, medium compact organic layers and deep organic layers decreases. Thereby, vegetation dries up and becomes highly flammable. Accordingly, drought indices related to wildfire risk (FFMC, DC and DMC) and fire behavior indices associated with them (*i.e.* FWI, ISI, McArthur) increase. Canadian FWI, FFMC, DMC and DC have been found the most significant indices in most of regions (major habitat types).

Vegetation driest conditions occur mainly in summer, where most fires take place (Albertson *et al.* 2009; Ager *et al.* 2014), but also happen in early or late winter in those regions with marked seasonality, like the Mediterranean region (Costafreda-Aumedes and Vega-Garcia 2014). Wildfire occurrence is favored by the lack of precipitation during fire-days and previous dry-days (Cardil, Molina, *et al.* 2014). In this way, precipitation during the fire season increases relative humidity and soil water availability for vegetation while decreasing ignition potential. By contrast, annual and non-fire season precipitation increases fine fuels (especially grasses and shrubs) that will be later available for burning.

When considering physiography, elevation and slope have been the most selected variables in most of habitats / regions and studies. Generally, HCFs tend to occur in low areas and gentle slope. However, this behavior depends on human activity. Fires related to pastures and forests (González-Olabarria *et al.* 2015) are mainly located in the mountain areas and, arson (Vasconcelos *et al.* 2001) and negligence fires (Juan *et al.* 2012; Serra *et al.* 2013) occur most often in flat or moderate slopes.

Vegetation differs by major habitat types. However, it is possible to identify some trends around the world with regard to landscape composition. Conifers seems more prone to burning. For landscape configuration, wildland-agriculture and wildland-urban interfaces are significant factors in those major habitat types in which they have been considered. Urban, forest, and agriculture land uses coexist and intermix in these anthropic landscapes.

According to Chapter 5, landscape configuration reflects the impact of humans on the territory. I found as most significant landscape metrics on peninsular Spain, Shannon's diversity index, mean patch edge and mean shape index. They have been also found significant in other studies; Henry and Yool (2004) found that species diversity and shape and compactness of patches were included in the best model to predict fire occurrence in Arizona using remote sensing images. Ruiz-Mirazo *et al*. (2012) found that the occurrence of pastoral fires is boosted with high proportion of large patches of moderate and low grazing in the landscape with small and elongated patches of intensive grazing. When models include other spatial and temporal variables, the significance of landscape metrics differ. Martínez *et al*. (2009) tested fragmentation, patch density and median patch size, but only agriculture fragmentation was significant in their best model. Ortega *et al*. (2012) tested eight landscape metrics to model wildfire occurrence by periods and only landscape diversity and patch size were significant in 1985-1998. Gralewicz *et al*. (2012b) found that forest patch size was the main discriminant variable for Canadian wildfires, while the number and proportion of forest patches were not included in the best model. Finally, Martinez-Fernandez *et al*. (2013) found significant only the density of agricultural patches, but discarded land fragmentation.

In this thesis, HCF occurrence increases in diverse landscape mosaics with fewer edges and compact patches. The North Atlantic Spain landscape configuration (the region most affected by HCFs in Spain) comprises a set of small and highly fragmented patches with high diversity of land uses due to its diverse topography, rainfall and humidity. Its landscape is associated with traditional use of fire for livestock feeding and the low forest profit by local people (Torre Antón 2010). In the Mediterranean region, urban development (with compact patches), linked to population density, especially in summer, overlaps with dry weather to increase fire risk (Vilar del Hoyo *et al.* 2008). Most regions with low predicted HCFs are fertile croplands of the Ebro and Guadalquivir river basins and the Meseta Central, where landscape mosaics characterize by large extension of croplands and scarce natural vegetation coverage.

At more detailed scale (forest stand), HCF patterns also differ according to vegetation structure; tree or forest structure variables influence wildfire occurrence (González *et al.* 2006), but not always in a similar way. The understory of high tree density temperate forests is mainly composed by ferns and forbs (moist shrubs), and has low wildfire occurrence probability. By contrast, shrubs in other regions have low moisture content under warm and dry conditions, favoring wildfire occurrence (Badia *et al.* 2011; Oliveira *et al.* 2014). However, the combined influence of neighboring major habitat types in a study may mask particular vegetation patterns of fire occurrence.

HCF occurrence varies also by the presence or abundance of human constructions and activities (Oliveira *et al.* 2014) and their pattern determines the number and distribution of wildfires. This pattern varies geographically and temporally. In this way, in Spain (MAGRAMA 2015) and US (Morrison 2007) more than half of HCFs start along infrastructures such as roads, tracks, trails and railways and act as conveyers for arsonists, careless drivers and campers.

Regarding socio-economic indicators, population density is the most important factor related to the occurrence of HCFs. High population densities are related to high wildfire occurrence, except when high population density aggregates in large urban areas (*i.e*. Penman *et al.* 2013; Beccari *et al.* 2015) where there is lower availability of fuels. This is in agreement to Donoghue and Main (1985) who have observed an increase of HCFs when increasing the non-metropolitan population density. In relation to population density, HCFs occur most often near settlements or highly built-up areas, but this trend depends on the causality agent. In this way, Olabarria *et al.* (2015) have found that the distribution of arson, smokers, powerlines and camp fires in NE Spain occur near coastal areas, where the population density is higher.

Productive activities on the land seem related to wildfire occurrence. In this way, cropland coverage, proximity to them, or other variables related to intensive land use are risk factors. In addition, livestock density is often directly associated with HCF occurrence but relations are not linear and depend on the quantity of livestock. In this way, Dlamini (2010) and Romero-Calcerrada *et al*. (2008) concluded that intermediate livestock densities were associated with an increased occurrence of HCFs in Swaziland and Central Spain, respectively. Shrub removal for regenerating pastures and feeding livestock tend to locate in areas with lower population density and, in agreement to (*i.e*.) Gonzalez-Olabarria *et al*. (2015), further from metropolitan areas.

Outdoor recreational activities are risky activities related to negligent or careless fires. In this way, proximity to campgrounds or fishing areas are often carried out during bank holidays, weekends and holidays. They are especially popular in late spring and summer, being the most favorable periods for ignition. These fire ignitions mainly occur in low population density areas because they are linked to hiking, camping and hunting in public forests, which are usually located far from highly populated areas.

7.4. Spatio-temporal aggregation of HCFs in Spain

In turn, weather, physiography, vegetation and socioeconomic activities that take place in Spain determine the spatio-temporal aggregation of HCFs. These spatial and temporal distances for wildfire aggregation increase with increased fire occurrence, which is coherent with higher risk levels caused by high number of fires over longer time spans and greater distances.

In agreement to Alonso-Betanzos *et al*. (2003), Telesca and Pereira (2010), Juan *et al*. (2012), Fuentes-Santos *et al*. (2013), Chas-Amil *et al*. (2015), Pereira *et al*. (2015), HCFs aggregate spatial and temporally in the Iberian peninsula. Results of Chapter 6 show that these aggregations maximize around 4 km and 180 days, for a selection of windows representing a variety of conditions in Spain. However, the aggregated structures lose strength when spatial and temporal distances increase. In general, shorter time spans than a month after a wildfire, HCF occurrence is high at any distance in the range 0-16 km. This is in agreement with the fact that in the short term, weather is the main driver of wildfire occurrence, and its effect are regional. At larger time spans of two years, the probability of fire occurrence is high only at distances closer than 3 km. The spatial aggregations are consistent with the presence of local structural risk factors independent of the season and weather conditions (*i.e*. arson, Serra *et al.* 2013). These results agree with Vega Orozco *et al*. (2012) and Pereira *et al*. (2015) which conclude that wildfire aggregations more often occur at local level and are not visible at large distances (15 – 50 km).

However, HCF spatio-temporal patterns vary throughout Spain in relation to fire frequency/return interval, weather and landscape structure. Aggregation patterns differ between Atlantic and Mediterranean Spain, as expected by their climatic and landscape structure that determine different fire regimes (Verdú *et al.* 2012). In the milder Atlantic region, the spatial aggregation for time lags under three months is determined by the duration of the bimodal fire season (February-April and June-August). The spatial aggregation is also the consequence of landscape fragmentation and high HCF risk and occurrence in the region. This pattern was identified in Portugal by Telesca and Pereira (2010) who linked it with the annual weather cycle and vegetation phenology. High rainfall and low maximum temperatures extend risk over longer periods than in the Mediterranean. The highest precipitation, the highest number of rainy days and, therefore, the lowest number of fire days (Garcia-Gonzalo *et al.* 2012; Boubeta *et al.* 2015) and the least aggregation over time spans (Gabriel and Diggle 2009) than extent in mild conditions.

In warm and dry Mediterranean regions, HCFs aggregate within fewer days. The annual weather cycle, with high temperature periods, favors the occurrence of multiple fires in low number of days during the fire season (De Haan and Icove 2011). These multiple-fire conditions require exhaustive management of the firefighting personnel and terrestrial and aerial units (Haight and Fried 2007). The occurrence of new HCFs is associated to spells of extreme weather conditions (Padilla and Vega-Garcia 2011; Barreal and Loureiro 2015) caused by heat waves (Cardil, Molina, *et al.* 2014) and, accordingly, the temporal aggregation of wildfires decreases and clusters in lower numbers of days.

Spatially, the aggregation pattern of HCFs is influenced by population density and landscape structure and composition. In agreement to Barreal and Loureiro (2015) and Chas-Amil *et al*. (2015), as seen in Chapter 4, HCF distance-aggregations are related to higher population density, which dilates the time lag for wildfire occurrence, though the correlations were not very high.

Landscape structure influences fire occurrence (from Chapter 5), and their spatio-temporal aggregations. Our results show that HCFs in Spain spatially aggregate in closer distances in diverse and fragmented landscapes with small and complex-shape patches. These results agree with the main conclusions of Chapter 6 where we found that HCFs are associated to diverse and highly fragmented landscapes with large number of small and compact patches. In addition, patch shape is relevant in combination with landscape composition, depending on the land use under consideration and its dominance in the landscape. Landscapes with higher coverage of non-fragmented, large and compact wildland patches favor larger spatial aggregation distances. These wildland landscapes are the common result of land abandonment processes (Vega-García and Chuvieco 2006) in SE Mediterranean countries for the last 60 years.

In relation to landscape composition, spatio-temporal HCF aggregation patterns in Spain are related to the presence of interfaces between land use classes. Previous studies found that wildfire occurrences have been linked to agricultural cover over wildland (Garcia-Gonzalo *et al.* 2012; Rodrigues and De la Riva 2014; Serra *et al.* 2014) and urban covers (Gonzalez-Olabarria *et al.* 2011). Our results show that wildland-urban and agriculture-urban interfaces decrease spatial aggregation distance, while the wildland-agriculture interfaces increase spatial aggregation distance. Accordingly, short spatial aggregation distances have been found with low proportion of wildland-agriculture interface and, thus, wildfires seem to aggregate close to the patch perimeters between both classes. These results agree with Gonzalez-Olabarria *et al*. (2011) and Martínez-Fernández *et al*. (2013) who have related higher proportion of wildland-agriculture interface to an increase of wildfire occurrence in Spain. Temporally, longer temporal lag for aggregation of human-caused wildfires is related to the presence of larger and complex agriculture patches and longest wildland edges, showing again the importance of wildland-agriculture interfaces in wildfire occurrence.

7.5. Identifying future research needs in HCF occurrence modeling

Traditionally, HCF occurrence has been considered at regional level, either by administrative divisions (townships, autonomous regions or countries), land ownership or other local arbitrary divisions. The current modeling trends on wildfire occurrence and risk analysis considers supranational regions (*i.e*. Oliveira *et al.* 2014 in Mediterranean Europe). In this way, Chuvieco *et al*. (2008), Krawchuck *et al*. (2009), Knorr *et al*. (2014) and Bedia *et al*. (2015) used remote sensing data (hotspots of burned area products) to study the global pattern of wildfires. These global wildfire ignitions become from remote sensing data that has been mainly recorded by MODIS, VIIRS and Seviri from the different fire data programs such as Globe Fire Data (www.globefiredata.org), Active Fire Data (earthdata.nasa.gov) or Global Fire Monitoring (www.gmes-atmosphere.eu).

In addition, and according to Finney (2005) fire records should be characterized by location, date and time, and cause , so the best accuracies in wildfire modeling come with high number of records and their associated information. However, the lack of complete fire occurrence data in some countries hinders accurately locating the ignition of each event and, therefore, to model adequately wildfires (due to lightning- and human-caused fires occur generally in different temporal conditions and spatial locations). Also, inaccuracies in sampling or the lack of records in the databases hinders subsequent modeling. Therefore, in those countries without fire history datasets or with missing records, the research or managerial communities should make an effort in registering accurately all wildfires occurred for increasing the global wildfire databases. Supranational initiatives such as JRC (EFFIS), which is compiling all wildfires occurred in 21 European countries since 2004 (Camia *et al.* 2010), are invaluable for these modelling purposes (Ganteaume *et al.* 2013; San-Miguel-Ayanz *et al.* 2013).

Traditional models further limit prediction capacity if they use simple or binary dependent variables. For example, binary regression models (fire / no fire) on administrative divisions do not consider all fires and only consider the first ignition (at least one), which loses information and, therefore, accuracy. In this regard, higher number of fire ignitions in longest periods and the improved computational capabilities allow using complex statistical methods related to point analysis and increase the accuracy of models. Accordingly, recent models are focused on the spatial-explicit fire ignitions (*i.e*. Amatulli *et al.* 2007) or their spatio-temporal-explicit pattern (*i.e*. Vega Orozco *et al.* 2012). These point pattern methods allow incorporating the space-time aggregations of HCFs showed in Chapter 6, which have not been considered in previous studies. Therefore, HCF occurrence models should consider that the occurrence of new fires is spatially and temporally influenced by nearby fires, but loses strength at higher spatial and temporal distances.

Most of previous models analyzed HCF occurrence in a long-time period, but the quantity and causative agent of wildfires varies seasonally (Costafreda-Aumedes and Vega-Garcia 2014) and, therefore, wildfire occurrence models should account for variability in space (Amatulli *et al.* 2007) but also in time.

Finally, the spatio-temporal point pattern models proposed for the future will allow the modelling of not only potential new fires, but also improving firefighting resources allocation when they are used in a mixed model. Therefore, the most important goal of these techniques in suppression management is to minimize the response time in firefighting arrival and the environmental and human losses.

Chapter 8.

General conclusions

8. Conclusions

1. This thesis aims to contribute to the advanced state of the art in wildfire occurrence modeling; it proves that it is possible to characterize the spatiotemporal pattern of HCF occurrence in Spain from different approaches, and account for regional differences. In turn, it would be possible to improve planning efficiency for prevention and control of fires in order to minimize vegetation damage and human losses.
2. The number of firefighting resources deployed in Spain increases in large fires, crown fires and long duration fires and in days without multiple-fire situations. However, deployment pattern varies throughout the territory. Mediterranean fires exhibit a strong relation between fire size and terrestrial and aerial units. Firefighting resources in the Atlantic region show unique deployment trends, since in Cantabria and Asturias more suppression resources are engaged in surface fires than in crown fires.
3. The first fire occurrence models developed worldwide were simple and did not consider causative agent (natural and people-caused), but the progressive implementation of new mathematical techniques and the improving of the ignition source analysis (through remote sensing and field investigation) allows nowadays the use of complex techniques, stratifying lightning- and human-caused fires. This progress also implies an increase in the accuracy of models.
4. The most relevant variables used worldwide in models include:
    - Temperature, precipitation and relative humidity, which are the most representative temporal variables in HCF modelling. High HCF occurrence occurs at high temperature and low precipitation and relative humidity. Under these conditions, vegetation dries and becomes combustible. Canadian FWI, FFMC, DMC and DC are the most significant weather-derived indices for most major habitat types.
    - The behavior of the spatial variables is similar throughout the world and, generally, when human presence increases, HCF occurrence increases. This pattern changes depending on the causative agent. Pastures and forests fires occur in mountain areas and low population densities while arson and negligence fires occur mostly in low or middle slopes, on holidays and weekends, with high human presence.

- The relation between HCFs and vegetation varies by major habitat type. However, HCFs tend to occur more frequently in conifer forests and in agricultural-forestry and wildland-urban interfaces. The main differences in vegetation are in the shrub response between warm and temperate habitats.

5. Landscape configuration in Spain determines the pattern of HCFs. Fires occur most frequently in landscapes with high land use diversity and compact patches with short edges, especially significant in NW Spain and coastal Mediterranean area.

6. The maximum spatiotemporal aggregation of HCFs in Spain occurs around 4 km and 180 days. These structures lose strength when the spatial and temporal distances increase.

   - The largest temporal aggregations occur in Atlantic regions with higher precipitation and lower maximum temperatures, and HCFs aggregate in shorter periods in hot and dry weather conditions as occur in the Mediterranean region.

   - The spatial aggregation of HCFs is influenced by population density and the landscape composition and configuration. In this way, the largest aggregation distance occurs with high population density, highly fragmented landscapes with compact patches low percentage of wildland-urban and agriculture-urban interfaces, and high percentage of wildland-agriculture interfaces.

7. This thesis offers new perspectives and approaches for HCF modelling in Spain. However, the analysis of wildfire occurrence at supranational level within similar major habitat types, and considering specific causes of ignition, should also render useful information on current and future trends. This larger scale is supported by the current higher availability of geodata and computational capacity, which allows complex methods, such as point pattern analysis, to be applied to larger study areas. In contraposition to more traditional methods, point pattern analysis can contribute to explain space-time HCF aggregations, like those observed in the study areas in Spain, in other world regions with high fire incidence.

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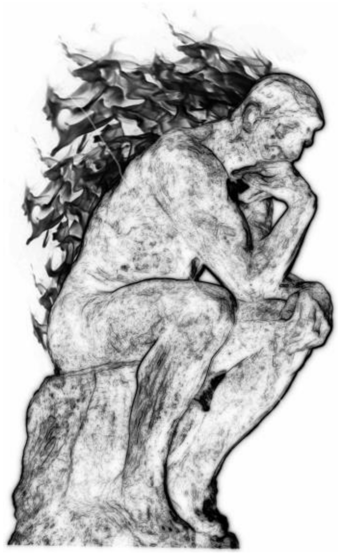

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